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ORIGINAL EMPIRICAL RESEARCH

Brand-generated social media content and its differential impact on loyalty program members

Blanca I. Hernández-Ortega[1] · Michael A. Stanko[2] · Rishika Rishika[2] · Francisco-Jose Molina-Castillo[3] · José Franco[1]

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Abstract
Social media and loyalty programs are mainstays of contemporary marketing, but despite their prominence—and their potential synergies—the two are seldom researched together. Here, drawing on the heuristic-systematic model, we theorize and demonstrate that the dimensions of customer experience in brand-generated social media content lead to different sales responses from loyalty program and non-loyalty program customers. Based on several thousand social media posts connected to both loyalty and non-loyalty program sales, we show that relational and intellectual content have greater effects in driving sales to loyalty program members while behavioral content drives greater sales to non-loyalty program members. These findings improve our understanding of the financial outcomes of social media tactics, providing researchers and marketers with an understanding of the differences in responses across customer groups and a framework to optimize social media content.

Keywords Brand-generated content · Loyalty programs · Customer experience · Social media

Introduction

Digital transformation has pushed firms to prioritize social media as a mainstream marketing communication channel (Moorman, 2020; Rietveld et al., 2020). Social media brings firms closer to the public and encourages brand-based user experiences (Colicev et al., 2018). Brand-generated content (BGC) is disseminated with the aim of enhancing brand exposure, generating web traffic, and improving firm performance (Kanuri et al., 2018; Kumar et al., 2016). Fortune 500 firms are all represented on at least one social network; 100% have an active account on LinkedIn, most also employ Twitter (96%), Facebook (95%), and Instagram (73%: Center for Marketing Research, 2020). Firms increasingly incorporate social media into a range of activities, with a particularly relevant role in areas related to customer management such as loyalty programs (Rehnen et al., 2017). While social media spending has grown dramatically, marketers have consistently rated social media's contribution to firm performance poorly and reported difficulty connecting social media with performance (Moorman, 2020).

Ensuring the effectiveness of social media tactics alongside a loyalty program is vital; both tools have the capacity to deepen customer relationships and foster retention (Stanko et al., 2019). Loyalty program members have been reported to be more likely to spread positive word of mouth (Bond, 2019), making them ideal customers to engage via social media. Some brands have attempted to capitalize on loyalty program members' enthusiasm by maintaining distinct social media accounts for their loyalty programs. For example, Virgin Red is a highly gamified loyalty program, attempting to build loyalty across the Virgin companies. The program is supported by distinct social

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✉ Michael A. Stanko
mike_stanko@ncsu.edu

Blanca I. Hernández-Ortega
bhernand@unizar.es

Rishika Rishika
r.rishika@ncsu.edu

Francisco-Jose Molina-Castillo
fjmolina@um.es

José Franco
jfs@unizar.es

1 Department of Marketing, University of Zaragoza, Gran Vía 2, 50005, Zaragoza, Spain

2 Poole College of Management, North Carolina State University, Campus Box 7229, Raleigh, NC 27695-7229, USA

3 Department of Management and Finance, University of Murcia, Campus de Espinardo, 30100 Murcia, Spain

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media content for Virgin Red members across multiple platforms (e.g., Facebook, Twitter, Instagram). On the other hand, many brands do not specifically tailor communication for loyalty program members via social media. For instance, Starbucks, which reported that its loyalty program accounted for 40% of US store transactions (Fantozzi, 2019), terminated its distinct Twitter account for its reward members in 2018, instead pushing these customers to the main Starbucks account. Of course, there are costs and complexity associated with running multiple social media accounts, though this study offers evidence that—when used appropriately—different types of content most effectively spur loyalty program members toward purchases. Despite strong managerial interest in improving both social media and loyalty programs, marketers lack a systematic understanding of how social media content increases firm performance and how users differentially react to this content depending on whether or not they are members of a firm's loyalty program.

We focus on BGC's ability to evoke experiences in users during social media interactions, an important but largely overlooked aspect of social media marketing (notably, Bleier et al., 2019 examine experiential dimensions in the context of web page design). Accordingly, we adopt the five dimensions of customer experience proposed by Schmitt (1999): relational (social reactions), intellectual (thoughts and cognition), affective (moods, feelings, and emotions), sensory (sensations and neurophysiological reactions), and behavioral (actions). This framework provides the most comprehensive possible starting point to address experiential content in the contemporary context of social media. Based on theoretical arguments grounded in the heuristic-systematic model (Chaiken, 1987), we propose and empirically demonstrate that these experiential dimensions of BGC have distinct sales effects on social media users belonging to the firm's loyalty program, due to differences in the depth of processing of the brand's messages between loyalty program members and non-members. Here, we distinguish between online sales made to loyalty and non-loyalty program members to examine differences in the effectiveness of these dimensions in driving sales. We analyze a longitudinal dataset that includes 3646 social media posts (following Berger & Milkman, 2012) from a European operator of snow tourism resorts—coupled with online sales data for both loyalty program and non-loyalty program sales. Findings demonstrate that relational and intellectual content are more effective at driving online sales to loyalty program members while behavioral content generates online sales disproportionately to non-loyalty program members.

There is growing research interest in BGC (de Vries et al., 2017; Kumar et al., 2016; Meire et al., 2019). Prior studies have investigated how message characteristics impact customers (Smith et al., 2012). One body of research examines the form employed; for instance, whether the message includes multimedia content (e.g., Kent et al., 2003). A second body of research explores the impact of message timing (Golder et al., 2007; Rutz & Bucklin, 2011), and a third focuses on the valence of the message (e.g., Colicev et al., 2018). Although these studies have generated relevant knowledge, they collectively ignore the experiences that BGC can evoke in users. To understand social media's effectiveness, we argue and demonstrate that it is essential to take a multidimensional viewpoint. The dimensions of customer experience break down BGC into a managerially practical framework based on the experience generated for the message recipient.

Most studies on BGC examine social media responses within the platform, such as likes, shares, and comments (de Vries et al., 2012; Sabate et al., 2014). On the other hand, only a few scant works connect BGC to financial metrics, such as spending behavior and stock market performance (Goh et al., 2013; Park et al., 2018). Generally, the literature has not yet thoroughly examined the influence of BGC on online sales. This study advances research in this area by showing a strong connection between dimensions of customer experience and sales.

Prior work largely assumes that all users process BGC in a similar way, regardless of their relationship with the firm. To the authors' knowledge, no prior study has examined the differential sales effects of experiential BGC characteristics on loyalty program and non-loyalty program customers (see Table 1). One relevant paper is Kumar et al. (2016), who find that the effect of BGC is greater for customers with lengthier brand experience. Building on this, we make a theoretically supported, managerially relevant contribution to the social media marketing and loyalty program literatures by showing that firms will have different levels of success with the same BGC for loyalty and non-loyalty program members. That is, we identify the dimensions of experiential content that have greater effects on sales based on loyalty program membership. This is a finding of tremendous practical relevance in a domain that has not yet been well examined by researchers. Specifically, we demonstrate that relational and intellectual experiential content have greater effects in driving online sales to loyalty program members while behavioral experiential content better generates online sales with non-loyalty program members. Thus, it seems advisable—where possible—for firms to post distinct content for each group.

The remaining sections are organized as follows. The next section develops the background for our research, reviewing key concepts. Following this, hypotheses are developed. We then describe the evaluation of posts and data assembly. The hypotheses are tested using two-step Generalized Method of Moments (GMM). We discuss implications from these findings before concluding with limitations and future research directions.

Table 1 Selected research on brand-generated content and loyalty programs

Study	Form	Timing	Valence	Customer Experience	Loyalty Program	DEPENDENT VARIABLE	
						Sales	Other
Current study	✓	✓	X	Relational, Intellectual, Affective, Behavioral, Sensory	✓	✓	No
Nisar et al. (2020)	X	X	✓	No	X	X	User engagement; Firm financial performance
Rietveld et al. (2020)	X	X	X	No	X	X	User engagement: likes, comments
Bleier et al. (2019)	✓	X	X	With respect to Web Page Design: Informativeness, Entertainment, Social Presence and Sensory Appeal	X	✓	No
Lu and Miller (2019)	X	✓	X	No	✓	✓	No
Meire et al. (2019)	X	✓	X	No	X	X	Customer sentiment
Yang et al. (2019)	X	X	X	No	X	X	Customer offline purchasing: spending and price insensitivity
Colicev et al. (2018)	✓	X	✓	No	X	X	Awareness, customer satisfaction, purchase intent
Kanuri et al. (2018)	X	✓	X	No	X	X	Link clicks
Kumar et al. (2016)	X	X	✓	No	X	X	In-store metrics: spending, cross-buying behavior and customer profitability
Martin et al. (2015)	X	X	X	Affective, Behavioral	X	X	Purchase intention
Goh et al. (2013)	✓	X	✓	No	✓	X	Purchase expenditure
De Vries et al. (2012)	✓	X	✓	No	X	X	Brand post likes and comments

Research background

Brand-generated content

Whether firms are successful in encouraging desirable user behaviors through social media depends to a great extent on the content published. Consistent with Kumar et al. (2016, p. 9), we define brand-generated content (BGC) as "firm-initiated marketing communication in its official social media pages." Thus far, in evaluating message characteristics, three coexisting categories have emerged: message form, timing, and valence.

First, message form refers to the vividness and interactivity of the message (Kent et al., 2003). Vividness is the ability to depict a virtual situation in ways that approximate reality (Liu-Thompkins & Shrum, 2002), while interactivity is defined as "the degree to which two or more communication parties can act on each other, on the communication medium or on the content and the degree to which such influences are synchronized" (Liu-Thompkins & Shrum, 2002, p. 54). de Vries et al. (2012) and Cvijikj and Michahelles (2013) demonstrate positive effects of vividness on the number of likes, but non-significant (de Vries et al., 2012) and negative effects of interactivity (Cvijikj & Michahelles, 2013) have also been observed.

Second, research related to message timing analyzes how the day of the week (e.g., working days vs. weekend) and the time of day (e.g., business vs. leisure hours) of the post impact its effectiveness (Golder et al., 2007; Rutz & Bucklin, 2011). Social media scheduling is recognized as an important marketing tactic with the potential to increase revenue (Kumar et al., 2016).

Third, message valence refers to the positivity or negativity of the message. Research on BGC valence highlights the effect of positivity in instilling good feelings in consumers, creating a favorable brand image and promoting purchases (Wu et al., 2018).

There are varying perspectives on analyzing message content beyond these categories. Studies have classified content in various ways, such as informative and brand-personality related content (Lee et al., 2018) or informational, promotional, and community-building content (Saxton & Waters, 2014). The distinction between informative and emotional appeals appears meaningful (Akpinar and Berger 2017; Lee et al., 2018; Nisar et al., 2020; Rietveld et al., 2020). It is noteworthy that, while these research themes pertain to the content published, very few studies have deeply considered the customer experiences that BGC can evoke (Table 1), a gap which we intend to address.

Regarding responses to BGC, existing research can be placed in two categories: (1) studies that address user reactions within the social network, and (2) studies that address the consequences of BGC outside the social network. Research in the first category has largely focused on Facebook, analyzing social interactions that spread BGC within the network (de Vries et al., 2012; Kim & Yang, 2017). Most of these studies investigate outcomes such as likes, comments, and shares, viewing these micro-reactions as proxies for brand popularity and customer engagement (Kim & Yang, 2017; Sabate et al., 2014), and taking for granted that this engagement drives sales (Meire et al., 2019). Equating micro-reactions such as likes and shares with financial success is something that marketers have been skeptical of (Hoffman & Fodor, 2010), posing a challenge for marketing researchers to connect social media tactics with financial outcomes.

The second (less developed) line of research focuses on the consequences of BGC beyond the social network. Recent work in this area explores how BGC affects consumer awareness (Dabbous & Barakat, 2020), attitude (Wang et al., 2019), loyalty (Hajli et al., 2017), and commitment (Demiray & Burnaz, 2019). Other studies examine customer-level metrics such as purchase behavior, expenditures, and price sensitivity (Goh et al., 2013; Kumar et al., 2016; Mochon et al., 2017). Kumar et al. (2016) analyze the effect of firm-generated social media content on in-store metrics: spending behavior, cross-buying behavior, and customer profitability. Most research in this category focuses on the individual customer, overlooking important firm-level metrics (Stephen & Galak, 2012 is one exception). This work intends to fill this gap by examining the effect of BGC on the entirety of a firm's online sales.

Customer experience

Holbrook and Hirschman (1982) present an experiential perspective on consumption, proposing that products are consumed within the individual's awareness with connections to symbolic meanings, hedonic responses, and aesthetic criteria. Customer experience is a view of consumption that goes beyond the rational approach applied in the economic literature (Schmitt, 1999). Experience is viewed as the response customers have to direct or indirect contact with the firm. Direct contact occurs during the purchase and use of a product or service, and is usually initiated by the customer, while indirect contact takes the form of word-of-mouth recommendations or criticism, advertising, news reports, and so forth (Meyer & Schwager, 2007). During this contact, consumers are exposed to various brand-specific stimuli, such as colors, shapes, typefaces, slogans, and characters (Veryzer & Hutchinson, 1998), which are part of the brand's design, identity, and environment. These elements make up part of the stimuli to consumer responses that Brakus et al. (2009) labeled "brand experience." Brand experiences vary in strength and valence, being more or less intense, positive or negative. These experiences can also be short-lived or long-lasting. Overall, strong, positive, and long-lasting customer experiences generate desirable marketing outcomes, such as positive attitudes, satisfaction, and loyalty (Brodie et al., 2013).

Scholars have taken several viewpoints on the dimensionality of customer experience. On one hand, some researchers measure the concept in an aggregated way, examining the effect of experience through a single factor (Srivastava & Kaul, 2016). On the other hand, many authors consider experience to be a multidimensional concept (Rose et al., 2012). Each dimension may take on varying importance depending on the situation. Schmitt's (1999) framework is one of the earliest and most influential multidimensional frameworks of customer experience, proposing five modules with which marketers can create customer experiences: relate, think, feel, act, and sense. While Schmitt's framework has been widely adopted, his theoretical framework has also subsequently been employed by others in a reduced form. For instance, Brakus et al. (2009) use only four dimensions of brand experience: intellectual (i.e., think), affective (i.e., feel), behavioral (i.e., act), and sensory (i.e., sense), considering relational experience to be subsumed within the affective dimension. Similarly, Verhoef et al. (2009) highlight the multidimensional nature of the experience in retail branding, considering cognitive, affective, emotional, social, and physical responses. Homburg et al. (2015) suggest that customer experience is the evolution of a person's sensorial, affective, cognitive, relational, and behavioral responses to a brand developed over a series of touchpoints.

Social media messages published by the firm can also evoke experiences in users. Thereby, we propose the importance of testing a multidimensional framework of experience in this contemporary context as a starting point toward understanding each dimension's performance implications. Given that this is the first application of a customer experience framework to social media, we adopt Schmitt's (1999) full set of five dimensions to take the most comprehensive viewpoint possible. These dimensions are well established in past research (e.g., Lemon and Verhoef 2016) and allow us to connect our theorization and findings to research on customer experiences in other contexts.

Loyalty programs and information processing

Loyalty programs are attempts at building customer relationships to improve business performance through better retention (Gorlier & Michel, 2020). Loyalty program usage has expanded dramatically across industries since the early days of frequent flyer miles in the 1970s. Studies in this area span a variety of industries: retail (Bruneau et al., 2018; Evanschitzky et al., 2012; Hwang & Choi, 2020; Leenheer et al., 2007; Lewis, 2004; Maity & Gupta, 2016), financial (Gorlier & Michel, 2020; Kang et al., 2015), and travel (Liu & Yang, 2009; Steinhoff & Palmatier, 2016).

While loyalty programs have proliferated, questions have arose regarding the cost/benefit of implementation (Henderson et al., 2011; Liu-Thompkins & Shrum, 2002), particularly given the saturation of competing loyalty program offerings (Chaudhuri et al., 2019; Zhang & Breugelmans, 2012). Recent contributions in this area have explored the role of gamification for loyalty programs (Hwang & Choi, 2020), the impact on store loyalty (Meyer-Waarden, 2015), and how to maintain long-lasting customer relationships (Bruneau et al., 2018).

The effectiveness of loyalty programs has come under particular scrutiny for firms that market their products online (Dorotic et al., 2014). Importantly, our literature review reveals a paucity of studies at the intersection of social media and loyalty programs. In two rare exceptions, Rehnen et al. (2017) find that social media engagement can increase the effectiveness of intrinsic motivation for customers to remain loyal, while Lu and Miller (2019) conclude that long-term loyalty program customers are more responsive to social media posts with environmental themes. Looking at the literature, it is clear that the current state of research does not provide managers with meaningful, comprehensive advice in terms of managing social media for loyalty program success. This study intends to bridge this gap.

The heuristic-systematic model (Chaiken, 1987) proposes two co-existing modes of information processing: *systematic* and *heuristic*. *Systematic processing* involves attempting to thoroughly understand information through careful analysis (Chaiken & Ledgerwood, 2011) and only occurs when an individual has the motivation and ability to take on this deeper processing of information (the *sufficiency principle*; Chaiken & Ledgerwood, 2011). When applying systematic processing, judgments are responsive to the content of information, rather than more superficial cues (Chen & Chaiken, 1999). On the other hand, *heuristic processing* is relatively automatic and focuses on salient and easily processed cues that activate judgmental shortcuts by which individuals exert little cognitive effort, processing information by means of simple schemas. We consistently argue that loyalty program members have a higher level of desired expertise regarding the brand and, thus, they are more able and motivated to process brand-originated social media messages through systematic processing (Griffin et al., 2002). This desire takes shape for several reasons, which are consistent with the motivators for selective information processing theorized by the heuristic-systematic model. First, loyalty program members are more likely to benefit from increased knowledge (i.e., there is a greater importance of having accurate brand knowledge—the *accuracy* motivation is more deeply engaged), given their signal of an ongoing relationship with the brand. Second, loyalty program members have a heightened tendency to protect their established view of the brand (the *defense* motivation) and preserve existing viewpoints (Chen & Chaiken, 1999). Third, loyalty program members are more motivated to systematically process information congruent with the community of customers that they are affiliated with (the *impression motivation*; Chaiken et al., 1996; Chen & Chaiken, 1999). Overall, the increased presence of these motivations leads us to expect that loyalty program customers are more apt to process brand-originated messages systematically, consistent with prior work showing personal relevance to be associated with systematic processing (Todorov et al., 2002).

Accordingly, we present arguments below that social media messages demanding a greater amount of processing from recipients (messages that are, for instance, highly intellectual) will have a greater effect in driving sales to loyalty program members. On the contrary, non-loyalty program members are more likely to consider brand-originated social media postings to be just another social media post in a distraction rich digital environment. Thus, they are not as willing to invest cognitive resources in deeply processing these posts and are more responsive to content that can be appreciated with less effort. Given this, we argue that immediately and easily understandable messages (for instance, highly behavioral messages) more strongly encourage consumption from non-loyalty program members. This is consistent with Chen and Chaiken's (1999, p. 93) view "that there may be particular instances in which heuristic processing contributes as much or even more than systematic processing" to persuasion.

While the hypotheses put forward below do not constitute a direct test of the heuristic-systematic model, we present a pilot study that tests the premise that loyalty program members are more apt to systematically process brand-originated social media messages in Web Appendix A. In this study, MTurk participants were shown a brand originated social media message. Those participants who belong to the brand's (Starbucks was used for the pilot study) loyalty program report significantly higher levels of systematic processing of the social media post than did participants who were not loyalty program members ($p = .001$).

Hypotheses

The following arguments relate each of Schmitt's (1999) five experiential dimensions with sales to both loyalty program members and non-members. These hypotheses consistently argue that those experiential dimensions requiring a greater amount of processing from recipients will drive sales to loyalty program members more so than to non-loyalty program members.

Relational content

The relational (sometimes referred to as social) dimension refers to the extent that a message "expands beyond the individual's personal, private feelings, thus relating the individual to something outside her/his private state" (Schmitt, 1999, p. 62). Individual consumers develop brand relationships (both on and offline) in a pattern that promotes their identification with the brand (Cha et al., 2015). For loyalty program members, their pre-existing brand identification (signaled through membership) allows social media messages with themes affiliating the brand with customers' social systems to more strongly resonate and generate sales. On the contrary, non-loyalty program members, who have less established brand relationships, will not be moved toward purchase by social media messages that attempt to connect the (less familiar) brand with a larger sense of the message recipient's self and with others. The heuristic-systematic model holds that systematic processing depends in part on the message recipient's ability to thoughtfully process the message (Chaiken & Ledgerwood, 2011). Given their increased identification with and knowledge of the brand, the ability of loyalty program members to deeply process relational messages that align the brand with their social systems is enhanced when compared to non-loyalty program members.

The processing of relational content logically connects with the heuristic-systematic model's impression motivation. When the impression motivation is engaged, individuals are more likely to systematically process information pertaining to their social objectives (Chen et al., 1999). Thus, we argue that posts which are high on the relational dimension will more meaningfully impact sales to loyalty program members, given that the increased social relevance of the message makes deeper, systematic processing more likely for this group. When directed to non-loyalty program members, relationally themed messages will be more likely to trigger distraction as recipients' attention shifts away from the stimulus (Teixeira et al., 2012), rendering relationally themed posts less effective.

H1 Relational content will have a more positive effect on sales to loyalty program members when compared to non-loyalty program members.

Intellectual content

Intellectual communication with social media users requires thoughtful, logical message processing for messages to be understood and to effectively prompt consumer response. Generally, individuals are motivated to hold correct attitudes (the accuracy motivation; Chaiken & Ledgerwood, 2011), which can be upheld by intellectual arguments. However, recipients will only engage in critical thinking regarding their brand-based beliefs when they are highly involved with a brand, motivated by the brand's established personal relevance (consistent with the sufficiency principle). Given that loyalty program members have signaled their involvement with the brand and demonstrated brand relevant experience, they are more willing to deeply process intellectual messaging; thus, this variety of message will have a greater effect in driving sales to loyalty program members. Loyalty program members may also have an increased desire for detailed content related to the brand's service and technical procedures (Raab et al., 2015), making intellectual content even more engaging for this group of consumers (Kaplan, 2012).

On the contrary, we argue that non-loyalty program members are generally less involved with the brand and, thus, are less motivated to allocate cognitive effort to process the brand's social media messages. In this case, intellectual content may not be fully understood or appreciated by recipients, rendering intellectual messaging less impactful on non-loyalty program members. This argument represents our purest test of heuristic-systematic logic; more cognitively demanding social media messages require deeper, more effortful processing to be effective.

H2 Intellectual content will have a more positive effect on sales to loyalty program members when compared to non-loyalty program members.

Affective content

Research grounded in dual process models of information processing, including work grounded in the heuristic-systematic model as well as related work drawing on the Elaboration Likelihood Model (ELM), has included debate regarding the most effective processing path for affective persuasive cues (Petty et al., 2003). Accordingly, we put forward competing hypotheses concerning the relative impact of the affective dimensions on loyalty and non-loyalty program members.

First, some research has made an association between affect and low effort, even unconscious processing (Kitchen et al., 2014). Emotional words are relatively easy to process (Gendron et al., 2012) and affect can be simply understood as a signal of positivity (Guo et al., 2020), losing its impact in situations that require investing more cognitive resources (Vakratsas & Ambler, 1999). Therefore, if message recipients are relying on shallower processing, affective content may be an appropriate path to persuasion since it allows them to relatively effortlessly associate emotions with the brand (Petty et al., 2003).

However, a competing argument is also viable, which considers the arguments of theorists who have viewed cognition to have an "emotional core", meaning that affective content may be more impactful under systematic processing (Kitchen et al., 2014; Petty et al., 2003). Having a personal interest is central to experiencing emotion (Teixeira et al., 2012). Loyalty program customers have already established affective relationships with the brand, so they are prone to process emotional information that is consistent with their current view (the defense motivation; Chaiken & Ledgerwood, 2011). Accordingly, loyalty program customers may be more apt to access this emotional core when processing a message from the brand, the affective experience becoming central to their decision making (Petty et al., 1988). Thus, messages with emotional themes may be more impactful on loyalty program members with relatively deep brand connections.

Given these opposing arguments, we see fit to propose competing hypotheses:

H3a Affective content will have a less positive effect on sales to loyalty program members when compared to non-loyalty program members.

H3b Affective content will have a more positive effect on sales to loyalty program members when compared to non-loyalty program members.

Behavioral content

Behavioral content focuses on physical experiences, showing message recipients alternative ways of doing things. As Schmitt (1999) discusses, behavioral, or "act" tactics serve to motivate the viewer by, in some cases, providing role models of behaviors associated with the brand. Examples include Nike's "Just do it" campaign as well as Patagonia's sustainability messaging. Generally, these easily understandable messages do not require deep, cognitive processing to be well understood; recipients are able to quickly and effortlessly relate their own behavior to the product or brand. This connects to an important element of social media practice: while some BGC may set up future messages or develop previous themes (Batra & Keller, 2016), behavioral content is generally relatable on its own. In this way, behavioral content is an ideal dimension to reach non-loyalty program members.

We consistently argue that customers with less established brand connections (i.e., non-loyalty program members) have less motivation to deeply process message content. Therefore, behaviorally themed messages, which easily relate to customer behaviors and demand little in terms of cognitive resources, are better suited for these non-loyalty program customers. It is also noteworthy that seeing role models fostering consumption behaviors can have the additional benefit of exposing non-loyalty program members to the brands' service processes (Raab et al., 2015), which may further result in favorable outcomes from this group. Processing behavioral content through deep, systematic processing, which is more likely applied by loyalty program customers, has less effect given that behavioral content likely does not meaningfully add to their already established cognitive connections with the brand.

H4 Behavioral content will have a less positive effect on sales to loyalty program members when compared to non-loyalty program members.

Sensory content

Sensory content, which appeals to sight, sound, and other senses, should generate the most immediate visceral response from recipients (Malhotra, 2013). Humans innately respond to sensory cues, which require little cognitive effort to process—thus, systematic processing is not required. Sensory content establishes low cognitive effort association to the brand (Petty et al., 2003), well suited to non-loyalty program members. Kaplan (2012) discusses a related classification of social media brand followers that they label "quick-timers," akin to non-loyalty program members in our context. These quick-timers require instantaneously stimulating content, as many of these users will not devote high levels of cognitive processing to these messages, given their lack of brand identification. Immediately appreciable, stimulating sensory content is well suited to the less thoughtful processing that non-loyalty program members are more likely to allocate to social media messages from the brand. As with behavioral content, sensory content does not need to build on previously established themes (Batra & Keller, 2016), making this dimension ideal for reaching non-loyalty program members.

H5 Sensory content will have a less positive effect on sales to loyalty program members when compared to non-loyalty program members.

Methodology

Data

To fulfill the study's objectives, we draw on two unique datasets from a prominent operator of snow tourism resorts in Europe. Information on 1) the nature and content of the social media posts and 2) online sales data are compiled into the respective datasets.

The first dataset comprises detailed information on the social media posts of the firm between October 2015 and April 2017. During this time, the primary social media platform used by the firm to communicate with customers was Facebook, from which we draw all data regarding its social media activity. It should be taken into account that Facebook had the highest number of users in the firm's home country (Statista, 2019). The focal firm only posted content organically (i.e., not paid social media advertising) and did not create unique content for any user groups. That is, both loyalty program members and non-members were exposed to the same social media content.[1] The raw dataset includes 4457 non-sponsored social media posts made by the firm. After a data cleaning process that involved eliminating posts during any time period when the e-commerce application was not available, we arrived at the final dataset, which includes 3646 social media posts made by the firm. This dataset includes (1) date and time of publication of the social media post, (2) content of the post, (3) reach of the post, i.e., the number of people who viewed the post, (4) destination related to the post, and (5) weather favorability for snow tourism.

The second dataset tracks the firm's online sales. We focus on online sales as the firm only runs its loyalty program online. Overall, online sales constitute 45% of the firm's sales providing a substantial dataset to test our hypotheses. Specifically, online sales captured in this variable are generated through an online platform that exclusively sells ski-passes—the core offering of this firm—to both loyalty program members and non-members. We note that hotel bookings are handled by an independent firm and are not included in this dataset. Customers pay ahead of time to purchase ski passes; the amount cannot be refunded. The dataset includes detailed information related to each online transaction including: (1) date and time, (2) amount, (3) destination for the transaction, and (4) whether or not the sale was within the firm's loyalty program.

These datasets were merged using individual social media posts as the matching variable. Thus, the unit of our analysis is the individual social media post, with online sales as the main outcome. Online sales are tracked for both loyalty program members and non-members; the data is structured with observations for both loyalty program and non-loyalty program sales for each post. Sales are attributed to a focal social media post if they occurred between the time of the publication of the focal social media post and the next social media post. We refer to this time period as the active time period of a social media post. This approach has been applied by other research on BGC that analyzes firm-level metrics (e.g., Stephen & Galak, 2012) and by previous studies on user-generated content, which examine the influence of customers' opinions on product sales (e.g., Dellarocas et al., 2007; Marchand et al., 2017). We find that 72% of the sales occur in the first-half life of the post, the first half of the time period between two consecutive posts, suggesting that a substantial degree of online sales can be attributed to these social media posts.

Operationalization of variables

Dependent variable Our dependent variable is the natural log of online sales generated during the time period between a focal post and the next social media post. Sales has been considered a desirable dependent variable for social media research, going beyond easily available non-financial metrics such as likes and shares (de Vries et al., 2012; Sabate et al., 2014), allowing the examination of social media's effect on financial performance (Chevalier & Mayzlin, 2006; Nga et al., 2013). Online sales are recorded separately for loyalty program members and non-members for each post.

Independent variables As explained above, our key independent variables of interest are the five dimensions of customer experience, that is, relational, intellectual, affective, behavioral, and sensory content. All posts were rated independently on each of these five dimensions (using five-point scales) by human raters. It is possible for a post to have the highest (or the lowest) score on multiple dimensions. Human raters can classify content that cannot be measured by automated coding systems, such as the simultaneous employment of several formats (that is, text, photos, and videos), the inclusion of tools with meaning (e.g., emoticons or GIFs) and the existence of certain characteristics in the message (e.g., sense of humor, anger, or irony). In these cases, human raters can apply homogeneous criteria to evaluate each post. Given the different types of messages posted on Facebook (compared to other predominantly textual networks such as Twitter), we rely on human raters to quantify the extent to which each post evokes each dimension of customer experience. After demonstrating an understanding of the different formats, tools and message characteristics, as well as the ability to manage databases, three human raters evaluated the firm's posts. Raters were blind to our hypotheses. Web Appendix B shows one example of an actual social media post with the scores obtained on each of the five content dimensions (somewhat akin to Kim et al., 2021). This Appendix also presents 10 examples of social media posts that have obtained the highest and lowest possible scores on each experiential dimension including the scores on the other dimensions (posts in Web Appendix B have been translated). The evaluation process was divided into six phases (Berger & Milkman, 2012) and is described in detail in Web Appendix C.

The loyalty program variable indicates whether sales were made to the firm's loyalty program members.

Control variables We have several control variables in our analyses to account for other factors that may influence sales. Specifically, we account for weather favorability for snow tourism, the season of publication of the social media post, the reach of the post measured by the number of unique users who saw the post in their news feed, the length of the post (number of words), whether the social media post contains multimedia content or only text, whether the post mentions a specific event, whether the post was published during holidays, the

[1] Importantly, the firm did not conduct member-only events. That is, the same offerings were available to both loyalty and non-loyalty program customers.

time of day the post was published, and the destination related to the post.

These variables, their operationalization and descriptive statistics are detailed in Table 2. Table 3 includes correlations for all variables. Figures 1, 2, 3 plot noncumulative sales across published posts, distinguishing between loyalty and non-loyalty program sales.

Model formulation

The key objective of this study is to understand how the dimensions of experience in BGC differentially influence a firm's online sales depending on whether the customer belongs to its loyalty program. Thus, we formulate the following model:

$$\begin{aligned} Ln\left(Sales_j\right) = \beta_0 &+ \beta_1\ Relational\ Content_j \\ &+ \beta_2\ Intellectual\ Content_j \\ &+ \beta_3\ Affective\ Content_j \\ &+ \beta_4\ Behavioral\ Content_j \\ &+ \beta_5\ Sensory\ Content_j \\ &+ \beta_6\ Loyalty\ Program_j \\ &+ \beta_7\ Relational\ Content_j{*}Loyalty\ Program_j \\ &+ \beta_8\ Intellectual\ Content_j{*}Loyalty\ Program_j \\ &+ \beta_9\ Affective\ Content_j{*}Loyalty\ Program_j \\ &+ \beta_{10}\ Behavioral\ Content_j{*}Loyalty\ Program_j \\ &+ \beta_{11}\ Sensory\ Content_j{*}Loyalty\ Program_j \\ &+ \beta_{12}\ Weather\ Favorability_j + \beta_{13}\ Season_j \\ &+ \beta_{14}\ Ln\left(Reach_j\right) + \beta_{15}\ Ln\left(Word\ Count_j\right) \\ &+ \beta_{16}\ Multimedia_j + \beta_{17}\ Specific\ Event_j \\ &+ \beta_{18}\ Holidays_j + \mu_j + \lambda_j + \varepsilon_j \end{aligned}$$

Where *Ln(Sales$_j$)* is the logarithmic value of firm sales related to a post *j, Relational Content$_j$* is the relational experiential rating of post *j, Intellectual Content$_j$* is the intellectual experiential rating of post *j, Affective Content$_j$* is the affective experiential rating of post *j, Behavioral Content$_j$* is the behavioral experiential rating of post *j, Sensory Content$_j$* is the sensory experiential rating of post *j. Loyalty Program$_j$* is a dummy variable that takes the value 1 if the firm sales related to the post *j* belong to the loyalty program and 0 otherwise, *Weather favorability$_j$* is a dummy variable that takes the value 1 for favorable weather and 0 otherwise, *Season$_j$* is an indicator variable that can take values 1 or 2 depending on the season when the post *j* was published (2015–16 or 2016–17, respectively), *Ln(Reach$_j$)* is the logarithmic value of the reach variable that measures the number of unique users the social media post *j* reached, *Word Count$_j$* is the total word count of the post *j*, *Multimedia$_j$* is a dummy variable that takes the value 1 if the social media post *j* has multimedia content (i.e., photos and/or videos) and 0 if it contains only text, *Specific Event$_j$* is a dummy variable that takes the value 1 if the social media post *j* refers to a specific event and 0 otherwise, *Holidays$_j$* is a dummy variable that takes value 1 if the post *j* is published during holidays and 0 otherwise, μ_j are the time fixed effects related to the time of day the social media post *j* is published, and λ_j are the destination fixed effects related to the destination of the social media post *j*.

We checked for heteroscedasticity by conducting the Breusch-Pagan/Cook-Weisberg test statistic, which indicated that the regression disturbances are related to the independent variables ($\chi^2 = 11.76$; $p < 0.01$). To avoid the problems associated with heteroscedasticity of unknown form, we employed the two-step Generalized Method of Moments (GMM) estimator (Baum et al., 2003; Greene, 2000).

Possible confounds related to endogeneity are potentially critical for our empirical analysis (e.g., Chintagunta et al., 2010). The model is subject to dynamic endogeneity because our dependent variable, *Sales$_j$*, is determined in part by its past realizations. This type of endogeneity relates to the effect of unobservable firm characteristics. Sales associated with a new post are determined not only by the content of the post but also by unobserved variables whose importance is reflected in previous sales. To account for such endogeneity, we propose a dynamic model and include the lag of the dependent variable as an explanatory variable in our econometric model.

We also investigate another potential source of endogeneity. It seems likely that the control variable, *Reach$_j$*, is endogenous. While *Reach$_j$* is likely to influence sales, it is also possible that customers, after purchasing a firm's product, may browse the firm's social network and be exposed to recently published posts. Following this argument, we propose that *Reach$_j$* may be an endogenous variable and therefore, we need to use an instrument to account for this source of endogeneity. We test the equation for potential endogeneity using the Durbin-Wu-Hausman test (difference-in-Sargan statistic for GMM estimations). The results affirm that this equation is affected by endogeneity for *Reach$_j$*: $\chi^2 = 27.00$; $p < 0.01$), thus this variable should be instrumented in order to avoid bias. An appropriate instrumental variable should fulfill two criteria to correct endogeneity: the relevance and exclusion restrictions (Angrist et al. 1996). To find appropriate instruments, we utilize a unique feature of our data that provides us information on posts across similar destinations. Specifically, we use "the average reach of all prior posts published by the other similar destinations of the firm except the focal one" as the instrumental variable. This instrument

Table 2 Operationalization of variables and descriptive statistics

Variable	Operationalization	Mean	S.D.
Relational content	Variable indicating if the post appeals to the bond that the individual maintains with her/his social systems (friends, family, partners, etc.). Measured with a five-point scale by human raters (see Web Appendix C).	2.18	0.77
Intellectual content	Variable indicating if the post appeals to the individual's conscious mental processes related to the practical resolution of problems, the stimulation of curiosity, or the application of the individual's creativity. Measured with a five-point scale by human raters (see Web Appendix C).	3.16	1.03
Affective content	Variable indicating if the post appeals to the individual's affective system through the feelings and emotions (s)he can experience during the interaction and consumption. Measured with a five-point scale by human raters (see Web Appendix C).	1.86	0.68
Behavioral content	Variable indicating if the post appeals to the individual's physical or behavioral actions. Measured with a five-point scale by human raters (see Web Appendix C).	2.29	0.97
Sensory content	Variable indicating if the post appeals to human senses with the aim of developing sensorial experiences: sight, hearing smell, taste, and touch. Measured with a five-point scale by human raters (see Web Appendix C).	2.48	0.85
Loyalty program	Dummy variable indicating if the firm sales related to the post *j* are made to a loyalty program member (value 1). Obtained from firm's internal data.	n.a.	n.a.
Weather favorability	Dummy variable indicating if the weather conditions are favorable (1) or adverse (0). Measured by a public weather station.	0.52	0.50
Season	Variable indicating the season when the post was published, with 1 for 2015–16 and 2 for 2016–17. Measured by Facebook Insights.	1.48	0.50
Reach	Variable indicating the number of the unique users (i.e., the number of people) who had the post displayed on their screen. This is a continuous variable, Ln transformed, obtained from Facebook Insights.	17,011.31	52,786.81
Word count	Variable indicating the number of words included in the post. This is a continuous variable, Ln transformed, measured by Linguistic Inquiry and Word Count (LIWC; Pennebaker et al., 2015).	36.05	26.71
Multimedia	Dummy variable indicating if the post contains multimedia content (i.e., photos and/or videos) (1) or if it includes only text (0). Measured by human raters and Facebook Insights.	0.99	0.08
Specific event	Dummy variable indicating if the post refers to specific events (value 1). Coded by human raters.	0.03	0.16
Holidays	Dummy variable indicating if the post is published during holidays (value 1). Measured by human raters and Facebook Insights.	0.20	0.45
Time fixed effects	Five dummy variables indicating if the post was published during certain hours. The first indicator variable served as the default: 1. at night, 00.01–08.00; 2. morning work hours, 08.01–12.00; 3. afternoon work hours, 12.01–16.00; 4. after work, 16.01–20.00; 5. after dinner, 20.01–00.00. Coded by human raters from Facebook Insights.	n.a.	n.a.
Destination fixed effects	Dummy variables indicating the destination related to the post. Coded by human raters from Facebook Insights.	n.a.	n.a.
Online sales	Online sales made to loyalty or non-loyalty program members that occurred during the active time period of the post. This period begins when the post is published and finishes when a new post appears. This is a continuous variable that is Ln transformed, obtained from firm's internal data.	3098.60	5708.78

measures the reach of posts published by similar destinations ensuring that there is no correlation with the error term and any variations in focal reach will be reflected similarly across the destinations. We note that similar approaches have been advocated and applied in recent studies (Dinner et al., 2014; Rutz & Watson, 2019).

To specifically check the relevance and the exclusion restriction criteria for the chosen instrument, we performed several analyses. First, we computed the Sanderson-Windmeijer (SW) χ^2 statistic, which tests the null hypothesis that the endogenous regressor in question is unidentified (Rutz & Watson, 2019; Sanderson & Windmeijer, 2016). The results demonstrate that the null hypothesis is rejected: $\chi^2 = 638.19$, $p < 0.01$. We also estimated the SW F and Stock-Wright S statistics which test the null hypothesis that the coefficient of the endogenous regressor in the structural equation is equal to zero. The results confirm that the equation is not weakly identified: $F(1, 7254) = 636.19$ and $\chi^2 = 51.38$, $p < 0.01$, respectively, verifying the strength of the instrument. Finally, we analyzed that the instrument is not significantly correlated with the error term ($r = 0.013$, $p > 0.10$) and that its explanatory capacity regarding the error is not significant ($\beta = 0.00$, $p > 0.10$). Based on these results, we feel the choice of our instrumental variable is appropriate in our context.

Results

The results of the estimation of our proposed model are presented in Table 4. This table first presents results from a model with only control variables followed by a model that includes

Table 3 Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Relational content	1												
2. Intellectual content	−0.009**	1											
3. Affective content	0.272***	−0.277***	1										
4. Behavioral content	0.109***	0.354***	−0.142***	1									
5. Sensory content	−0.058***	−0.404***	0.276***	−0.123***	1								
6. Weather favorability	0.076***	−0.091***	0.038**	0.033***	0.037***	1							
7. Season	0.022	−0.059***	0.118***	0.057***	0.064***	0.078***	1						
8. Ln(Reach)	0.096***	−0.183***	0.299***	−0.034***	0.439***	−0.023*	0.191***	1					
9. Ln(Word count)	0.273***	0.473***	0.125***	0.440***	−0.021*	−0.092***	0.106***	0.136***	1				
10. Multimedia	0.055***	−0.032***	0.029**	0.074***	0.119***	0.0348**	0.066***	0.023*	0.006	1			
11. Specific event	0.156***	0.093***	−0.024**	0.122***	−0.076***	0.036***	0.005***	−0.008	0.096***	0.015	1		
12. Holidays	0.129***	−0.085***	0.064***	−0.087***	0.021*	0.011	−0.012	0.070***	−0.052***	−0.020*	−0.050***	1	
13. Ln(Online sales)	0.108***	0.058***	0.055***	0.068***	0.147***	0.205***	0.130***	0.209***	0.019	0.016	0.049***	−0.004	1

Number of observations: 3646

* p < 0.10; ** p < 0.05; *** p < 0.01

the control and independent variables (i.e., five dimensions of experiential content and loyalty program membership). Finally, it reports findings that include the main effects of the experiential dimensions and hypothesized interactions. We find that the proposed model has a superior fit in terms of the adjusted R-square. Three dimensions of experiential content significantly impact online sales: relational ($\widehat{\beta}_1$ = 0.151, p < .05), intellectual ($\widehat{\beta}_2$ = 0.149, p < .01), and behavioral ($\widehat{\beta}_4$ = 0.325, p < .01) content. However, the affective and sensory dimensions do not have significant effects ($\widehat{\beta}_3$ = −0.055, $\widehat{\beta}_5$ = −0.006, both p > .10) on sales. The negative coefficient of the loyalty program membership dummy variable indicates that total sales to loyalty program members are lower than to non-members. This occurs since there are many more non-loyalty program customers when compared to the number of loyalty program customers.

Regarding the interaction effects, we find that the relational and intellectual content dimensions have greater effects on loyalty program sales ($\widehat{\beta}_7$ = 0.201, p < .05 and $\widehat{\beta}_8$ = 0.163, p < .05, respectively), while behavioral content influences non-loyalty program sales to a greater extent ($\widehat{\beta}_{10}$ = −0.178, p < .05). Interaction effects between affective and sensory content dimensions and loyalty program are not significant ($\widehat{\beta}_9$ = 0.109, p > .10; $\widehat{\beta}_{11}$ = −0.105, p > .10, respectively). Thus, we find that hypotheses H1, H2, and H4 are supported while neither H3's competing hypotheses nor H5 are supported.

Robustness checks

To ensure that our results hold across differing conditions we conduct several robustness checks (Tables 5, 6, 7 and Web Appendix D). These include an alternative dependent variable, re-estimation after controlling for transactional posts, models with additional customer information, alternative time period, and additional analysis to account for the role of weather conditions. We discuss each of these checks below.

First, we re-estimate the model with a new dependent variable: *Average ticket per transaction,* which refers to the natural log of the average ticket purchased by customers during the active time period of a social media post. Table 5 shows that these results are similar to our main reported effects. Specifically, we find that the relational and intellectual content dimensions have positive and significant effects on the average ticket per transaction made by loyalty program customers ($\widehat{\beta}_7$ = 0.146, p < .05 and $\widehat{\beta}_8$ = 0.091, p < .10, respectively), while behavioral content significantly influences the average transaction with non-loyalty program customers ($\widehat{\beta}_{10}$ = −0.112, p < .05). The main inference that we can make from this analysis is that these experiential dimensions of BGC not only positively impact total online sales but also increase the

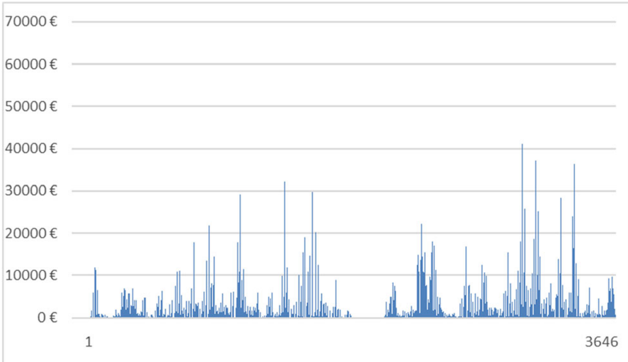

Fig. 1 Loyalty program sales across published posts

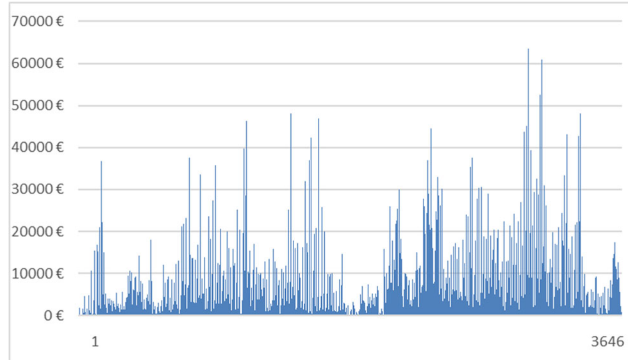

Fig. 3 Total sales across published posts

average amount that each customer spends on a transaction. It is noteworthy that the coefficient for the loyalty program dummy variable is negative, indicating that the average ticket per transaction is higher for non-loyalty program members. This occurs since non-loyalty program members typically opt for longer holidays in larger groups, requiring a more sizeable ski-pass purchase as indicated by our data. On the contrary, loyalty program members visit more frequently, but make shorter trips with fewer guests.

Second, we note that some of the posts in our data have a more pronounced transactional focus. These posts intend to increase sales by explicitly including a call to purchase, containing specific information about promotions or prices. Raters noted posts with a transactional focus, using an indicator variable (n = 432). To ensure that the transactional focus of social media posts does not confound our results, we re-estimate our model with a sample that excludes such posts. Our results are robust to this new sample (see Panel A, Table 6). As an additional related check, we also estimate a new model with transactional focus as a control variable. We note that our results continue to hold in these alternate analyses (see Panel B, Table 6).

Third, we estimate a model that includes additional loyalty program customer information. It is conceivable that a few high spending loyalty program customers could disproportionately drive sales, leading to inaccurate or biased estimates. To control for this potential confound in our analysis, we include the average spending of a loyalty program customer as a control variable in our model and re-estimate it. The findings from this analysis are consistent with our main results discussed earlier (see Table 7).

Web Appendix D includes two additional robustness checks which demonstrate the stability of the results with respect to time period and weather conditions.

Overall, the results are robust to alternative specifications, additional controls, and sampling approaches, increasing our confidence in the reported hypothesis tests, which again support H1, H2 and H4. It is interesting to consider possible explanations with respect to the lack of significant effects relating to H3 and H5. Regarding H3, consistent with the literature on the processing of affective content (e.g., Ruiz & Sicilia, 2004), it seems likely that message recipients may have varied processing tendencies. These results indicate that the implications of the application of systematic processing to affective content may depend on other characteristics. It is also conceivable that the two competing processes hypothesized each occur in some customers, which leads to a non-significant effect for the sample as a whole. With regard to H5, sensory content does not significantly influence sales to either group, nor show significant differences between groups. While prior work has proposed that this kind of content can drive liking behavior (Cvijikj & Michahelles, 2013; de Vries et al., 2012), our findings suggest that it is not significant in generating sales, though further study will be needed to confirm this in other contexts. It does seem plausible that the contemporary social media context is stimulating to the point that sensory content is not a predictable method of generating sales with either of the customer groups examined here. The employment of imagery (e.g., pictures, videos) is so commonplace in the online environment that sensations may not be evoked. Nevertheless, in other emergent technological contexts, such as virtual assistants or chatbots, sensory stimulation may come into play during customer interactions derived

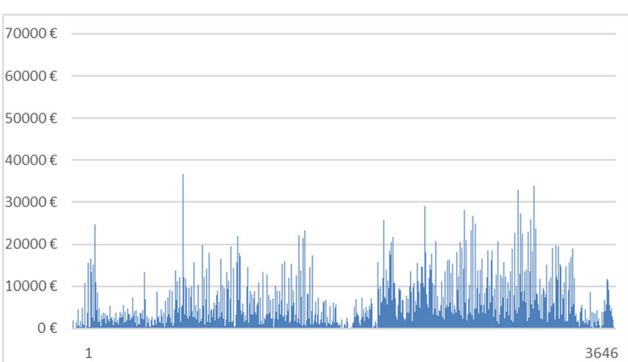

Fig. 2 Non-loyalty program sales across published posts

Table 4 Influence of brand-generated content on total online sales

	Parameter Est.[a]	Std. Error	Parameter Est.[b]	Std. Error	Parameter Est.[c]	Std. Error
Relational content			**0.251*** **	**0.049**	**0.151** **	**0.069**
Intellectual content			**0.231*** **	**0.044**	**0.149*** **	**0.057**
Affective content			−0.000	0.056	−0.055	0.077
Behavioral content			**0.236*** **	**0.039**	**0.325*** **	**0.054**
Sensory content			−0.058	0.072	−0.006	0.082
Loyalty program			**−1.198*** **	**0.069**	**−1.688*** **	**0.431**
Relational content * Loyalty program					**0.201** **	**0.087**
Intellectual content * Loyalty program					**0.163** **	**0.070**
Affective content * Loyalty program					0.109	0.100
Behavioral content * Loyalty program					**−0.178** **	**0.071**
Sensory content * Loyalty program					−0.105	0.081
Weather favorability	0.679***	0.069	0.717***	0.069	0.717***	0.068
Season	0.099	0.083	0.205**	0.079	0.205**	0.079
Ln(Reach)	0.773***	0.098	0.802***	0.107	0.802***	0.106
Ln(Word count)	−0.168***	0.056	−0.581***	0.076	−0.581***	0.075
Multimedia	−0.368	0.399	−0.437	0.397	−0.436	0.395
Specific event	0.761***	0.197	0.465**	0.195	0.465**	0.196
Holidays	−0.275***	0.076	−0.277***	0.075	−0.277***	0.075
Time fixed effects	Yes		Yes		Yes	
Destination fixed effects	Yes		Yes		Yes	
Lag Ln(Sales)	0.438***	0.011	0.371***	0.012	0.371***	0.012
Constant	−5.882***	0.925	−5.969***	0.936	−5.728***	0.961
Adjusted R-squared	0.292		0.329		0.331	
Number of observations	7292					

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Note: [a] Control effects; [b] Control and main effects; [c] Control, main and interaction effects

from artificial intelligence features, generating experiential value (Hoyer et al., 2020; Pagani et al., 2019).

Discussion

Social media has achieved widespread consumer adoption while being put to near ubiquitous use by marketers, though key issues related to its efficacy remain unanswered. Research related to BGC has focused on message characteristics such as timing, valence and format, but hardly any studies have yet addressed how customer experiences can be induced or how the effects of these experiences may shift across customer groups (see Table 1). Since BGC can include numerous experiential dimensions, each with a different impact on customers, it becomes vital to identify and study these dimensions to understand how they can be effectively leveraged to engage different customer groups. Thus, in our manuscript, we examine the effects of multiple experiential dimensions of BGC on a firm's sales to loyalty program vs. non-loyalty program customers. Our results show that these dimensions differentially impact loyalty and non-loyalty program members. In this way, we demonstrate the importance of looking beyond on-platform responses and show the relevance of jointly analyzing two topics that are rarely examined together in past work (Table 1): social media and loyalty programs.

Those dimensions requiring deeper processing on behalf of the recipient, particularly relational and intellectual content, have a greater effect in driving sales to loyalty program members. Although these dimensions influence both groups of customers, an increased ability and motivation to deeply process these messages renders their effect greater in loyalty program customers, who have established relationships with the brand. On the contrary, behavioral content, which is intuitive and demands little cognitive effort, boosts sales to non-loyalty program customers more effectively. This finding supports Chen and Chaiken's (1999) speculation that there may exist particular instances under which shallower processing can be more impactful in determining persuasion.

Table 5 Influence of brand-generated content on the average ticket per transaction

	Parameter Est.[a]	Std. Error	Parameter Est.[b]	Std. Error	Parameter Est.[c]	Std. Error
Relational content			**0.169*** **	**0.033**	**0.096** **	**0.047**
Intellectual content			**0.169*** **	**0.029**	**0.125*** **	**0.040**
Affective content			0.025	0.038	0.014	0.054
Behavioral content			**0.134*** **	**0.026**	**0.189*** **	**0.038**
Sensory content			0.030	0.052	0.069	0.060
Loyalty program			**−1.077*** **	**0.049**	**−1.272*** **	**0.293**
Relational content * Loyalty program					**0.146** **	**0.058**
Intellectual content * Loyalty program					**0.091* **	**0.048**
Affective content * Loyalty program					0.021	0.068
Behavioral content * Loyalty program					**−0.112** **	**0.048**
Sensory content * Loyalty program					−0.078	0.055
Weather favorability	0.425***	0.047	0.467***	0.047	0.468***	0.046
Season	0.096*	0.057	0.170***	0.054	0.170***	0.054
Ln(Reach)	0.342***	0.073	0.353***	0.080	0.354***	0.079
Ln(Word count)	−0.077**	0.039	−0.348***	0.052	−0.348***	0.052
Multimedia	−0.091	0.282	−0.193	0.278	−0.193	0.277
Specific event	0.354***	0.129	0.207*	0.126	0.207*	0.126
Holidays	−0.104**	0.053	−0.113**	0.051	−0.113**	0.051
Time fixed effects	Yes		Yes		Yes	
Destination fixed effects	Yes		Yes		Yes	
Lag Ln(Average ticket per transaction)	0.406***	0.012	0.304***	0.013	0.303***	0.013
Constant	−2.871***	0.667	−2.776***	0.676	−2.680	0.696
Adjusted R-squared	0.259		0.317		0.318	
Number of observations	7292					

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Note: [a] Control effects; [b] Control and main effects; [c] Control, main and interaction effects

Our key takeaways for researchers and practitioners are as follows:

Takeaway 1: Social media marketers should harness the power of experiential content. The experiential dimensions of BGC emerge as an organizing framework for digital marketing that provides the necessary vocabulary to understand customers' experiences in social media and to consciously emphasize different types of content to optimize results with particular customer groups.

Takeaway 2: Social media marketers should coordinate loyalty programs and BGC. Content will be more effective in driving sales if it is adapted to different customer groups, here our focus was membership in the firm's loyalty program. Our findings help to better explain how to intelligently shift away from producing static "one-size-fits-all" content to effectively developing and presenting optimal content to distinct customer groups.

Takeaway 3: Social media marketers should develop relational and intellectual content to drive sales to loyalty program members, and behavioral content to sell to non-loyalty program members most effectively. In particular, while intellectual content could include polls, riddles, and quizzes, relational content could focus on consumption situations that emphasize the importance of family, friends, and close connections in life. Behavioral content could illustrate actions related to the brand, such as demonstrating and encouraging alternative uses of its products. In this way, firms can drive customer response by consciously planning, executing, and monitoring different kinds of content - particularly those dimensions that have shown past effectiveness for the firm. A firm monitoring its posts may notice a lack of recent content reflecting one or more of these three dimensions and address this in future posts. Setting targets for the number of weekly posts that focus on each of these dimensions should be a best practice.

Table 8 shows the percentage increase (decrease) in online sales expected from a one standard deviation change from the mean for each dimension of the experiential content, for both loyalty and non-loyalty program members. While these values

Table 6 Influence of brand-generated content on total online sales, controlling for the transactional focus of the post

	PANEL A		PANEL B	
	Deleting posts with transactional focus		Including an additional control variable	
	Parameter Est.	Std. Error	Parameter Est.	Std. Error
Relational content	**0.142***	**0.075**	**0.151****	**0.068**
Intellectual content	**0.116***	**0.062**	**0.152*****	**0.057**
Affective content	−0.049	0.083	−0.054	0.077
Behavioral content	**0.344*****	**0.059**	**0.323*****	**0.054**
Sensory content	−0.091	0.088	−0.004	0.082
Loyalty program	**−1.861*****	**0.459**	**−1.679*****	**0.431**
Relational content * Loyalty program	**0.163***	**0.095**	**0.200****	**0.087**
Intellectual content * Loyalty program	**0.220*****	**0.075**	**0.162****	**0.071**
Affective content * Loyalty program	0.115	0.109	0.109	0.100
Behavioral content * Loyalty program	**−0.129***	**0.078**	**−0.178****	**0.071**
Sensory content * Loyalty program	−0.113	0.085	−0.107	0.081
Weather favorability	0.686***	0.075	0.719***	0.069
Season	0.182**	0.087	0.202**	0.079
Ln(Reach)	0.955***	0.115	0.802***	0.106
Ln(Word count)	−0.625***	0.084	−0.579***	0.075
Multimedia	−0.279	0.409	−0.436	0.395
Specific event	0.436**	0.204	0.465**	0.196
Holidays	−0.317***	0.078	−0.277***	0.075
Time fixed effects	Yes		Yes	
Destination fixed effects	Yes		Yes	
Transactional focus	–	–	0.452*	0.273
Lag Ln(Sales)	0.358***	0.013	0.371***	0.012
Constant	−7.215***	1.124	−5.725***	0.960
Adjusted R-squared	0.307		0.331	
Number of observations	6428		7292	

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

are substantial, we note that our dependent variable only includes online sales and Facebook was the firm's primary online presence, making for a highly sensitive test. With regard to the other two dimensions, our results suggest that (at least in our context) social media marketers should not particularly emphasize affective and sensory content. Here, these dimensions do not significantly impact sales to either customer group examined. Importantly, we note that these findings are based on an experiential offering and challenge future researchers to extend these findings in other contexts below.

Theoretical contributions

Our manuscript offers two important contributions:

First, although the base of research on BGC has grown dramatically in recent years, examining issues such as message form, timing, and valence (Ashley & Tuten, 2015; Colicev et al., 2018; Golder et al., 2007; Rutz & Bucklin, 2011), this is one of the first studies to examine how experiences induced by brand-generated content affect financial outcomes for the firm. Schmitt's (1999) framework is shown to be theoretically meaningful and applicable in the important context of digital marketing. In this regard, our study represents an important step for the discipline, applying the full set of five dimensions to advance our understanding of the effects of social media experiences evoked by firms, and demonstrating their distinct financial consequences on important customer groupings.

Second, this research makes significant contributions to the literature on loyalty programs, adding insights from the contexts of online retailing (Dorotic et al., 2014) and social media marketing (Rehnen et al., 2017). Prior research is silent on how to generate a stronger response from loyalty program or non-loyalty program members through social media, especially research connecting these tactics directly to firm performance. While Kumar et al. (2016) show that consumers with

Table 7 Influence of brand-generated content controlling for average loyalty program customer spending

	Parameter Est.	Std. Error
Relational content	**0.152****	**0.069**
Intellectual content	**0.140****	**0.057**
Affective content	−0.054	0.077
Behavioral content	**0.325*****	**0.054**
Sensory content	−0.003	0.082
Loyalty program	**−1.953*****	**0.429**
Relational content * Loyalty program	**0.207****	**0.087**
Intellectual content * Loyalty program	**0.187*****	**0.070**
Affective content * Loyalty program	0.101	0.100
Behavioral content * Loyalty program	**−0.179*****	**0.070**
Sensory content * Loyalty program	−0.077	0.087
Weather favorability	0.702***	0.068
Season	0.238***	0.079
Ln(Reach)	0.786***	0.106
Ln(Word count)	−0.579***	0.075
Multimedia	−0.447	0.386
Specific event	0.482**	0.194
Holidays	−0.300***	0.074
Time fixed effects	Yes	
Destination fixed effects	Yes	
Average loyalty program customer spending	0.297***	0.052
Lag Ln(Sales)	0.368***	0.012
Constant	−5.539***	0.957
Adjusted R-squared	0.340	
Number of observations	7292	

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

more brand experience respond more favorably to BGC, this study identifies specific experiential dimensions that loyalty program members are more responsive to. As has been shown for online shopping (Bleier et al., 2019; Martin et al., 2015), our findings show that dimensions of customer experience are also impactful through social media. Drawing on the heuristic-systematic model (Chaiken, 1987), we theorize and empirically demonstrate that experiential dimensions of brand-generated content do not generate a common, generalized response across all users. Experiential dimensions' efficiency depends on the depth of recipients' processing, rendering these dimensions differentially impactful on loyalty and non-loyalty program members. Loyalty program members, based on their deepened connection to the brand (Steinhoff & Palmatier, 2016), are more willing to put forward the effort to process cognitively demanding social media posts. They have an increased capacity to interpret complex messages (Gorlier & Michel, 2020) and are more likely to be prompted to purchase by intellectual and relational content. Conversely, non-loyalty program members are more influenced by messages that demonstrate customer action (i.e., behavioral content). Thus, advancing our knowledge of which types of content more strongly impact particular customer groups is critically important. Better understanding the differences in the effectiveness of social media communication depending on loyalty program membership marks a meaningful contribution of this study.

It is interesting to note that affective content is not seen to significantly influence sales, while relational content effectively prompts sales from both groups and has even more effect with loyalty program customers. This finding contrasts with previous research on BGC, which has shown that emotional content can influence customer response (e.g., Berger & Milkman, 2012; Lee et al., 2018) though this work has often overlooked relational content. In this way, we demonstrate the importance of investigating these logically connected but distinct dimensions in tandem so as to distinguish the effects of affective vs. relational content.

Limitations and future research

This manuscript is the first study to examine how experiential content in social media impacts online sales, distinguishing between loyalty and non-loyalty program members. As with any study, limitations should be acknowledged. First, our research questions are investigated in context of an experiential offering (tourism), which may limit generalizability. Future research that can examine potential differences in the effectiveness of BGC dimensions across product categories (e.g., hedonic vs. utilitarian products) may prove interesting. Specifically, work in other contexts that is also able to distinguish the affective and relational dimensions of BGC is warranted. Furthermore, we do not control for all possible forms of informational cues in this research. Future work that is able to, for instance, control for the effects of cues pertaining to different product attributes may prove interesting.

Some recent work has argued that user reactions differ by platform (Schweidel & Moe, 2014). While this study analyzes data exclusively from the most widely used social network, it would also be interesting to compare and contrast effects across different social media platforms (e.g., Instagram, TikTok, Twitter). This type of analysis may provide evidence of generalizability, or identify particularities of each social network, due to, for instance, the effects of Facebook's algorithms in presenting posts to viewers. Additionally, given the rise of mobile social marketing (Grewal et al., 2020), it would also likely prove worthwhile to examine the intersection of recipient location, experiential dimension, and loyalty program membership.

Supported by a pilot study (Web Appendix A) and findings from our hypotheses testing, we consider loyalty program customers to be more apt to process the firm's social media messages through systematic processing. The pilot study did

Table 8 Expected percentage sales change from a one standard deviation shift from the mean for each type of experiential content

	NON-LOYALTY PROGRAM CUSTOMERS		LOYALTY PROGRAM CUSTOMERS	
	−1 Std. Dev.	+1 Std. Dev.	−1 Std. Dev.	+1 Std. Dev.
Relational content	−10.98%	12.33%	−23.74%	31.13%
Intellectual content	−14.23%	16.59%	−27.48%	37.90%
Behavioral content	−27.04%	37.06%	−13.29%	15.33%

This table can be interpreted as follows: a one standard deviation decrease (from the mean) in terms of a post's relational content would be expected to be associated with a 10.98% decrease in sales to non-loyalty program customers

not find significant differences in processing time allocated to a brand's message across loyalty program members and non-members. Future experimental research that focuses on uncovering differences between these two groups in terms of other objective measures will likely prove fruitful. Beyond this, there are other interesting questions regarding systematic processing. For instance, there may exist non-loyalty program customers (e.g., new customers) who are highly involved in information search and thus process messages systematically. Future work that focuses on tactics to identify and target customers with gaps between their desired and actual knowledge levels is likely to prove worthwhile and may help firms effectively promote their loyalty programs. Loyalty program joining behavior is another meaningful outcome of interest that we challenge future researchers to examine.

It may also prove worthwhile to take more fine-grained approaches to the sensory and affective dimensions. For instance, Harmeling et al. (2015) show differing effects across retreat and agonistic emotions, which may (conceivably) both be spurred by sensory content. Finally, since our study focuses on firm generated content's impact on sales, we use data pertaining only to communication from the firm via social media. Future research that jointly examines the effects of brand-generated content and user generated content will prove fruitful; experiential dimensions may also be meaningful in related contexts such as consumer to consumer buzz (Houston et al., 2018).

Finally, while the data employed for this project (a census of online loyalty and non-loyalty program sales connected to social media posts) allow us to derive rich and meaningful implications, other approaches to related questions may also generate insights not available using the post as the unit of analysis. For instance, access to disaggregated customer data could further illuminate the underlying mechanisms. Connecting the firm's social media tactics to blended online and offline consumption may provide other valuable insights. Beyond this, controlled experiments or netnographic research could examine the customer's journey to loyalty program membership, and perhaps how this journey impacts future responses to social media.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Ashley, C., & Tuten, T. (2015). Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement. *Psychology & Marketing, 32*, 15–27.

Batra, R., & Keller, K. L. (2016). Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing, 80*, 122–145.

Baum, C., Schaffer, M., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *Stata Journal, 3*, 1–31.

Berger, J., & Milkman, K. L. (2012). What makes online content viral? *Journal of Marketing, 49*, 192–205.

Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. *Journal of Marketing, 83*, 98–119.

Bond. (2019). *The loyalty report*. Available at: https://info.bondbrandloyalty.com/loyalty-report-2019

Brakus, J. J., Schmitt, B. H., & Zarantonello, L. (2009). Brand experience:What is it? How is it measured? Does it affect loyalty? *Journal of Marketing, 73*, 52–68.

Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research, 66*, 105–114.

Brown, D. (2019). "Starbucks rewards change." In *USA Today*.

Bruneau, V., Swaen, V., & Zidda, P. (2018). Are loyalty program members really engaged? Measuring customer engagement with loyalty programs. *Journal of Business Research, 91*, 144–158.

Center for Marketing Research. (2020). *Oversaturation & disengagement: The 2019 fortune 500 social media dance*. Available at: https://www.umassd.edu/cmr/research/2019-fortune-500.html

Cha, M.-K., Yi, Y., & Bagozzi, R. P. (2015). Effects of customer participation in corporate social responsibility (csr) programs on the csr-brand fit and brand loyalty. *Cornell Hospitality Quarterly, 57*, 235–249.

Chaiken, S. (1987). "The heuristic model of persuasion." In *Social Influence:* The Ontario Symposium, 3–39.

Chaiken, S., Giner-Sorolla, R., & Chen, S. (1996). Beyond accuracy: Defense and impression motives in heuristic and systematic information processing.

Chaiken, S., & Ledgerwood, A. (2011). *A theory of heuristic and systematic information processing*. Volume One.

Chaudhuri, M., Voorhees, C. M., & Beck, J. M. (2019). The effects of loyalty program introduction and design on short-and long-term sales and gross profits. *Journal of the Academy of Marketing Science, 47*, 640–658.

Chen, S., & Chaiken, S. (1999). The heuristic-systematic model in its broader context. In *Dual-process theories in social psychology* (pp. 73–96). Eds.

Chen, S., Duckworth, K., & Chaiken, S. (1999). Motivated heuristic and systematic processing. *Psychological Inquiry, 10*, 44–49.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43*, 345–354.

Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science, 29*, 944–957.

Cicchetti, D. (1994). Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instrument in psychology. *Psychological Assessment, 6*, 284–290.

Colicev, A., Malshe, A., Pauwels, K., & O'Connor, P. (2018). Improving consumer mindset metrics and shareholder value through social media: The different roles of owned and earned media. *Journal of Marketing, 82*, 37–56.

Cvijikj, I. P., & Michahelles, F. (2013). Understanding the user generated content and interactions on a Facebook brand page. *International Journal of Social and Humanistic Computing, 2*, 118.140.

Dabbous, A., & Barakat, K. A. (2020). Bridging the online offline gap: Assessing the impact of brands' social network content quality on brand awareness and purchase intention. *Journal of Retailing and Consumer Services, 53*, 101966–101976.

de Vries, L., Gensler, S., & Leeflang, P. S. H. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing, 26*, 83–91.

de Vries, L., Gensler, S., & Leeflang, P. S. H. (2017). Rffects of traditional advertising and social messages on brand-building metrics and customer acquisition. *Journal of Marketing, 81*, 1–15.

Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing, 21*, 23–45.

Demiray, M., & Burnaz, S. (2019). Exploring the impact of brand community identification on Facebook: Firm-directed and self-directed drivers. *Journal of Business Research, 96*, 115–124.

Dinner, I. M., Heerde Van, H. J., & Neslin, S. A. (2014). Driving online and offline sales: The Cross-Channel effects of traditional, online display, and paid search advertising. *Journal of Marketing Research, 51*, 527–545.

Dorotic, M., Verhoef, P. C., Fok, D., & Bijmolt, T. H. A. (2014). Reward redemption effects in a loyalty program when customers choose how much and when to redeem. *International Journal of Research in Marketing, 31*, 339–355.

Evanschitzky, H., Ramaseshan, B., Woisetschlaeger, D. M., Richelsen, V., Blut, M., & Backhaus, C. (2012). Consequences of customer loyalty to the loyalty program and to the company. *Journal of the Academy of Marketing Science, 40*, 625–638.

Fantozzi, J. (2019). Starbucks launches revamped rewards program with communication hiccups. *Nation's Restaurant News*.

Gendron, M., Lindquist, K. A., Barsalou, L., & Barrett, L. F. (2012). Emotion words shape emotion percepts. *Emotion Words Shape Emotion Percepts. Emotion, 12*, 314–325.

Goh, K.-Y., Heng, C.-S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content. *Information Systems Research, 24*, 88–107.

Golder, S. A., Wilkinson, D. M., & Huberman, B. A. (2007). *Rhythms of social interaction: Messaging within a massive online network* (pp. 41–66). Springer London.

Gorlier, T., & Michel, G. (2020). How special rewards in loyalty programs enrich consumer-brand relationships: The role of self-expansion. *Psychology & Marketing, 37*, 564–577.

Greene, W. H. (2000). *Econometric analysis* (4th ed.). Prentice– Hall.

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: A multidisciplinary perspective. *Journal of the Academy of Marketing Science, 48*, 1–8.

Griffin, R. J., Neuwirth, K., Giese, J., & Dunwoody, S. (2002). Linking the heuristic-systematic model and depth of processing. *Communication Research, 29*, 705–732.

Guo, J., Wang, X., & Wu, Y. (2020). Positive emotion Bias: Role of emotional content from online customer reviews in purchase decisions. *Journal of Retailing and Consumer Services, 52*, 101891.

Hajli, N., Shanmugam, M., Papagiannidis, S., Zahay, D., & Richard, M.-O. (2017). Branding co-creation with members of online brand communities. *Journal of Business Research, 70*, 136–144.

Harmeling, C., Magnusson, P., & Singh, N. (2015). Beyond anger: A deeper look at consumer animosity. *Journal of International Business Studies, 46*

Henderson, C. M., Beck, J. T., & Palmatier, R. W. (2011). Review of the theoretical underpinnings of loyalty programs. *Journal of Consumer Psychology, 21*, 256–276.

Hoffman, D., & Fodor, M. (2010). Can you measure the roi of your social media marketing? *MIT Sloan Management Review,* 52

Holbrook, M. B., & Hirschman, E. C. (1982). The experiential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research, 9*, 132–140.

Homburg, C., Jozić, D., & Kuehnl, C. (2015). Customer experience management: Toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science, 45*, 377–401.

Houston, M. B., Kupfer, A.-K., Hennig-Thurau, T., & Spann, M. (2018). Pre-Release Consumer Buzz. *Journal of the Academy of Marketing Science, 46*, 338–360.

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing, 51*, 57–71.

Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision Support Systems, 57*, 321–343.

Hwang, J., & Choi, L. (2020). Having fun while receiving rewards?: Exploration of gamification in loyalty programs for consumer loyalty. *Journal of Business Research, 106*, 365–376.

Kahlor, L., Dunwoody, S., Griffin, R. J., Neuwirth, K., & Giese, J. (2003). Studying heuristic-systematic processing of risk communication. *Risk Analysis: An International Journal, 23*, 355–368.

Kang, J., Alejandro, T. B., & Groza, M. D. (2015). Customer-company identification and the effectiveness of loyalty programs. *Journal of Business Research, 68*, 464–471.

Kanuri, V. K., Chen, Y., & Sridhar, S. (2018). Scheduling content on social media: Theory, evidence, and application. *Journal of Marketing, 82*, 89–108.

Kaplan, A. M. (2012). If you love something, let it go Mobile: Mobile marketing and mobile social media 4x4. *Business Horizons, 55*, 129–139.

Kent, M. L., Taylor, M., & White, W. J. (2003). The relationship between web site design and organizational responsiveness to stakeholders. *Public Relations Review, 29*, 63–77.

Kim, C., & Yang, S.-U. (2017). Like, comment, and share on Facebook: How each behavior differs from the other. *Public Relations Review, 43*, 441–449.

Kim, H., Jiang, J., & Bruce, N. I. (2021). Discovering heterogeneous consumer journeys in online platforms: Implications for networking investment. *Journal of the Academy of Marketing Science, 49*, 374–396.

Kitchen, P., Kerr, G., Schultz, D. E., McColl, R., & Pals, H. (2014). The elaboration likelihood model: Review, critique and research agenda. *European Journal of Marketing, 48*, 2033–2050.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing, 80*, 7–25.

Lee, D., Hosanagar, K., & Nair, H. S. (2018). Advertising content and consumer engagement on social media: Evidence from facebook. *Management Science, 64*, 5105–5131.

Leenheer, J., van Heerde, H. J., Bijmolt, T. H. A., & Smidts, A. (2007). Do loyalty programs really enhance behavioral loyalty? An empirical analysis accounting for self-selecting members. *International Journal of Research in Marketing, 24*, 31–47.

Lewis, M. (2004). The influence of loyalty programs and short-term promotions on customer retention. *Journal of Marketing Research, 41*, 281–292.

Liu, Y., & Yang, R. (2009). Competing loyalty programs: Impact of market saturation, market share, and category expandability. *Journal of Marketing, 73*, 93–108.

Liu-Thompkins, Y., & Shrum, L. J. (2002). What is interactivity and is it always such a good thing? Implications of definition, person, and situation for the influence of interactivity on advertising effectiveness. *Journal of Advertising, 31*, 53–64.

Lu, Q. S., & Miller, R. (2019). How social media communications combine with customer loyalty management to boost green retail sales. *Journal of Interactive Marketing, 46*, 87–100.

Maity, M., & Gupta, S. (2016). Mediating effect of loyalty program membership on the relationship between advertising effectiveness and brand loyalty. *Journal of Marketing Theory and Practice, 24*, 462–481.

Malhotra, A. (2013). How to create brand engagement on facebook. *MIT Sloan Management Review,* 54

Marchand, A., Hennig-Thurau, T., & Wiertz, C. (2017). Not all digital word of mouth is created equal: Understanding the respective impact of consumer reviews and microblogs on new product success. *International Journal of Research in Marketing, 34*, 336–354.

Mariani, M., Felice, M., & Mura, M. (2016). Facebook as a destination marketing tool: Evidence from Italian regional destination management organizations. *Tourism Management, 54*, 321–343.

Martin, J., Mortimer, G., & Andrews, L. (2015). Re-examining online customer experience to include purchase frequency and perceived risk. *Journal of Retailing and Consumer Services, 25*, 81–95.

Meire, M., Hewett, K., Ballings, M., Kumar, V., & Van den Poel, D. (2019). The role of marketer-generated content in customer engagement marketing. *Journal of Marketing, 83*, 21–42.

Meyer, C., & Schwager, A. (2007). Understanding customer experience. *Harvard Business Review, 85*(116–126), 157.

Meyer-Waarden, L. (2015). Effects of loyalty program rewards on store loyalty. *Journal of Retailing and Consumer Services, 24*, 22–32.

Miles, M. B., Huberman, A. M., & Saldana, J. (1984). *Qualitative data analysis: A sourcebook of new. Methods*. SAGE Publications.

Mochon, D., Johnson, K., Schwartz, J., & Ariely, D. (2017). What are likes worth? A facebook page field experiment. *Journal of Marketing Research, 54*, 306–317.

Moorman, C. (2020). *CMO survey. Duke Fuqua / Deloitte / American marketing association.* Available at: https://cmosurvey.org/

Nga, H.-D., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: Do brand strength and category maturity matter? *Journal of Marketing, 77*, 37–53.

Nisar, T. M., Prabhakar, G., Ilavarasan, P. V., & Baabdullah, A. M. (2020). Up the ante: Electronic word of mouth and its effects on firm reputation and performance. *Journal of Retailing and Consumer Services, 53, 101726.*

Pagani, M., Racat, M., & Hofacker, C. F. (2019). Adding voice to the Omnichannel and how that affects Brand Trust. *Journal of Interactive Marketing, 48*, 89–105.

Park, E., Rishika, R., Janakiraman, R., Houston, M. B., & Yoo, B. (2018). Social dollars in online communities: The effect of product, user, and network characteristics. *Journal of Marketing, 82*, 93–114.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWC2015. *UT Faculty/Researcher Works*

Petty, R., Fabrigar, L., & Wegener, D. (2003). Emotional factors in attitudes and persuasion. In R. J. Davidson, K. R. Scherer, & H. H. Goldsmith (Eds.), *Series in affective science. Handbook of affective sciences (p. 752–772)*. Oxford University Press.

Petty, R. E., Cacioppo, J. T., Sedikides, C., & Strathman, A. J. (1988). Affect and persuasion: A contemporary perspective. *American Behavioral Scientist, 31*, 355–371.

Raab, C., Berezan, O., Krishen, A. S., & Tanford, S. (2015). What's in a word? Building program loyalty through social media communication. *Cornell Hospitality Quarterly, 57*, 138–149.

Rehnen, L.-M., Bartsch, S., Kull, M., & Meyer, A. (2017). Exploring the impact of rewarded social media engagement in loyalty programs. *Journal of Service Management, 28*, 305–328.

Rietveld, B., Dolen, W., Mazloom, M., & Worring, M. (2020). What you feel, is what you like influence of message appeals on customer engagement on instagram. *Journal of Interactive Marketing, 49*, 20–53.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. *Journal of Retailing, 88*, 308–322.

Ruiz, S., & Sicilia, M. a. (2004). The impact of cognitive and/or affective processing styles on consumer response to advertising appeals. *Journal of Business Research, 57*, 657–664.

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research, 48*, 87–102.

Rutz, O. J., & Watson, G. F. (2019). Endogeneity and marketing strategy research: An overview. *Journal of the Academy of Marketing Science, 47*, 479–498.

Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal, 32*, 1001–1011.

Sanderson, E., & Windmeijer, F. (2016). A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics, 190*, 212–221.

Saxton, G., & Waters, R. D. (2014). What do stakeholders like on Facebook? Examining public reactions to nonprofit organizations' informational, promotional, and community-building messages. *Journal of Public Relations Research, 26*, 280–299.

Schmitt, B. (1999). Experiential marketing. *Journal of Marketing Management, 15*, 53–67.

Schweidel, D. A., & Moe, W. W. (2014). Listening in on social media: A joint model of sentiment and venue format choice. *Journal of Marketing Research, 51*, 387–402.

Smith, A. N., Fischer, E., & Yongjian, C. (2012). How does brand-related user-generated content differ across youtube, facebook, and twitter? *Journal of Interactive Marketing, 26*, 102–113.

Srivastava, M., & Kaul, D. (2016). Exploring the link between customer experience–loyalty–consumer spend. *Journal of Retailing and Consumer Services, 31*, 277–286.

Stanko, M. A., Hernández Ortega, B. I., Molina-Castillo, F.-J., Rishika, R., & Franco, J. (2019). Using social media to connect with your Most loyal customers. *Harvard Business Review* (online). Available at: https://hbr.org/2019/12/using-social-media-to-connect-with-your-most-loyal-customers. Accessed 01/05/2022.

Statista. (2019). *Social media & user-generated content*. Available at: https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/.

Steinhoff, L., & Palmatier, R. W. (2016). Understanding loyalty program effectiveness: Managing target and bystander effects. *Journal of the Academy of Marketing Science, 44*, 88–107.

Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research, 49*, 624–639.

Teixeira, T., Wedel, M., & Pieters, R. (2012). Emotion-induced engagement in internet video advertisements. *Journal of Marketing Research, 49*, 144–159.

Todorov, A., Chaiken, S., & Henderson, M. D. (2002). The heuristic-systematic model of social information processing. *The persuasion handbook: Developments in theory and practice*, 195–211.

Vakratsas, D., & Ambler, T. (1999). How advertising works: What do we really know? *Journal of Marketing, 63*, 26–43.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. *Journal of Retailing, 85*, 31–41.

Veryzer, R. W. J., & Hutchinson, J. W. (1998). The influence of unity and prototypicality on aesthetic responses to new product designs. *Journal of Consumer Research, 24*, 374–394.

Vishwanath, A. (2016). Mobile device affordance: Explicating how smartphones influence the outcome of phishing attacks. *Computers in Human Behavior, 63*, 198–207.

Wang, X.-W., Cao, Y.-M., & Park, C. (2019). The relationships among community experience, community commitment, brand attitude, and purchase intention in social media. *International Journal of Information Management, 49*, 475–488.

Wu, B., Sun, Y., Yada, K., & Ieee (2018). The short-term impact of an item-based loyalty program. *IEEE International Conference on Systems, Man, and Cybernetics*, 1846–1851.

Yang, Z., Zheng, Y., Zhang, Y., Jiang, Y., Chao, H.-T., & Doong, S.-C. (2019). Bipolar influence of firm-generated content on customers' offline purchasing behavior: A field experiment in China. *Electronic Commerce Research and Applications, 35*, 100844.

Yang, Z. J., Aloe, A. M., & Feeley, T. H. (2014). Risk information seeking and processing model: A Meta-analysis. *Journal of Communication, 64*, 20–41.

Yang, Z. J., Rickard, L. N., Harrison, T. M., & Seo, M. (2014). Applying the risk information seeking and processing model to examine support for climate change mitigation policy. *Science Communication, 36*, 296–324.

Zhang, J., & Breugelmans, E. (2012). The impact of an item-based loyalty program on consumer purchase behavior. *Journal of Marketing Research, 49*, 50–65.