Article

Journal of Marketing
2019, Vol. 83(6) 21-42

DOI: 10.1177/0022242919873903
journals.sagepub.com/home/jmx

The Role of Marketer-Generated Content in Customer Engagement Marketing

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Abstract

Despite the demonstrated importance of customer sentiment in social media for outcomes such as purchase behavior and of firms' increasing use of customer engagement initiatives, surprisingly few studies have investigated firms' ability to influence the sentiment of customers' digital engagement. Many firms track buyers' offline interactions, design online content to coincide with customers' experiences, and face varied performance during events, enabling the modification of marketer-generated content to correspond to the event outcomes. This study examines the role of firms' social media engagement initiatives surrounding customers' experiential interaction events in influencing the sentiment of customers' digital engagement. Results indicate that marketers can influence the sentiment of customers' digital engagement beyond their performance during customers' interactions, and for unfavorable event outcomes, informational marketer-generated content, more so than emotional content, can enhance customer sentiment. This study also highlights sentiment's role as a leading indicator for customer lifetime value.

Keywords

customer engagement, customer lifetime value, customer sentiment, econometric modeling, marketer-generated content, social media

Online supplement: https://doi.org/10.1177/0022242919873903

A growing trend among marketers is the use of social media to drive customer engagement (Goh, Heng, and Lin 2013; Hanson, Jiang, and Dahl 2019; Harmeling et al. 2017; Sheng 2019). Customer engagement initiatives, defined as organizational initiatives that facilitate firm–customer interactions to foster emotional or psychological bonds between customers and firms (Gill, Sridhar, and Grewal 2017; Kumar and Pansari 2016) are increasingly used by marketers. Such engagement initiatives on social media involve marketers' posts surrounding experiential events, defined as firm–customer interactions that are finite in time (Nicolao, Irwin, and Goodman 2009). This study examines how firms should leverage such initiatives based on firm performance during experiential events. Consider, for example, an event such as a professional sports competition. Following a poor performance, such as a loss, can the team effectively engage fans and enhance the sentiment of those fans' social media contributions based on the team's posts on social media, and if so, what should those posts say? Should the team's posts appeal to fans' emotions or instead offer informational content such as contributing factors for a disappointing outcome? Similarly, after a win, should the team post on social media, and should the content be emotional in nature (e.g., images of elated fans or players) or informational (e.g., game or player statistics or details regarding upcoming events)? The goal of this study is to provide insight regarding important customer outcomes from strategically adjusting marketer-generated

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content (MGC) surrounding customers' experiential events based on marketers' performance during those events.

We examine how marketers should adjust both the volume and content of their social media posts based on the firm's performance during such experiential events. Our key outcome of interest is customers' digital engagement, defined as "brand-related cognitive, emotional or behavioral activity during or related to focal consumer-brand interactions" (Eigenraam et al. 2018, p. 102), and our focus is social media engagement activities. In particular, we are interested in the sentiment, or valence (negative or positive), of consumers' comments on brand-related social media pages in reaction to firms' social media content surrounding consumer–brand interactions. Whereas organizers of events such as concerts or sports competitions often share emotional content to drive engagement during or after performances, marketers also use social media to provide informational content surrounding such events. For example, during an extensive delay before the first-ever concert (Garth Brooks) at the Mercedes Benz stadium in Atlanta, the venue's management took to social media to keep fans informed regarding efforts to resolve sound issues in the stadium in an attempt to reduce negative sentiment expressed by attendees based on their disappointing experience (Bennett 2017).

We define "event outcomes"[1] as the observed level of firm performance during customers' experiential interactions. In formulating our conceptual arguments, we draw on customer engagement theory, which proposes that customers' brand- or firm-related experiences influence their emotional or affective states, which then influence the nature of their indirect engagement with firms, including contributing positive word of mouth on social media (Pansari and Kumar 2017). We argue that MGC surrounding event outcomes will influence the sentiment of customers' digital engagement beyond firms' objective performance during those events. In testing these relationships, we address two key questions:

1. Can marketers' posts (i.e., MGC) surrounding event outcomes influence the sentiment of consumers' comments above and beyond the characteristics of the event outcomes themselves?
2. What type of content is most effective in moderating the relationship between experiential event outcomes and the sentiment of customers' digital engagement?

In answering these questions, this study makes several important contributions. First, it demonstrates how MGC content, whether informational or emotional, can moderate the relationship between event outcomes and the sentiment of customers' digital engagement. In doing so, it offers guidance to firms in strategically managing both the volume and content of their social media contributions based on their performance. Second, this study captures the richness of customers' digital engagement by focusing on the sentiment of such engagement as its key outcome, as opposed to metrics such as comment volume or sharing activity, which do not consider the tone of customers' social media contributions. Third, this study provides a granular view of the environment in which firms make decisions regarding their MGC strategies by focusing on the customer-event level as opposed to an aggregated series of events. Furthermore, given its emphasis on firms' objective performance during customers' experiential events, its findings may be particularly applicable for firms with the ability to adjust MGC in accordance with their own internal performance metrics, without requiring data from customers.

Although research has begun to examine the value of customers' social media contributions for firms, most studies have examined customers' digital engagement without aligning with MGC or customers' brand- or firm-related experiences. The lack of research aligning these concepts is surprising because many firms track buyers' offline interactions (e.g., presence at events), design online content to coincide with customers' experiences, and face varied performance during events, enabling the modification of MGC based on event outcomes. Studies focusing on customers' brand- or firm-related interactions have also tended to use experimental approaches, introducing such interactions through scenarios (He et al. 2016; Lopez-Lopez, Ruiz-de-Maya, and Warlop 2014) or selecting respondents on the basis of negative experiences (Misopoulos et al. 2014; Presi, Saridakis, and Hartmans 2014) rather than using objective data on firm performance during the interactions. One body of work incorporating customer perceptions of firm performance during such interactions is that focusing on customer reviews on sites such as Amazon or travel-related forums (Farhadloo, Patterson, and Rolland 2016; Gu and Ye 2014). However, most of these studies either do not examine the role of MGC (Farhadloo, Patterson, and Rolland 2016) or do not consider the content of MGC (Gu and Ye 2014; Homburg et al. 2015).

Table 1 compares our study with relevant research focusing on empirical investigations of firms' efforts to drive customer engagement through their social media contributions, irrespective of whether customers' engagement is digital. We also identify whether studies include objective performance data regarding customers' firm- or brand-related interactions, as we do.

To answer our questions, we conducted two studies. For the first, we built an unprecedented longitudinal database featuring brand-related customer-level social media metrics including marketers' posts surrounding events and customers' comments on those posts. The context is a European soccer team's Facebook fan page, which provides regular chances for brand interaction and enables us to capture variance in event outcomes. We also capture objective characteristics of event outcomes, including firm performance and expectations regarding those outcomes. Attending brand-sponsored experiential events such as sports is also common in settings such as entertainment or

[1] We use the terms "events," "customer interactions," "interaction events," and "experiential events" interchangeably, with each referring to a customer's brand- or firm-related experiences during events that are finite in time.

Table 1. Study Comparison with Relevant Literature.

				Accounted for in the Model				
				MGC		UGC		Objective
Citation	Research Focus	Context	New Insights	Content	Volume/ Presence	By Focal Customer	By Others	Event Outcome
This study	Interplay between firms' MGC and objective event outcomes in influencing sentiment of customers' digital engagement	European soccer team's Facebook fan page surrounding customers' experiential events	MGC surrounding experiential events can influence sentiment of customers' digital engagement beyond firms' objective performance during those events.	X	X	X	X	X
Tellis et al. (2019)	Drivers of online sharing of MGC	Online video ads on YouTube for 109 brands	Informational content negatively affects sharing, except in risky contexts, whereas positive emotions positively affect sharing.	X	X	X		
Grewal, Stephen, and Coleman (2019)	How posting about products on social media affect consumers' purchase intentions	Lab and MTurk experiments using FB and Pinterest, with outcomes measured for backpack/tote bag brands	Posting products on social media framed as identity-relevant can reduce purchase intentions for the same and similar products.		X	X		
John et al. (2017)	Whether "liking" a brand influences brand evaluations	Lab experiments using soda brands' FB pages	Endorsement on FB is less effective than endorsements external to FB.		X[b]	X[a]	X	
Mochon et al. (2017)	How FB page likes affect offline customer behavior	Wellness brand's FB page	Likes on FB pages drive customers' offline behavior.		X[b]	X[a]		
Baker, Donthu, and Kumar (2016)	How WOM conversations about a brand relate to purchase and retransmission intentions	Survey regarding WOM conversations for 15 product categories	Positive, mixed, and negative sentiment increases intentions to retransmit WOM messages.			X		
Kumar et al. (2016)	MGC's effect on customer behavior and profitability	Wine and spirits retailer's social media page	MGC in social media affects customer behavior beyond other communication tools.		X	X		
Saboo, Kumar, and Park (2016)	Assessing both consumer responsiveness and real-time ROI of direct-marketing efforts	Home improvement retailer's online direct marketing campaign	Influence of direct marketing on sales varies significantly over the customer life cycle.		X			
Beukeboom, Kerkhof, and De Vries (2015)	Whether following a brand's FB updates affects brand evaluations	Paint brand's FB page	Following a brand's FB updates affects evaluations.		X	X		

(continued)

Table 1. (continued)

				Accounted for in the Model				
				MGC		UGC		Objective
Citation	Research Focus	Context	New Insights	Content	Volume/ Presence	By Focal Customer	By Others	Event Outcome
Homburg, Ehm, and Artz (2015)	Consumer reactions to firms partaking in consumer-to-consumer conversations	Do-it-yourself retailer's online community	Consumers show diminishing returns to digital engagement with a firm.		X	X	X	
Manchanda, Packard, and Pattabhiramaiah (2015)	Effect of customers' joining firm social media community on expenditures	Media retailer's online community	Joining an online community leads to greater expenditures.			X		
Xie and Lee (2015)	Effects of exposures to earned and owned social media activities on purchase	Fast-moving consumer goods firm group online fan page	Exposure to brands' social media activities influences brand purchase likelihood.		X		X	
Zadeh and Sharda (2014)	Customer reactions to firms' crowd engagement activities	Twitter information streams of >120 brands	Popularity growth patterns of brand post contents can be simulated via point process models.		X	X	X	
Kumar et al. (2013)	How social media can be used to generate WOM and influence performance	Ice cream brand's FB and Twitter pages	Social media campaigns affect sales, ROI, and positive WOM on social media.		X	X	X	
Goh, Heng, and Lin (2013)	Impacts of both UGC and MGC on repeat purchase behaviors	Asian apparel retailer's social media fan page	Digital engagement positively impacts purchase expenditures.	X[c]		X	X	
Rishika et al. (2013)	Effect of participation in firm social media efforts on customer value	Wine and spirits retailer FB page	Customer participation in firm social media efforts impacts frequency of customer visits.			X	X	
Nam, Manchanda, and Chintagunta (2010)	Effect of service quality on customer acquisition, accounting for spillover effects from WOM	Video-on-demand service	Effects of negative WOM from poor performance are greater than effects of positive WOM from good performance.				X[d]	X

[a]UGC captured as "Likes."
[b]MGC captured as invitation or incentive to join FB page.
[c]MGC captured as information richness.
[d]Not modeled directly; rather, assumed based on geographic proximity to other subscriber.
Notes: FB = Facebook; WOM = word of mouth; ROI = return on investment.

fundraising activities. As evidence of these sectors' importance, the value of the global entertainment and media market alone is expected to top $2.2 trillion by 2021 (Watson 2018). For the second study, we conducted a scenario-based experiment on Amazon Mechanical Turk (MTurk), modifying the levels of event outcome and MGC in the different scenarios.

We find that marketers can influence the sentiment of customers' digital engagement beyond the marketers' objective performance during experiential events—and in the case of unfavorable event outcomes, informational MGC, more so than emotional content, offers a substantial means to improve the sentiment of customers' digital engagement. Through a series of post hoc analyses, we find that with as few as two additional informational posts following a negative event outcome, marketers can increase the sentiment of customers' digital engagement by approximately 10%. Emotional content has a positive and significant influence regardless of the outcome of the event. Drawing on our ability to link social media variables to transactions, we also highlight in our implications section sentiment's role as a leading indicator of customer lifetime value (CLV). Whereas Gill, Sridhar, and Grewal (2017) describe engagement initiatives as creating value for customers but not intending to prompt sales, we explore the potential association of such initiatives with customer purchases.

Conceptual Framework

Customer engagement theory (Pansari and Kumar 2017) serves as an overarching theoretical perspective in which to ground our conceptual framework. We furthermore build on related research focusing on the concept of customer engagement initiatives (Gill, Sridhar, and Grewal 2017). From a customer engagement perspective, we argue that (1) customers' positive (negative) brand- or firm-related experiences will be associated with positive (negative) affective states (Nicolao, Irwin, and Goodman 2009); (2) customers' affective states will, in turn, influence the nature of their digital engagement with the firm (Pansari and Kumar 2017), which we capture through sentiment; and (3) by managing the information environment in which firms and customers interact, as with their customer engagement initiatives, firms can influence the sentiment of customers' digital engagement. In other words, through their social media activities, firms can reinforce positive experiences or enhance customers' knowledge about a brand when questioning poor experiences (Van Doorn et al. 2010), thereby enhancing the sentiment of their digital engagement. We also explore the role of the sentiment of customers' digital engagement as a leading indicator of CLV, consistent with research linking customer sentiment to purchases (Baker, Donthu, and Kumar 2016; Goh, Heng, and Lin 2013).

Next, we conceptualize our key variables. We then describe the expected relationships, drawing on customer engagement theory with supporting arguments from research related to firms' use of social media to influence customer mindset metrics (Colicev et al. 2018) and drive customers' digital engagement (Gill, Sridhar and Grewal 2017).

Conceptualization of Key Variables

Sentiment of digital engagement. We conceptualize our dependent variable, the sentiment of customers' digital engagement, as the tone or valence (negative or positive) of customers' comments on brand-related social media pages in reaction to firms' social media content surrounding particular consumer–brand interactions. We focus specifically on comments posted by individuals on brand-related social media pages in response to firms' own posts, consistent with the notion of firms' efforts to facilitate firm–customer interactions (Gill, Sridhar, and Grewal 2017). In addition, our emphasis is on comments that are (1) not commercially motivated, (2) not incentivized by firms, and (3) interactive in nature (Baker, Donthu, and Kumar 2016). Outside our purview are (1) consumers' comments controlled by firms (e.g., firm posts of buyer testimonials; Colicev et al. 2018), (2) online word of mouth not on a brand-related social media page (e.g., reviews on sites such as Amazon, consumer posts on non-brand-related issues), and (3) content incentivized by firms.

Event outcomes. As mentioned previously, event outcomes refer to the observed firm performance during customers' brand- or firm-related interactions. We focus on individuals' experiential interactions with a firm or brand, consistent with research on service encounters (Micu et al. 2017), and postconsumption product perceptions (Babić Rosario et al. 2016). While overall satisfaction (Farhadloo, Patterson, and Rolland 2016; He et al. 2016; Misopoulos et al. 2014) and brand perceptions (Schweidel and Moe 2014) reflect customers' experiences, these concepts are often broader, reflecting a series of interactions or experiences. These concepts are also perceptual as opposed to objective. In one of the few studies to include objective measures of firm performance during customers' firm or brand-related interactions, Gijsenberg, Van Heerde, and Verhoef (2015) examine the impact of successful railway connections on service quality perceptions. However, their measure is aggregated to a monthly level. In Web Appendix W1, we summarize related concepts, highlighting distinctions with that used in this study.

MGC. Drawing from Colicev et al. (2018), we define MGC as a firm or brand's communication created and shared through online social network assets. In conceptualizing MGC, we also draw on research examining message content categories in social media. Categories used in related research include information-focused, emotion-focused, or commercial content (Tellis et al. 2019); directly informative and brand-personality related content (Lee, Hosanagar, and Nair 2018); information-sharing, emotion-evoking, and action-inducing content (Taecharungroj 2017); informative and persuasive/emotional content (Goh, Heng, and Lin 2013); informational, promotional, or community-building content (Saxton and Waters 2014); and entertainment and information (Weiger, Hammerschmidt, and Wetzel 2018), among others. After reviewing our data, we conclude that posts in our data set can be cleanly grouped into two types of content: informational and emotional. Moreover, we observe a great deal of overlap between our categories and those in other studies, as described previously, and with categorizations used in traditional advertising as well (e.g., informational and transformational advertising, as described by Puto and Wells [1984]).

We define informational content as MGC in which the content is neither directly promotional in nature nor aimed at prompting audience engagement (e.g., providing updates on events without directly encouraging attendance). Emotionally oriented content is defined as messages that employ affect-laden content and are aimed at evoking sensory or emotional

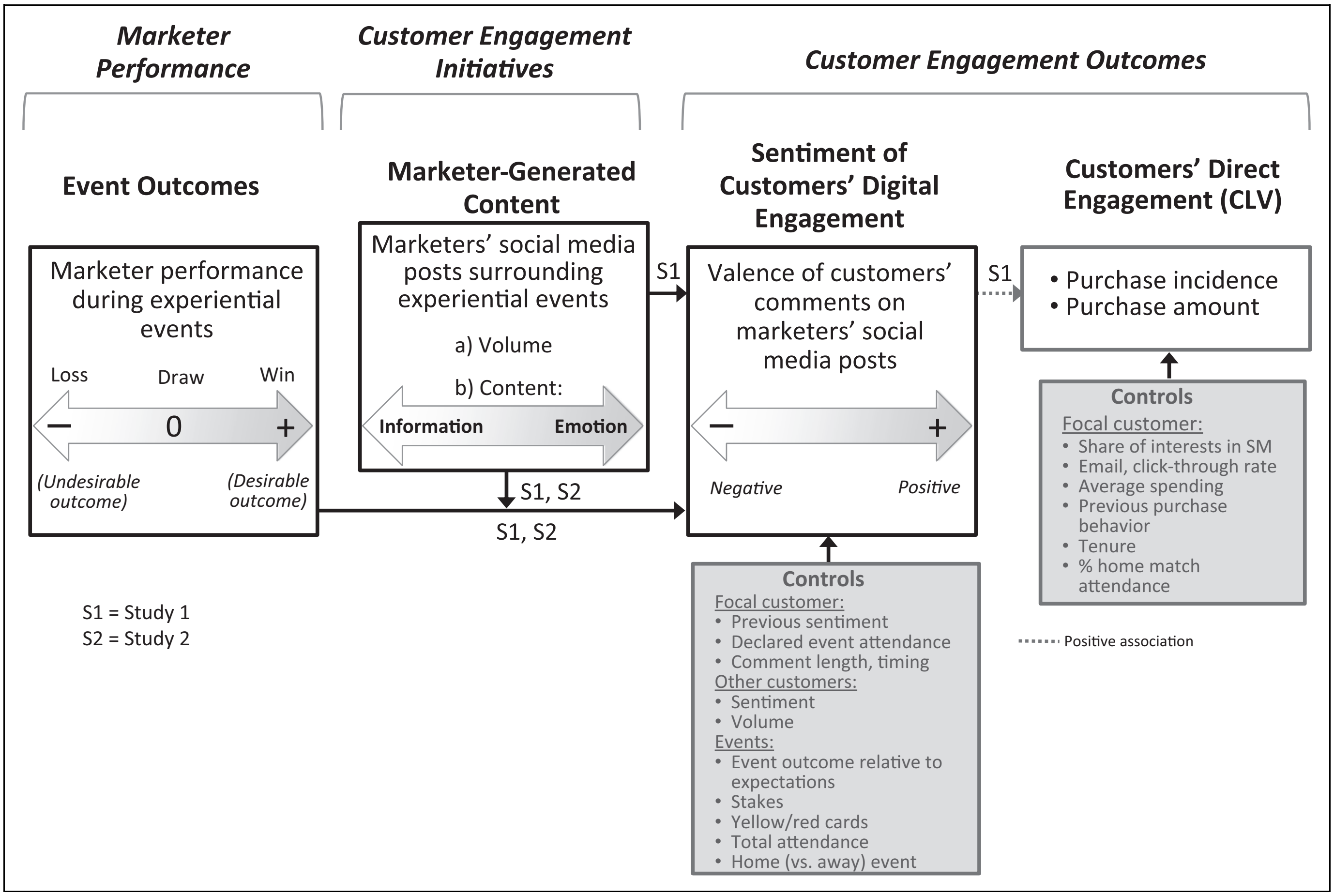

Figure 1. Conceptual framework.

experiences (Dubé, Chatthopadhyay, and Letarte 1996). Details regarding the coding of marketer posts, including examples, are provided in the description of the independent variables for Study 1.

Conceptual Arguments

In this section, we present our conceptual arguments for the relationships in our conceptual framework, depicted in Figure 1. We also summarize the expected relationships in our framework through a series of propositions (Table 2).

Event outcomes and the sentiment of customers' digital engagement. We first propose that firm performance during experiential events will influence customers' affective states, which will in turn influence the sentiment of their digital engagement with the firm (see P_1 and P_2 in Table 2). That is, we expect event outcomes to positively influence the sentiment of customers' digital engagement such that more positive (negative) event outcomes will lead to a positive (negative) sentiment. From an engagement theory perspective, the relative quality of customers' experiences is associated with the likelihood of positive customer engagement behaviors such as providing supportive online reviews (Van Doorn et al. 2010). There is also evidence that marketers' (dis)satisfactory performance during experiential events leads to positive (negative) affective states (Nicolao, Irwin, and Goodman 2009). Also, consistent with the service-profit chain (Anderson and Mittal 2000), customers' perceptions of their experiences are an important antecedent of positive customer engagement behaviors such as contributing positive word of mouth on social media. Indeed, research in general confirms that positive word of mouth on social media is a key outcome of positive experiences (Klein et al. 2016). This relationship has also been argued to be important for experiential purchases in particular (Pelletier and Collier 2018).

MGC volume and the sentiment of customers' digital engagement. On average (i.e., for both positive and negative event outcomes), we expect a greater MGC volume to positively impact customer sentiment (P_3). From a customer engagement perspective, firms' engagement initiatives, such as posting content on social media, can lead to heightened customer interactive participation with the firm on social media (Gill, Sridhar, and Grewal 2017). Consistent with

Table 2. Summary of Propositions and Conceptual/Theoretical Arguments.

Number	Proposed Relationship	Conceptual/Theoretical Arguments
P_1 P_2	Positive event outcomes lead to positive customer sentiment.[a] Negative event outcomes lead to negative customer sentiment.	• The relative quality of customers' brand- or firm-related experiences is associated with customers' affective states and the likelihood of positive (negative) customer engagement behaviors, including contributing positive (negative) word of mouth in social media (Van Doorn et al. 2010).
P_3	MGC content that is either informational or emotional leads to positive customer sentiment.	• Posts by marketers on their own social media channels, as with customer engagement initiatives, can make brands more salient in consumers' minds, triggering positive brand-associated thoughts, which result in more positive customer sentiment (Colicev et al. 2018). • The greater the extent to which firms are viewed as fostering interactivity, the more positive the customer sentiment that should result (Hajli et al. 2017).
P_4	If a negative event outcome is observed, informational MGC content is more influential than emotional MGC content on customer sentiment.	• Undesirable outcomes can lead to negative affective states, which foster consumers' use of more analytical processing strategies focusing on detailed information (Schwarz 1990) . • To overcome negative affect, individuals will try to change their current situation by assessing the situation based on an analysis of potential causal links among its features—informational content will be more useful than emotional content for this purpose (Cohen and Andrade 2004).
P_5	If a positive event outcome is observed, emotional MGC content is more influential than informational MGC content on customer sentiment.	• Positive affective states signal that an individual's personal world is a satisfactory place, and there is little need to seek information to make sense of it; therefore, informational MGC will be less influential on the sentiment of customers' digital engagement (Schwarz 1990). • Message content with less of an emphasis on information tends to include affective appeals, often aimed at evoking sensory or emotional experiences (Dubé, Chatthopadhyay, and Letarte 1996).

[a]Note that we use "customer sentiment" here to refer to the sentiment of customers' digital engagement.

arguments regarding the role of firms' social media investments (Colicev et al. 2018), posts by marketers on their own social media channels (e.g., their Facebook page) can make brands more salient in consumers' minds, triggering positive brand-associated thoughts, which, in turn, should result in a more positive sentiment in terms of customers' digital engagement. Related research offers evidence that the more interactive an online community, and the more contributions by both firms and customers, the greater the relationship-building, trust, and loyalty outcomes (Hajli et al. 2017). Greater fan interactivity on a brand's social media page has also been demonstrated to lead to a greater affective and cognitive engagement with the brand (Helme-Guizon and Magnoni 2019) and more positive brand attitudes (Kim and Lee 2019). Accordingly, the greater the extent to which firms are perceived as fostering interactivity, the more positive the sentiment of customers' digital engagement should be. In support of this expectation is Kumar et al. (2016)'s finding that buyer reactions to firm social media posts can improve brand evaluations.

The moderating role of MGC content. From a customer engagement perspective, firms' efforts to manage the information environment in which firms and customers interact, which occurs when marketers post content on social media, can enable them to influence the sentiment of customers' digital engagement. That is, firms' own social media activities can motivate customers to voice concerns or compliments, thereby reinforcing positive experiences, or to enhance their knowledge about a brand when questioning poor experiences (Van Doorn et al. 2010). We propose that consumers will respond differently to different types of MGC content surrounding negative versus positive event outcomes. In particular, we expect informational MGC to be more influential on the sentiment of customers' digital engagement when a negative event outcome is observed (P_4) and emotional MGC to be more influential when a positive event outcome is observed (P_5).

Support for this expectation comes from the "feelings as information" theoretical perspective (Schwarz 1990) used to explain the role of affective states in message processing. According to this perspective, undesirable outcomes can lead to negative affective states, which then foster the use of more analytical processing strategies focusing on detailed information (Schwarz 1990). Negative affective states can prompt an individual to try to change their current situation by assessing the situation through information seeking and analyzing potential causal links among its features. Consistent with this perspective, we argue that informational content may be useful in overcoming negative affect surrounding undesirable event outcomes, akin to the notion of mood repair (Cohen and Andrade 2004).

In the case of desirable event outcomes, the feelings-as-information perspective suggests that positive affective states resulting from such outcomes require less explanation than negative ones and will therefore promote less effortful heuristic strategies in processing messages. As summarized by Schwarz (1990), positive affective states signal that an individual's personal world is a satisfactory place, and that there is little need to seek information to make sense of it. Whether due to reduced motivation or cognitive capacity constraints, both shown to be associated with positive affective states (Wegener, Petty, and Smith 1995), these customers are less likely to focus on and process informational content. Thus, following desirable event outcomes, informational MGC will be less relevant and therefore less influential on customer sentiment, whereas content focused less on information will be more influential.

Message content with less of an emphasis on information tends to include affective appeals, often aimed at evoking sensory or emotional experiences (Dubé, Chatthopadhyay, and Letarte 1996). Emotional messages are argued to be particularly impactful for experiential products (Holbrook and O'Shaughnessy 1984). Lee and Heere (2018) argue that sports consumption is primarily for affective purposes and that emotional appeals aimed at evoking arousal are more likely to be positively received. When consumers are in positive affective states, we expect existing emotional bonds with the team and the emotional experience of the recent event to be salient. In such cases, messages employing affect-laden content should enhance the sentiment of customers' digital engagement.

Overview of Studies

The ideal experiment to study MGC effects such as those examined here would entail a randomized controlled design in a field setting in which the cells are combinations of three factors: customers' expectations regarding performance during their experiences, the marketer's actual performance, and MGC content (emotional, informational, none), where the cells in which MGC is none would constitute a control group. There are two issues that preclude this ideal experiment in our observational context: self-selection and the strategic nature of MGC. In addition, practically, it would be difficult to convince a marketer in a field setting to intentionally perform poorly during customer interactions.

Because the ideal experiment is infeasible, we conduct two studies to provide evidence of the key causal effects underlying MGC's moderation of the link between event outcomes and customer sentiment. The first study employs real-life, longitudinal, observational data and accommodates self-selection with a Heckman selection model and the endogenous nature of MGC with a control function approach. In the second study, we run a randomized controlled scenario-based experiment on MTurk. The strength of the first study is its high degree of realism, while the second study's advantage is the randomized assignment of participants, the gold standard for determining causality. We find the results of Studies 1 and 2 to be highly consistent. Next, we describe each study.

Study 1

Data and Sample

Study 1's context is a European soccer team's Facebook fan page, and we focus on the dominant social media platform: Facebook (John et al. 2017). All social media data were collected through Facebook's application programming interface with consent from users. We extracted all customers' digital engagement in the form of comments on posts on the team's official Facebook page, yielding 265,530 comments from 52,431 users between June 2011 and June 2015 (i.e., the four seasons following the team's Facebook fan page launch in November 2010). We also collected the team's posts during this period. Finally, we gathered declared match attendance using Facebook's application programming interface and matched conditions and outcomes, expectations (odds), and stakes (match attendance) using publicly available websites.

To address selection effects, we merged the Facebook data with the team's internal data, keeping customers active at any point in the study's time frame. We merged the data via names, the only personal information available for those posting comments. Names occurring twice or more were deleted to ensure matching quality. The internal data comprise transactional (e.g., purchase frequency), customer (e.g., name, gender, birthday), and privacy-related data (phone and identity card number disclosure). Of 53,794 customers, we matched 9,424 (people who made one comment or more more) who made 21,604 comments. The actual number of users and comments in our main analysis is more restricted because we focus on positive and negative comments only (discussed next).

Dependent Variable

We model the sentiment of a customer's digital engagement using comments on team posts[2] through each user's expressed sentiment during each of 212 potential experiential events (matches) over 48 months. We restrict user-generated content (UGC) to comments on the team's Facebook posts within a two-day window after an event (match) to (1) increase the chance that comments relate to a particular event and reduce "noise" (i.e., comments unrelated to firm interactions) and (2) reduce the chance of capturing comments regarding multiple events because matches can be as close as three days. We use a

[2] Besides possibly reacting to team posts, users have no other opportunities to post messages on this Facebook page.

Table 3. Characteristics and Examples of Informational and Emotional MGC.

	Informational MGC	Emotional MGC
Defining characteristics of MGC	• Informing customers about the product (in this case, e.g., match results, player injuries; Lee, Hosanagar, and Nair 2018; Stephen, Sciandra, and Inman 2015) • Messages informing the customers about relevant events and conditions (Muntinga, Moorman, and Smit 2011) • Messages providing information about the company in general (e.g., facts; Lee, Hosanagar, and Nair 2018; Stephen, Sciandra, and Inman 2015)	• Messages containing emotions (Lee, Hosanagar, and Nair 2018) • Messages evoking sensory emotions (Dubé, Chatthopadhyay, and Letarte 1996) • Messages high in arousal (Stephen, Sciandra, and Inman 2015) • Messages containing calls to action and persuasive content (Stephen, Sciandra, and Inman 2015) and promotion and mobilization (Saxton and Waters 2014) • Messages containing entertaining content (De Vries, Gensler, and Leeflang 2012) • Messages focusing on community building and dialogue (Saxton and Waters 2014)
Examples of MGC[a]	"The coach's vision on the injuries, the international football break and his strikers" "Important: When you charge your card online, use the card number that is at the top right of your season ticket" "Get to know the five possible opponents in the Champions League play-offs." "Player X plays his 150th official match for our team tomorrow. Player Y his 120th official game."	"Everything stays possible! Come in great numbers to the stadium on Thursday and push the team to the next round in the cup!" "All Together Now!" "Thanks fans for your fantastic support yesterday! We are one team!" "There will be a Twinterview with player X on our Twitter account on Wednesday! Follow us, ask your question and get a chance to win a jersey!" "Share and support the team!"

[a]Comments were translated to English and anonymized.

classification algorithm based on a sentiment lexicon to determine sentiment (Goh, Heng, and Lin 2013) and use only positive and negative comments, yielding 10,345 user-match records for 3,749 customers. This choice is based on evidence of a much smaller effect of neutral versus positive or negative comments (Sonnier, McAlister, and Rutz 2011) and on claims that positive and negative comments are most relevant for extracting sentiment (Tirunillai and Tellis 2012).[3]

Independent Variables

MGC. Consistent with Homburg, Ehm, and Artz (2015) and Goh, Heng, and Lin (2013), we capture MGC through the focal team's posts on its own Facebook page between the end of an experiential event and the posting time of a particular user's comment. Informational (emotional) MGC is operationalized as the number of focal team informational (emotional) posts between the end of match m and posting time of comment c by user u (Homburg, Ehm, and Artz 2015). We use content analysis to model informational versus emotional posts. Given the relatively low number of posts and the absence of ready-to-use dictionaries, we opt for manual labeling rather than an (un)supervised approach (e.g., Kim and Kumar 2018, Lee, Hosanagar, and Nair 2018). We follow the typical steps used in the literature (Stephen, Sciandra, and Inman 2015). First, we define a set of coding instructions, leveraging existing literature and adapting some of these concepts to our context. With regard to informational content, we use dimensions identified by Resnik and Stern (1977) and operationalized by Lee, Hosanagar, and Nair (2018) and complement them with insights identified by other content-coding research (e.g., Muntinga, Moorman, and Smit 2011). In general, informational content is focused on the focal team, its services (matches), and other relevant information regarding these services. Similarly, for emotional content, we based our dimensions on research revealing constructs to measure emotional, persuasive, and engaging content (De Vries, Gensler, and Leeflang 2012; Lee, Hosanagar, and Nair 2018; Stephen, Sciandra, and Inman 2015). We continued the process until we found no new dimensions.

In the second step, two of the authors used the coding handbook to independently classify a subset of 100 posts. We first used this subset to ensure that all instructions were clear, resolve any remaining issues, and identify any dimension not identified in the literature. The coders then independently classified the remaining posts. We allowed posts to be classified as both informational and emotional; however, this occurred in a very limited set of cases (10). The Fleiss κ-index for interrater reliability was .864, which indicates a high agreement (Landis and Koch 1977). For posts for which initially no agreement was reached, the coders discussed the content and reached congruence. Table 3 summarizes the defining characteristics of

[3] We note that by setting up the data frame, several forms of selection biases might occur: (1) omitting neutral sentiment, (2) including only actual customers, and (3) restricting comments to a two-day window. We evaluate each of these potential biases in the robustness checks.

informational and emotional MGC and gives several (translated into English) examples for both types.

To assess MGC's moderating effect on the relationship between the event outcome and the sentiment of customers' digital engagement, we include both the number of (informational and emotional) team posts on its Facebook page (Informational $MGC_{u,c,m}$ and Emotional $MGC_{u,c,m}$) and the interaction between the event outcome and the MGC measures.

Event outcomes. We include match result to reflect the firm's objective performance during each experiential event (win, loss, or draw; $Result_m$).

Control Variables

Consistent with prior research incorporating odds to account for customer expectations (Bartling, Brandes, and Schunk 2015), we gather preplay betting odds for each outcome per event (win, loss, or draw, from the focal team's point of view).[4] We compare the actual result with expectations (odds) and identify unexpected results in case actual and expected results differ (see Web Appendix W2). We include a binary variable, Unexpected Result, and its interaction with event outcome (result) to account for implications of unexpected results. In line with prior research (Dolton and Mackerron 2018), unexpected results should amplify reactions (i.e., unexpected wins [losses] should be viewed more [less] positively than expected wins [losses]).

We control for event attendance (Total Event $Attendance_m$)[5] to measure stakes. According to the uncertainty-of-outcome hypothesis (Rottenberg 1956), attendance will be higher with higher stakes. We include the number of focal team red and yellow cards ($RedCards_m$ and $YellowCards_m$) because they are penalties and contribute to negative experiences (Castellano, Casamichana, and Lago 2012). We define prior customer sentiment (Customer $Sentiment_{u,m-1}$) on the basis of comments during the previous match window in which a user commented. For first-time comments, it is zero. Intentions to attend an event (yes/no; indicated on social mediaSM) ($EventFacebook_{u,m}$) are a form of online team identification and should positively relate to sentiment (Branscombe and Wann 1992).

We include previous comment volume in the thread ($OtherUGCVolume_{u,c,m}$). We assess comment context through the valence of the last comment before a focal comment (losing the first per thread; $OtherUGCValence_{u,c,m}$) and expect a positive relationship with sentiment (Homburg, Ehm, and Artz 2015; Moe and Trusov 2011). Comment length is captured through a word-count log (Comment $Length_{u,c,m}$; Homburg, Ehm, and Artz 2015) and should negatively affect sentiment.

Finally, there is evidence that customer sentiment is highly influenced by events shortly after they occur, but this effect ebbs over time (Dolton and Mackerron 2018). Thus, we include a variable that measures (in hours) the time between match end and focal comment. Because this effect can vary on the basis of event outcome, we also include its interaction with the event outcome.

Model Specification

Because we have a binary dependent variable (positive/negative sentiment) and want to include random effects to account for both customer and match heterogeneity, we use a generalized linear mixed-effects model (with a probit link function) to model sentiment:

$$\begin{aligned}
&\text{Customer Sentiment}_{u,c,m}\\
&\quad = \alpha_0 + \alpha_{1,u} + \alpha_{2,m} + \alpha_3\,\text{Result}_m\\
&\qquad + \alpha_4\,\text{Informational MGC}_{u,c,m}\\
&\qquad + \alpha_5\,\text{Informational MGC}_{u,c,m} \times \text{Result}_m\\
&\qquad + \alpha_6\,\text{Emotional MGC}_{u,c,m}\\
&\qquad + \alpha_7\,\text{Emotional MGC}_{u,c,m} \times \text{Result}_m\\
&\qquad + \alpha_8\,\text{Unexpected Result}_m\\
&\qquad + \alpha 9\,\text{Unexpected Result}_{u,c,m} \times \text{Result}_m\\
&\qquad + \alpha_{10}\,\text{TotalEventAttendance}_m\\
&\qquad + \alpha_{11}\,\text{TotalEventAttendance}_m \times \text{Result}_m\\
&\qquad + \alpha_{12}\,\text{RedCards}_m + \alpha_{13}\text{YellowCards}_m\\
&\qquad + \alpha_{14}\,\text{Home Game}_m + \alpha_{15}\text{EventFacebook}_{u,m}\\
&\qquad + \alpha_{16}\,\text{Customer Sentiment}_{u,c,m-1}\\
&\qquad + \alpha_{17}\,\text{OtherUGCValence}_{u,c,m}\\
&\qquad + \alpha_{18}\,\text{OtherUGCVolume}_{u,c.m}\\
&\qquad + \alpha_{19}\,\text{Comment Length}_{u,c,m} + \alpha_{20}\text{Comment Time}_{u,c,m}\\
&\qquad + \alpha_{21}\text{Comment Time}_{u,c,m} \times \text{Result}_m + \alpha_{22}\theta_m + \varepsilon_{u,c,m},
\end{aligned} \tag{1}$$

where Customer $Sentiment_{u,c,m}$ denotes the sentiment of digital engagement for user u, expressed in comment c for match m; $\alpha_{1,u}$ and $\alpha_{2,m}$ represent the user and match random elements, respectively; and $\varepsilon_{u,c,m}$ is the error term. The variable θ_m represents a vector of year dummies accounting for factors that vary by year, and Result and UnexpectedResult are also captured as dummy vectors. Finally, we interact Informative MGC, Emotional MGC, UnexpectedResult, TotalEventAttendance, and CommentTime with event outcome.[6]

[4] These odds are also called 1 $\times$ 2 odds. The odds were gathered using the website https://www.oddsportal.com/, which captures odds from different bookmakers and presents the average of all odds so that we do not rely on one specific bookmaker. The preplay odds are closed just before the start of the match, thus taking into account all information that is also available to customers.

[5] Source of the spectator data: https://www.transfermarkt.nl/.

[6] We use match result in particular, and not other aspects of the match, because it is arguably the performance outcome over which the team has the greatest control.

Self-Selection

Because we worked with an online population and used observed behavior, it is likely that our sample suffers from self-selection bias (e.g., Goh, Heng, and Lin 2013). People commented on team Facebook posts and, as a result, became part of our study. However, these people may not be representative of the entire population under study (the team's customer base) because there may be unobserved factors influencing both the decision to comment and the sentiment of this digital engagement. For example, these people may already be more positive toward the company than others, biasing the parameter estimates upward. This self-selection potentially leads to an endogeneity issue due to omitted variables bias (Wies and Moorman 2015), which can be alleviated by implementing a binary probit choice model as a Heckman selection model (Heckman 1979).

The probit regression models the propensity to comment on the team's post and provides a correction factor for self-selection to be included in the sentiment model. The regression is defined as a linear function of three categories of variables that help identify which customers will comment on team posts (Goh, Heng, and Lin 2013; Kumar et al. 2016). These include the following:

1. *Demographic variables such as age, gender, and language*. We expect younger men to post more comments, given young people's high digital awareness and the relatively masculine soccer culture. Moreover, those who do not speak the language used on the team's Facebook page may have a lower propensity to comment.
2. *The number of online ticket purchases (in contrast to offline purchase)*. This is based on the expectation that online purchasers have higher technological savviness and are inclined to use social media more often (Kumar et al. 2016).
3. *Variables indicating team involvement*. This is based on an expectation that more highly involved customers are more likely to comment on posts, for which we use recency of the last purchase and tenure.

We need at least one (significant) independent variable in the selection equation that does not affect sentiment to satisfy the exclusion restrictions and allow identification (Puhani 2000). The online purchase–related variable helps in meeting the exclusion restriction because there is no obvious reason to believe online purchasers are a priori more positive or negative toward the company. The regression can be defined as:

$$\begin{aligned}\mathrm{Commenting_u} = \beta_0 + \beta_1\mathrm{Age_u} + \beta_2\ \mathrm{Gender_u} + \beta_3\ \mathrm{Language_u} \\ + \beta_4\mathrm{OnlinePurchase_u} + \beta_5\mathrm{Customer\_tenure_u} \\ + \beta_6\ \mathrm{Recency_u} + \varepsilon_u. \qquad (2)\end{aligned}$$

We derive the inverse Mills ratio (IMR) from the probit regression as follows:

$$\lambda = \varphi(\beta X)\Phi(\beta X), \qquad (3)$$

where λ as usual indicates the IMR, and φ and Φ indicate the probability and cumulative density functions, respectively. The IMR is a monotone decreasing function of the probability of an individual's self-selecting into the sample. The customer sentiment model is the second step of the selection model, which depends on the selection equation. By including the IMR in the customer sentiment model as an explanatory variable, we correct for potential endogeneity issues resulting from self-selection. If the IMR coefficient is significant, self-selection is an issue.

Endogeneity Correction for MGC

In addition to random shocks to MGC (due to, e.g., changes in the team's communication staff, game outcomes), firms may strategically choose both their MGC volume and content on the basis of their expectations of future comment sentiment (Homburg, Ehm and Artz 2015). Firms' expectations of future consumer sentiment are not observed by the researcher and reside in the error term in Equation 1. However, because firms' expectations of future comment sentiment also affect MGC content choice and volume, the error term in Equation 1 may correlate to MGC content and volume, inducing potential endogeneity. To help isolate MGC's potential endogeneity, we use a control function approach, preferred in the case of a limited dependent variable (Petrin and Train 2010). First, we model the endogenous variables (informational and emotional MGC) as a function of exogenous and instrumental variables. We control for each event's context (result, red/yellow cards, [un]expected result, number of attendees, and whether the team is playing at home) and time elapsed between the MGC posting and the event's end.

We require instrumental variables to fulfill the exclusion restriction requirement (Petrin and Train 2010). We use lagged differences in MGC content (difference in volume of emotional and informational posts between the first and second month preceding the focal post)[7] as an instrument because these differences can capture trends in team posting behavior indicative of the team's overall activity level for each post type. One could argue that lagged MGC values potentially reveal trends in team performance that also influence sentiment (thereby passing the test of relevance). One could also argue that lagged differences in MGC are unrelated to the sentiment of customers' digital engagement (thereby passing the exclusion restriction test). Note that the differences also include non-event-related posts and sum all MGC over a month, making it unlikely that the difference is related to the sentiment of customers' comments on team posts surrounding a finite event. If previous events influence sentiment, more weight is given to the most recent experiences, which is not the case for the instrumental variables. Finally, we note that older MGC is not

[7] To classify all 7,692 posts as informational or emotional, we build a random-forest predictive model that uses the 2,149 manually labeled posts (within a two-day time frame after the game) as a training data set.

very visible on Facebook (unless users scroll down extensively), and customers therefore almost exclusively react to the most recent post. Thus, it is unlikely that the posting behavior from one to two months earlier will have a direct influence on customer sentiment; rather, any possible influence will go through the latest MGC post. In summary, we conclude that our instrumental variables satisfy both relevance and exclusion criteria.[8] As robustness, we also include trends in Equation 1 as a control in the sentiment equation.

The control function dependent variables (i.e.., the volume of informational and emotional MGC before the focal post p) are counts and are zero-inflated. In other words, when there is only one post, it can be either informational or emotional; therefore, the other variable will take the value of zero. We add random effects to account for match-specific factors not captured by exogenous variables; formally, the regressions are specified as zero-inflated random-effects Poisson models:

$$\begin{aligned}\text{Informational MGC}_{p,m} = {} & \gamma_{10} + \gamma_{11,m} + \sum\nolimits_{i=2}^{9} \gamma_{1i} Z_m \\ & + \gamma_{110} \Delta\text{Informational Posts}_m \\ & + \gamma_{111} \Delta\text{Emotional Posts}_m + \vartheta_m,\end{aligned} \tag{4}$$

$$\begin{aligned}\text{Emotional MGC}_{p,m} = {} & \gamma_{20} + \gamma_{21,m} + \sum\nolimits_{i=2}^{9} \gamma_{2i} Z_m \\ & + \gamma_{210} \Delta\text{Informational Posts}_m \\ & + \gamma_{211} \Delta\text{Emotional Posts}_m + \vartheta_m,\end{aligned} \tag{5}$$

where Z is the matrix of exogenous variables and ΔInformationalPosts (ΔEmotionalPosts) is the lagged difference in informational (emotional) MGC volume between the previous two months before the focal MGC. The regressions are the same except for the dependent variable. We include the instrumental variables in both (Papies, Ebbes, and Van Heerde 2017). The final step of the endogeneity correction approach is to include residuals (ϑ_m) of the control equations as independent variables in the customer sentiment regression. This allows us to test for the presence of endogeneity using the standard z-test, after bootstrapping the standard errors (Papies, Ebbes, and Van Heerde 2017). The final customer sentiment model includes correction terms for self-selection and endogeneity.

We provide all main sentiment model variables in Table 4, and the correlation matrix in Table 5. Web Appendix W3 provides descriptive figures for the selection and control equations.

Results

First, we discuss the results of the selection and endogeneity control equations (Tables 6 and 7, respectively). The results of the selection regression indicate which customers self-select into our sample. The overall model is significant (likelihood-ratio $\chi^2(6) = 3{,}017.4$; $p < .01$). All variables except gender are significant and have expected signs; younger people and native speakers of the language are more likely to comment ($\beta_2 = -.335, p < .01$; $\beta_3 = .309, p < .01$). Customers who buy tickets online ($\beta_4 = .083, p < .01$) and with longer tenure ($\beta_5 = .135$, $p < .01$) and who bought tickets more recently ($\beta_6 = -.124$, $p < .01$) are more likely to comment.

For the first-stage endogeneity correction regressions, the instrumental variables are all significant in at least one regression. The difference in volume of informational (emotional) posts is positive and significantly related to informational (emotional) MGC volume (informational: $\gamma_{110} = .125$, $p < .01$; emotional: $\gamma_{211} = .419, p < .01$). However, the instrumental variables are only significant in one of the control functions; the variable related to informational posts is not significant in the control function for emotional posts, and vice versa. Thus, we have ensured that each (potentially) endogenous variable is identified by at least one unique instrumental variable. Moreover, similar to a traditional F-test, we test whether the instrumental variables significantly affect the log-likelihood of the regressions by comparing our models with models without the instrumental variables. We confirm that this is the case (likelihood-ratios of $\chi^2(2) = 78.16$ and $\chi^2(2) = 61.9$ for informational and emotional MGC respectively, both $ps < .01$).

Table 8 presents the Akaike information criterion (AIC) for several models, going from a model without MGC to the final model (discussed subsequently). As shown in Table 8, MGC and the different self-selection and endogeneity corrections significantly improve our model. The coefficients of the final customer sentiment model are presented in Table 9. The parameter estimates related to experiential event outcomes show that variables have expected signs but not all are significant. However, all are significant before the inclusion of event-specific intercepts (results not shown); these intercepts account for most of the variance in the parameters. Wins result in higher sentiment versus draws ($\alpha_3 = .251$ for wins, $p < .01$), while losses do not lead to more negative sentiment versus draws. Thus, as we suggest in P_1, positive event outcomes lead to positive sentiment. Furthermore, as we suggest in P_2, we find that the sentiment of customers' digital engagement in the case of a loss is lower (more negative) than in the case of a win.

Next, we examine the variables related to MGC content. Please note that a draw serves as the reference event outcome category in our results. Thus, the main effect of informational MGC refers to the impact of informational MGC in the case of a draw. The interaction terms show the additional effects in case of losses and wins. To facilitate interpretation of the results, we provide interaction plots for informational MGC and emotional MGC in Figure 2, Panels A and B. For informational MGC, the effect of MGC for draws is not significant ($\alpha_4 = .057$, $p > .10$), nor is the effect in the case of wins. Importantly, we find a positive impact of informational MGC on customer sentiment with a loss (total effect in case of losses is .382 [.057 + .325], $p < .05$). The effect is only significant for losses, and it is so pronounced that with more informational

[8] We also tested the robustness of our instrumental variable choice by adding the average number of all league competitors' informational and emotional posts in the previous month as instrumental variables. By averaging across competitors, and not only those from focal events, we conclude that it is unlikely that this influences customer sentiment for this event. These variables are significant, though the effect in the final customer sentiment model was minimal, and our results and conclusions replicate.

Table 4. Description of Variables Used in the Main Model.

Variable	Description	M	SD	Range
Dependent	Measure of Subjective Sentiment in Customers' Comments			
$CustomerSentiment_{u,c,m}$	Dependent variable. Customer u sentiment, as expressed in comment c, during match m. (binary variable)	.73	.45	[0, 1]
Event Outcome	Objective Measures of Performance during Events			
Result $(Lost)_m$	Dummy variable indicating whether the match m was lost by the focal team (in contrast to a draw)	.32	.47	[0, 1]
Result $(Won)_m$	Dummy variable indicating whether the match m was won by the focal team (in contrast to a draw)	.46	.50	[0, 1]
MGC Variables	Measures of Marketer-Generated Content			
Informational $MGC_{u,c,m}$	Number of informational posts on Facebook by the focal team between the end of match m and the time of posting of comment c by user u (comment on post p)	2.42	4.43	[0, 49]
$Result_m \times$ Informational $MGC_{u,c,m}$	Interaction effect between Result of match m and informational MGC			
Emotional $MGC_{u,c,m}$	Number of emotional posts on Facebook by the focal team between the end of match m and the time of posting of comment c by user u (comment on post p)	2.45	6.09	[0, 47]
$Result_m \times$ Emotional $MGC_{u,c,m}$	Interaction effect between Result of match m and emotional MGC			
Control Variables	Control Variables for Customer Sentiment			
Unexpected $Result_m$	Dummy variable indicating whether the result of match m is in line with the expectations based on the odds	.42	.49	[0, 1]
$Result_m \times$ Unexpected $Result_m$	Interaction effect between actual result of match m and the dummy variable Unexpected Result			
$TotalEventAttendance_m$	The number of spectators for game m, which is a proxy for the importance of the game and quality of the opponent	18,156	9,192	[1,819, 65,110]
$Result_m \times TotalEventAttendance_m$	Interaction effect between actual result of match m and the dummy variable Spectators			
$RedCards_m$	The number of red cards for the focal team in match m	.17	.39	[0, 2]
$YellowCards_m$	The number of yellow cards for the focal team in match m	1.90	1.24	[0, 6]
Home $Match_m$	Dummy indicating whether the match m is a home match	.50	.50	[0, 1]
$EventFacebook_{u, m}$	Dummy indicating whether user u has declared on Facebook to attend match m	.05	.23	[0, 1]
Customer Sentiment $_{u,m-1}$	Lag of measured customer sentiment of user u (1 for positive or 0 for negative)	.30	.46	[0, 1]
Other UGC Valence $_{u,c,m}$	Valence of the previous comment in the post thread of comment c by user u during match m (polarity score from -5 to $+5$ [with $+$ being positive])	.18	.56	[−2.9, 5]
Other UGC Volume $_{u,c,m}$	Volume of other user's comments in the post thread of comment c by user u during match m	110	141	[1, 1,106]
Comment $Length_{u,c,m}$	Length of the comment (number of characters) c by user u during match m (logarithm of length)	4.29	1.07	[1.10, 7.65]
Comment $Time_{u,c,m}$	Time (in hours) that has passed by (at the moment of posting comment c by user u) since the end of the match m (logarithm of time)	2.19	1.43	[.05, 9.62]
Result $_m \times$ Comment $Time_{u,c,m}$	Interaction effect between the result of match m and the comment time			
θ_m	Dummy variables indicating the year in which the match m was held			

posts, sentiment for losses is higher than for wins. Finally, emotional MGC has a significant positive impact on sentiment ($\alpha_4 = .122, p < .05$) that does not differ by outcome. Thus, as we suggest in P_3, we find a positive effect of emotional content on the sentiment of customers' digital engagement. Consistent with our arguments for P_4, we find a significantly greater influence of informational MGC on the sentiment of customers' digital engagement in the case of a loss. Finally, as suggested in P_5, we find no significant effect for informational content and a positive significant effect for emotional content in the case of a win.

With regard to our control variables, we provide plots in Figure 2, Panel C, to facilitate interpreting our results regarding unexpected event outcomes. While the results follow expectations, we find only unexpected wins to yield a significant positive impact on sentiment ($\alpha_9 = .269, p < .05$), with no significant negative effects of unexpected draws or losses. Figure 2, Panel D, shows the plot for event attendance (proxy for stakes and opponent quality) and match result. Results follow expectations: a win for a high-stakes match leads to more positive sentiment, whereas high-stakes draws or losses result in more negative sentiment. However, only the effect for draws is

Table 5. Pairwise Correlation Coefficients.

Variable	1	2	3	4	5	6	7	8	9	10
1. Informational $MGC_{u,c,m}$	1									
2. Emotional $MGC_{u,c,m}$	.008	1								
3. $TotalEventAttendance_m$	−.027	.005	1							
4. $RedCards_m$	.073	−.020	.027	1						
5. $YellowCards_m$	.088	.024	.044	.322	1					
6. Customer $Sentiment_{u,\ m-1}$	.001	.018	.015	−.009	−.005	1				
7. Other Sentiment $Valence_{u,c,m}$	−.181	−.073	−.078	−.035	−.105	−.021	1			
8. Other Sentiment $Volume_{u,c,m}$	.013	.017	.023	−.022	−.037	.010	−.017	1		
9. Comment $Length_{u,c,m}$	−.018	−.037	−.053	.050	.019	.061	.184	−.042	1	
10. Comment $Time_{u,c,m}$	.039	.026	.013	.001	−.011	−.012	−.023	.009	−.021	1

Notes: Only continuous variables are reported. Correlations above .019 are significant at a 5% level (N = 10,345).

Table 6. Results for Selection Equation for Customer Sentiment.

Variables	Estimate	z-score
Intercept	−1.288***	−25,760
Age	−.335***	−41.842
Gender	−.013	−.553
Language	.309***	6.896
OnlinePurchase	.083***	13.316
Tenure	.135***	19.500
Recency	−.124***	−16.987

***$p < .01$.
Notes: Coefficients are standardized.

significant.[9] One potential explanation for this result is that draws may indicate close matches that do not fulfill expectations related to high-stakes events.

Regarding the other controls, most are significant and have the expected signs. Significant, expected effects are found for the number of red cards, previous sentiment, both volume and valence of others' UGC, and comment length. As for the timing of comments in the case of a draw, sentiment increases over time, and for losses, the increase in sentiment is even larger over time (total effect is .245 [= .155 + .090]). For wins, we find a neutral total effect of time (.002 [=.155 – .153]), in line with expectations, as mood drops after a draw and even more after a loss, and gradually returns to a steady state (Dolton and Mackerron 2018). The effects of the number of yellow cards and others' UGC volume are not significant.

The IMR is marginally significant (.028, $p < .10$); thus, self-selection is likely an issue. Variables to correct for endogenous informational and emotional MGC content are significant ($p < .01$ and $p < .10$, respectively). The z-statistic can also serve as a way to perform a Hausman test in the control function approach, suggesting here the presence of endogeneity.

[9] While the parameter for Result Won × Total Event Attendance is significant, this merely indicates that it is different from the effect for draws. Using wins as reference makes it clear that the effect is not significant ($p < .28$).

Table 7. Results for Endogeneity Control Functions.

	Informational MGC Control Equation		Emotional MGC Control Equation	
Variables	Estimate	z-Score	Estimate	z-Score
Intercept	1.020***	7.01	−1.104***	−3.48
Result(Lost)	−.859***	−3.24	−.220	−.42
Result(Won)	−.435***	−2.75	.699**	2.09
Unexpected Result	−.398**	−2.03	.290	.69
ResultLost × Unexpected	.891***	2.78	−.528	−.82
ResultWon × Unexpected	.199	.71	.395	.70
Event Attendance	.057	.51	−.057	−.25
ResultLost × Event Attendance	−.061	−.40	.004	.01
ResultLost × Event Attendance	−.049	−.39	.210	.80
Red Cards	.313**	2.27	−.311	−1.05
Yellow Cards	.025	.48	.052	.51
Home	−.064	−.62	.872***	4.19
Post time	.567***	30.83	.428***	23.01
ΔInformational posts	.125***	2.66	−.045	−.47
ΔEmotional posts	−.083	−1.32	.419***	3.63

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Coefficients are standardized.

Robustness Checks and Additional Analyses

To investigate the influence of data and modeling choices and more generally check the robustness of our findings, we estimate several model variants related to different operationalizations of the dependent variable, MGC, sampling strategy, time frame, and elements outside the two-day timeframe that may influence sentiment and customer segments. First, we included a neutral sentiment. To do so, we ran a multinomial mixed regression, which models neutral versus negative comments and positive versus negative comments (see Web Appendix W4). The results, including interaction plots, show that results related to informational MGC hold for the neutral sentiment model. Emotional MGC does not affect the sentiment of customers' digital engagement. However, the effect sizes cannot

Table 8. Model Comparison.

	Model 1	Model 2	Model 3	Model 4	Main Model
Description	Standard model (no MGC, self-selection, or endogeneity correction)	Model 1 + MGC main effects	Model 2 + MGC interactions	Model 3 + self-selection correction	Model 4 + endogeneity correction
Log-likelihood	−5,606.9	−5,600.9	−5,591.9	−5,589.9	−5,586.0
AIC	11,265.88	11,257.86	11,247.18	11,245.70	11,242.0
χ^2-test		$\chi^2(2) = 12.02$ ($p < .01$)	$\chi^2(4) = 18.68$ ($p < .01$)	$\chi^2(1) = 3.47$ ($p < .06$)	$\chi^2(2) = 7.72$ ($p < .02$)

Table 9. Results for Main Customer Sentiment Model.

Variables	Estimate	z-score
Intercept	.717***	9.393
Result (Lost)$_m$	−.100	−.988
Result (Won)$_m$	.251***	3.548
Informational MGC$_{u,c,m}$	.057	1.493
ResultLost$_m$ × Informational MGC$_{u,c,m}$	.325***	2.579
ResultWon$_m$ × Informational MGC$_{u,c,m}$	−.044	−1.053
Emotional MGC$_{u,c,m}$	.122**	2.246
ResultLost$_m$ × Emotional MGC$_{u,c,m}$	−.007	−.099
ResultWon$_m$ × Emotional MGC$_{u,c,m}$	−.046	−.815
Unexpected Result$_m$	−.099	−1.167
ResultLost$_m$ × Unexpected $_m$	.060	.493
ResultWon$_m$ × Unexpected $_m$	.269**	2.207
TotalEventAttendance$_m$	−.118**	−2.429
ResultLost$_m$ × TotalEventAttendance $_m$	.095	1.497
ResultWon$_m$ × TotalEventAttendance $_m$	.148**	2.567
RedCards$_m$	−.043*	−1.891
YellowCards$_m$	−.022	−1.000
Home Game$_m$	−.050	−1.096
EventFacebook$_{u,\ m}$	.040	.596
Customer Sentiment$_{u,\ c,\ m\text{-}1}$	.087***	2.794
Other UGC Valence$_{u,c,m}$	.046***	3.189
Other UGC Volume$_{u,c,m}$	.042**	2.355
Comment Length$_{u,c,m}$	−.072***	−4.733
Comment Time $_{u,c,m}$	.155***	4.571
ResultLost$_m$ × Comment Time$_{u,c,m}$	.090**	2.003
ResultWon$_m$ × Comment Time$_{u,c,m}$	−.153***	−3.541
IMR$_u$	.028*	1.843
Endogeneity Correction Informational MGC$_m$	−.071***	−3.199
Endogeneity Correction Emotional MGC$_m$	−.039*	−1.793
Log-likelihood	−5,586.0	
AIC	11,242.0	

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Coefficients are standardized. The standard errors are bootstrapped.

be directly compared with the main model results due to the changes in the dependent variable. To enhance understanding of the model while including neutral comments, we create one continuous fractional dependent variable (representing the probability of a positive comment), as in Homburg, Artz, and Ehm (2015). We use a machine learning approach to determine customer sentiment. We present the results in Web Appendix W5. As we expected, overall sentiment scores are lower compared with the main analysis (as more neutral comments are included); however, our main relationships and conclusions still hold.

We investigated two nonlinear relationships between MGC and the sentiment of customers' digital engagement: a squared (level) model with squared MGC terms, and a logarithmic model including the natural logarithm of informational and emotional MGC, testing for a U-shaped relationship and diminishing positive returns, respectively (see Web Appendices W6 and W7, respectively). The AIC of the models shows that the squared model performs slightly worse than the linear model, but the log model performs better. However, the relationships provide the same insights as the linear model. Thus, we repeat our conclusions and add that effects may be more prevalent at lower MGC levels and flatten at higher levels.

Third, while our approach corrects for self-selection, we limit it to include the team's customers, although many comments come from noncustomers. This may introduce another selection effect. Thus, we run the model for all comments and replicate the results (Web Appendix W8). Fourth, we reestimate the model using a one-day window and replicate the results (Web Appendix W9) with only one difference: more informational MGC after a win results in more negative customer sentiment ($p < .05$). Fifth, we examine the effects of other factors that may affect sentiment, including focal users' comments from the week and month before a focal event, and find no significant effect of these comments on sentiment. Next, we include trends (total number of points gained over the last month and number of wins over the last five matches), next to the implicit inclusion of prematch expectations. These trends are not significant. Finally, we test whether our results vary across segments and find no differences for segments based on loyalty or commenting behavior.

Study 2

Participants and Design

Three hundred fifty-six participants (62.5% male; $M_{age} = 34.8$ years, SD = 10.5) recruited from MTurk for the scenario experiment were randomly assigned to conditions defined by expectations, match outcomes, and MGC. We used a 2 (expected to win or lose) × 2 (actual win or loss) × 3 (MGC: emotional, informational, none) between-subjects design. Participants commented on Facebook on average every few weeks (M = 4.05, SD = 2.3; 1 = "Less than once every 2–3 months,"

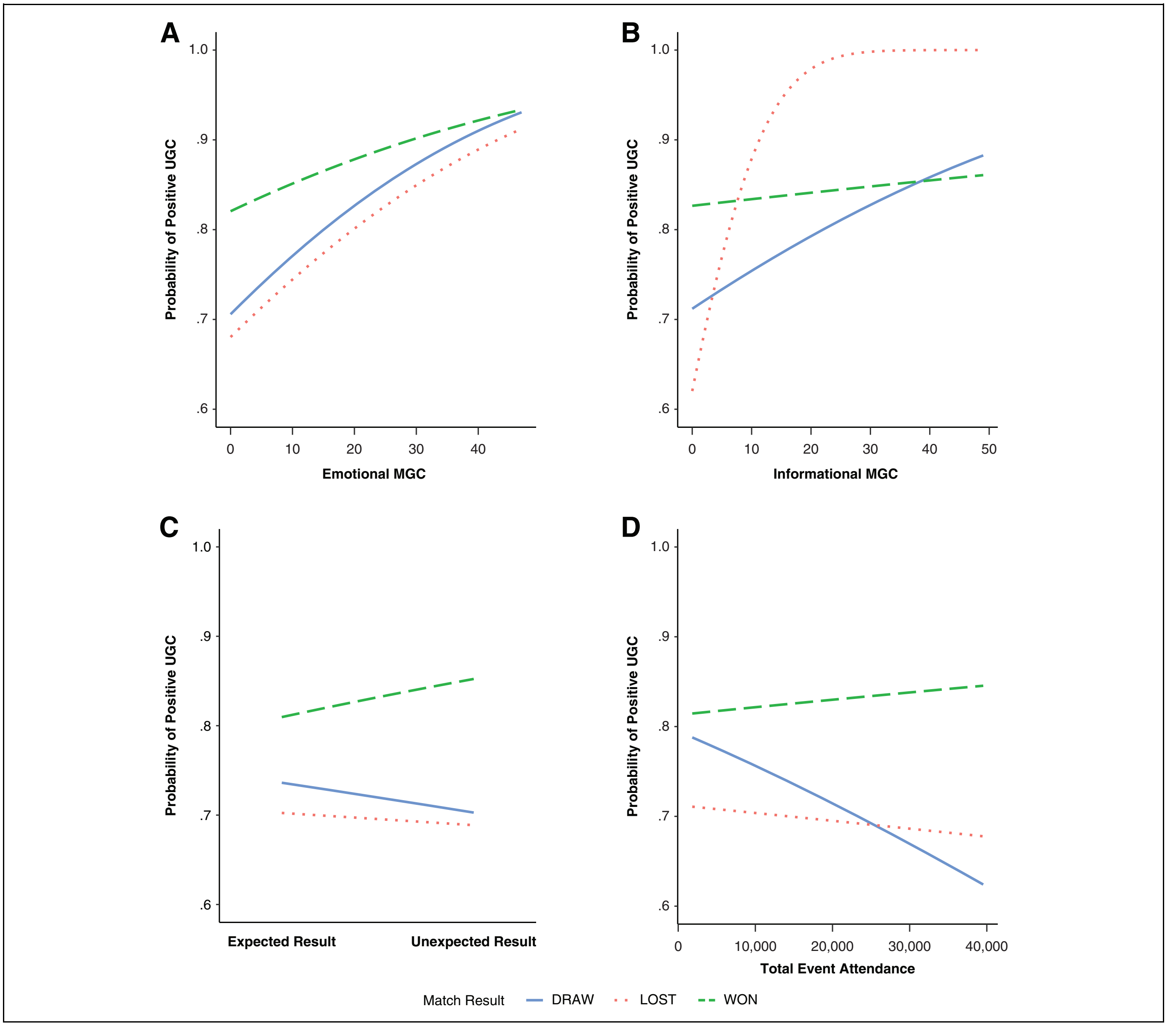

Figure 2. Effects of MGC on the sentiment of customers' digital engagement. (a) Effect of Emotional MGC on Sentiment for Different Event Outcomes, (b) Effect of Informational MGC on Sentiment for Different Event Outcomes, (c) Effect of an Unexpected Event Outcome on Sentiment for Different Event Outcomes, (d) Effect of the Total Event Attendance on Sentiment for Different Event Outcomes.

and 7 = "Daily"). Participants' sentiment ratings were elicited immediately following the scenario descriptions.

Procedure

Participants were asked to list their favorite team sport and sports team to help set the context. Then they read a scenario to which they were randomly assigned. All scenarios started as follows: "Imagine a situation in which you just watched a game of your favorite team-sport. Before the start of the game, your expectations were that your favorite team would [win/lose]. [Indeed/However], they [won/lost]." In the no-MGC condition, the scenario stopped here. In the MGC conditions, the respondents saw the following sentence: "You go to the team's Facebook page and see that the team has posted the following:" For the informational MGC condition, we used the following three sentences (because the mean MGC volume in our data set is also approximately three posts), reflecting several aspects of the game: "Our next game is against XYZ," "Did you know there were X spectators in the stadium today?," and "Player X played his 200th game today." For the emotional MGC condition, respondents read the following: "Come in great numbers to the stadium for the next game to encourage the team!," "Thanks fans for the fantastic support!," and "We are one team!." These posts reflect actual posts observed in the data.

Table 10. Results of the Scenario Experiment.

Variables	Estimate	t-Score
Intercept	−.22	−.08
Result Won	2.18***	8.61
Informational MGC	.27	1.20
Informational MGC × Result Won	−.50*	−1.81
Emotional MGC	.54**	2.39
Emotional MGC × Result Won	−.43	−1.56
Expected Win	.10	.66
Expected Win × Result Won	−.72***	−3.65
Comment Frequency Facebook	−.06***	−2.77
Age	.02***	3.88
Gender (male)	−.02	−.15

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: To avoid making the scenario experiment too complex, we included only two possible results (win and loss). We use a loss as reference category.

After reading the scenarios, respondents rated how they would feel in this scenario on a seven-point Likert scale. We base our dependent variable on the Positive and Negative Affect Schedule (Watson, Clark, and Tellegen 1988). We asked respondents to rate how they think they would feel based on each of the 20 emotions on five-point Likert scales (1 = "Not at all," and 5 = "Extremely") given the scenario. The ten positive emotions are interested, excited, strong, enthusiastic, alert, inspired, determined, attentive, proud, and active. The ten negative emotions are upset, guilty, scared, hostile, distressed, irritable, ashamed, nervous, jittery, and afraid. Affect (M = 1.30, SD = 1.17) is then computed as the mean of the positive emotions minus the mean of the negative emotions and used as our dependent variable.

Results

The results of our ordinary least squares regression ($R^2 = .433$) are shown in Table 10. The results are consistent with the results of our main study in that the coefficient for emotional MGC is significantly positive, informational MGC is not significant, the interaction between informational MGC and match result is significant and negative (i.e., informational MGC has significantly less impact in the case of a win) and the interaction between emotional MGC and result is not significant. This provides further evidence of the key causal relationships in our study and confirms MGC moderation on the match outcome–customer sentiment link.

General Discussion

This article examines the potential for firms' customer engagement initiatives on social media to influence the sentiment of customers' digital engagement. Regarding our first research question, we show that marketers can use MGC surrounding experiential events to influence the sentiment of customers' digital engagement even with no change in their objective performance during events. The volume of MGC positively influences the sentiment of customers' digital engagement, consistent with prior research (Colicev et al. 2018; Homburg, Ehm, and Artz 2015). However, we demonstrate these results related to customer interaction event outcomes, an important distinction from prior research, given firms' abilities to monitor their performance during such events and adapt their social media contributions in line with their performance. Furthermore, this study extends previous literature by more richly characterizing the complex nature of the social media environments in which firms and customers interact. Regarding our second research question, we find that while emotional content has a positive influence on the sentiment of digital engagement, informational content has a larger positive influence in the case of undesirable event outcomes. Thus, our findings contribute to understanding of how social media can be used effectively as a marketing tool. Next, we discuss our studies' implications, illustrating how managers can use our results and offering theoretical insights for researchers.

Theoretical Implications

We review here the implications of our results within the customer engagement framework and examine implications related to the concept of customer engagement marketing.

The role of customers' experiences for their engagement. Customer engagement theory is argued to have its roots in marketing's service-dominant logic, which proposes that important engagement-related customer outcomes are generated by their brand- or firm-related interactive experiences (Vargo and Lusch 2004). We link the concept of customer engagement and brand- or firm-related customer interactive experiences and furthermore extend the customer engagement theory framework developed by Pansari and Kumar (2017). Whereas Pansari and Kumar argue that marketing efforts can serve as an antecedent to customers' experiences (i.e., by creating awareness and motivating their initial purchase), we reveal the interactive role of such marketing efforts with those experiences and demonstrate their ability to influence the sentiment of customers' digital engagement.

Marketer-driven engagement. Our research lends empirical support to the value of customer engagement marketing proposed by Harmeling et al. (2017) and of formal customer engagement initiatives (Gill, Sridhar, and Grewal 2017). Harmeling et al. (2017) distinguish between task-based and experiential initiatives, with task-based initiatives involving customer actions, such as sharing brand knowledge with other customers on social media, and experiential initiatives incorporating sensory or emotional content that subsequently links to the mental representation of the brand or core offering. Our results suggest that such initiatives should be strategically adapted on the basis of firm performance during customers' interaction events. For example, with positive event outcomes, experiential initiatives leveraging multisensory and emotional content may be particularly effective at reinforcing any experience-related positive affect, further enriching customers' mental representations of a brand (MacInnis and Price 1987). For negative event outcomes, task-based engagement initiatives in which marketers share and then encourage others to share brand- or firm-related information might be more effective at enhancing customers' recall of brand-related information (Burke and Srull 1988).

Managerial Implications

Our results offer important implications for the use of MGC. Using our ability to link social media data and customers' transactions, we also highlight the potential role of the sentiment of customers' digital engagement as a leading indicator of CLV, a form of direct customer engagement.

Integrating sentiment and customer relationship management practices. Whereas prior research has revealed how firms can track sentiment on social media at an aggregate level, tracking it at an individual level can enable the design of tailored actions based on firm performance during customer interactions. Given estimates that 40% of consumers follow their favorite brands on social media (McCue 2018), there is sizable opportunity for firms to leverage MGC surrounding customer interactions to influence the sentiment of digital engagement.

Beyond designing tailored content, another potential implication of our research is that marketers may leverage insights from their one-to-one social media interactions with customers to enhance customers' experiences, enhancing the likelihood of customer engagement. For example, banks increasingly use social media to monitor customer sentiment and identify opportunities for service recovery, tailoring their posts to particular issues mentioned by customers. As noted by Homburg, Ehm, and Artz (2015), feedback detected from customers' social media content may be more timely than other sources (e.g., stock price fluctuations) and may furthermore enable well-timed online interventions. Relatedly, our findings might also extend to personalized communications sent by marketers' postpurchase. For instance, the beauty products chain Sephora sends recommendations and educational content to buyers immediately after they make a purchase (Sharma 2016). As part of firms' efforts to track UGC, a mechanism for responding in a customized manner may help further enhance the sentiment of customers' digital engagement and subsequent behaviors such as purchases, discussed further next.

MGC's role in influencing the sentiment of customers' digital engagement. Although our analysis does not allow us to make claims of causality between customer sentiment and direct engagement, existing research supports a causal link between sentiment and firm performance (Babić Rosario et al. 2016; Nejad, Amini, and Sherrell 2016). Given this link, the issue then becomes how to influence the sentiment of digital engagement—our primary goal. Purchase behaviors may not occur as frequently as social media posts. Thus, whereas monitoring purchases would potentially uncover at-risk customers, it can only do so after behaviors occur. Because, in our case, purchases only occur once per year, the firm would have limited opportunity to intervene to reverse the adverse effects of unfavorable performances. With regular access to the sentiment of customers' digital engagement, firms can intervene with marketing actions as well as learn from the success of those actions. It is also likely that many of a firm's customers are active on social media, providing regular chances to influence the sentiment of their digital engagement. To illustrate the potential influence of MGC content, we performed several post hoc analyses in which we varied informational or emotional MGC levels, comparing resulting sentiment (averaged across customers) for different event outcomes. Table 11 provides the results.

Table 11. Change in Sentiment Based on Increases in Informational and Emotional MGC.

	Informational MGC		Emotional MGC	
	$\Delta + 50\%$	$\Delta + 100\%$	$\Delta + 50\%$	$\Delta + 100\%$
Loss	10.07%	19.40%	3.20%	6.34%
Draw	1.28%	2.55%	2.89%	5.70%
Win	.33%	.66%	1.15%	2.26%

Notes: Percentages indicate the difference in resulting sentiment (averaged over all customers).

We simulate two levels of MGC increases, keeping all other variables the same. Variables are standardized; thus, increases refer to the percentage of those variables' standard deviations. With 50% more informational MGC (corresponding to 2.2 additional posts), customer sentiment in case of a loss would increase by 10%. However, in the case of a draw or win, this percentage is much lower (1.28% and .33%, respectively). A 100% increase (increase of 4.4 posts) would bring a 19.40% increase in customer sentiment when incurring a loss. With regard to emotional MGC, the increase in sentiment is smaller (larger) in the case of a loss (draw and win) compared with informational MGC. The differences (resulting from different levels of emotional MGC) between wins, losses, and draws are not significantly different.

Finally, increasing MGC has diminishing returns, consistent with prior research (Homburg, Ehm, and Artz 2015); increases at already high levels do not yield the same proportional increases as those at low levels. This finding is not entirely clear in Table 7 because MGC levels are still relatively low (e.g., the average level of informational MGC is 2.42 posts in a match window; SD = approximately 4.4 posts). In Figure 2, Panel B, the MGC interaction shows that, at this range, the lines are fairly proportional but flatten for higher MGC levels, a result confirmed in the robustness check using log-transformed MGC variables. This shows that firms may be able to influence the sentiment of customers' digital engagement with even minor adjustments in MGC volume and content. For firms that track objective performance during interaction, we encourage the use of adaptive MGC strategies.

Sentiment's role as a real-time leading indicator of CLV. While our focus is on the sentiment of customers' digital engagement, an indirect form of engagement, prior research has linked customer sentiment to purchase behavior (Manchanda, Packard, and Pattabhiramaiah 2015). Through our ability to link to transactions, and the common use of purchase incidence and amount in modeling CLV (Kumar et al. 2008), we aimed to explore customer sentiment's role as a leading indicator of CLV (for details, see Web Appendix W10). First, we decompose the CLV model in two regressions, binary purchase incidence and amount. We include a variable capturing the predicted sentiment of customers' digital engagement—based on our sentiment model and aggregated per year—as an independent variable in both regressions, along with typical variables used in CLV models and the team's social media share of interest (percentage of customer's team-related page likes). Results indicate that, even when controlling for transactional variables, predicted sentiment has a significant positive relationship with purchase incidence—an indicator of direct engagement (Pansari and Kumar 2017)—but not with purchase amount. Thus, we reveal the potential role of the sentiment of customers' digital engagement as a leading indicator of purchase incidence, with the benefit that it is available more frequently than actual purchases. Our findings also demonstrate the value of the additional information on social media beyond information typical in firms' customer databases.

Limitations and Future Research Directions

This research represents one of the few empirical demonstrations of the link between objective event outcomes, MGC, and the sentiment of customers' digital engagement. However, several limitations should be considered in evaluating our findings. First, while we argue that the sports context is ideal for the phenomena studied, other firm-specific factors, such as industry and customer involvement, vary across contexts and may be important. However, we believe our findings are relevant for marketers across contexts in which (1) marketers can identify individual customer interactions, whether group or individual experiences such as purchases or service experiences, and (2) customers are exposed to MGC on social media. Consumers regularly turn to social media to voice reactions to brand- or firm-related interactions across a variety of contexts. Firms also connect with customers on their own social media pages, posting content related to events such as performing arts (for an example in the motion pictures context, see, e.g., Moon, Bergey, and Iacobucci [2010]), sports, or promotional events. Across contexts, firms are interested in gauging customer perceptions of their experiences. Thus, MGC's importance for customer sentiment represents a valuable finding. Our approach could be extended to other settings such as purely contractual situations in which buyers have less discretion in purchase decisions.

Second, in an empirical study such as ours, it is challenging to completely address all potential endogeneity concerns. For example, it is possible that marketers use heuristics, past experience, and the context of a game when deciding which content to post to social media and how much, even when the company itself does not have a clearly defined social media posting strategy. Similarly, there may be factors that we do not account for that drive people to comment on company social media posts and drive self-selection. Despite our efforts to account for this (self-selection correction, instrumental variables, and a rigorous set of control variables), we cannot completely rule out endogeneity. However, the experiment in Study 2 verifies our results from Study 1, indicating that potential remaining endogeneity does not strongly influence the results.

Next, the use of social media data from Facebook alone may represent a limitation. While we argue that it is appropriate for our context, insights from other platforms may be valuable and supplement those from Facebook in helping firms assess and influence customer sentiment. However, whereas some researchers have argued that UGC can differ by the platform (Schweidel and Moe 2014), Smith, Fischer, and Yongjian (2012) find that positive brand-related sentiment in UGC does not differ across platforms (Facebook, Twitter, and YouTube) and argue that brand interactions in particular influence comments on Facebook. Future studies might assess the ability of other social networking sites to assess the role of MGC for customer sentiment.

Our exploration of MGC's moderating role considered two types of content, namely, informational and emotional. There is evidence that other types of content (e.g., promotional messages) can result in negative customer behaviors (Scholtz et al. 2018; Vargo 2016) or in increased warnings regarding consumer skepticism toward social media advertising (Saprikis 2013) and "spammy" content (*Forbes* Communication Council 2018). Due to the limited presence of promotional messages in our sample of MGC, we were unable to investigate the potential impact of such content here. Thus, future research should examine a broader set of content, including promotional messages on social media, in extending our findings regarding MGC's moderating role on the influence of event outcomes on customer sentiment on social media.

Although we do not find evidence that MGC's influence depends on customer segments, prior research has found differential effects of, for instance, social media participation for high and low social media users (Rishika et al. 2013). Thus, we see it as a fruitful avenue for further research to investigate possible conditions in which segmentation can become important (e.g., sector, industry, countries, social media venue).

Finally, our study is limited to four years. A longer window or more purchase occasions may yield additional insights not observable in our limited time frame.

Associate Editor

Hari Sridhar

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was supported by a grant from the Marketing Science Institute.

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