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Research Data Related to this Submission

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There are no linked research data sets for this submission. The following  
reason is given:

Data will be made available on request



- This study analyses the influence of marketers' and users' content published in social media on brand equity.
- Content on Facebook of a sample of international companies is examined on three dimensions: quality, valence and volume.
- Data collected for this research comprises 2,211 brand posts from 36 international brands published on their corporate Facebook fan pages.
- The findings confirm that all dimensions of content considered have effects on brand equity.

## HOW DOES MARKETERS' AND USERS' CONTENT ON CORPORATE FACEBOOK FAN PAGES INFLUENCE BRAND EQUITY?

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### ABSTRACT

There is scarce empirical research devoted to understanding if and how the social media efforts of brands have economically significant effects that reach beyond the online environment. Based on 2,211 brand posts from 36 international brands, published on their corporate Facebook fan pages, this study analyses the influence of marketers' and users' content on brand equity. Content on Facebook is examined on three separate dimensions: content quality, content valence, and content volume. This study extends previous literature by: (1) accounting not only for brand posts but also for user content; (2) jointly considering quality, valence, and volume dimensions to assess Facebook content; and (3) analysing the effects of such content beyond the online environment on brand equity. The findings confirm that all dimensions of Facebook content considered here have significant effects on brand equity. Important research and managerial implications are derived for improving content on social networking sites.

**Keywords:** Brand equity; corporate Facebook fan pages; marketer-generated content; social media strategy; user-generated content.

## 1. Introduction

The boom of social network applications—which empower customers and blur the boundaries for business-related communication originated by marketers and end-users alike—has sparked enormous interest into *marketer-generated content* (MGC) and *user-generated content* (UGC) and their implications (Kaplan and Haenlein, 2010; de Vries et al., 2012; Yang et al., 2019). With more than 2 billion users worldwide (in 2Q 2018), Facebook is the leading social networking site (Statista.com, 2018). Facebook continuously innovates to encourage end-user engagement with MGC and UGC, and increasingly emphasizes consumer engagement with UGC from friends and family on the social network (Mavrck, 2017). Such efforts developed by Facebook are in accordance with the view of WOM and e-WOM as the most trusted source of commercial influence (Luo, 2009).

One of the key challenges related to social network usage by companies is the identification of appropriate indicators in justifying marketing expenditures performed in online social networks (Colicev et al., 2016; Srinivasan and Hanssens, 2009). Indeed, there is an enormous interest for firms (and an opportunity through quantitative models) to more fully understand the effect and value of their marketing actions across media, digital and non-digital (MSI-Research Priority 1, 2017; Manser-Payne et al., 2017).

Less empirical research has been conducted on the *non-digital* effects versus the *digital world* outcomes of the MGC and UGC published on social media. Examples of *digital world* outcomes are brand popularity—considered as a combination of likes and comments assigned by users to MGC and UGC (de Vries et al., 2012; Jeon et al., 2016; Sabate et al., 2014), and brand engagement, considered as a combination of likes, comments, and shares (Coursaris et al., 2016; Luarn et al., 2015; Schultz, 2017). However, research analysing the *non-digital* effects is highly relevant to (1) understand if and how the social media efforts of brands have effects that reach beyond the online environment and (2) quantify the economic value of corporate usage of social media. The most prevalent *non-digital* outcomes in past research are sales (Floyd et al., 2014; You et al., 2015), purchase expenditures (Goh et al., 2013), or revenues (Baek et al., 2017). Yet, neither of these measures fully captures the firm's equity value (Luo et al., 2013), unlike brand equity. Brand equity is considered the ultimate measure of firm market performance, and has been used as a measure of firm financial performance (Cheng et al., 2019) and shareholders' wealth (Chen et al., 2012). The potential of MGC and UGC published on social networking sites for generating brand equity as the overall business value expressed in currency units, thus, remains a largely unexplored topic. Therefore, this study seeks to lend empirical support to the assumption that MGC and UGC generated in corporate Facebook fan pages will contribute to brand equity.

In addition, previous research related to the characteristics of MGC and UGC published on social media was classified by Peters et al. (2013) into three content dimensions: quality, valence, and volume, but these three dimensions have not been jointly considered in any empirical research. Past research has focused mostly on content quality in terms of vividness (also referred to as richness), inter-

activity, or content domain to describe posts published on social networks (de Vries et al., 2012; Cvijikj and Michahelles, 2013). There is also an important research stream analysing content volume (Colicev et al., 2016; Luo et al., 2013) and content valence (Moe and Trusov, 2011; Tirunillai and Tellis, 2012). Therefore, this study relies on Peters et al.'s (2013) classification of content published in social media to offer a broad and integrated account of such content.

This study aims to fill the aforementioned research gaps by developing a comprehensive model to analyse how the online social network strategy of companies on their Facebook fan pages affects the overall business economic value or brand equity. To properly address this question, both MGC and UGC comprising the key dimensions of content published on social networks—quality, valence and volume—are jointly considered as potential causal levers of business value (brand equity).

## 2. CONCEPTUAL FRAMEWORK AND HYPOTHESES

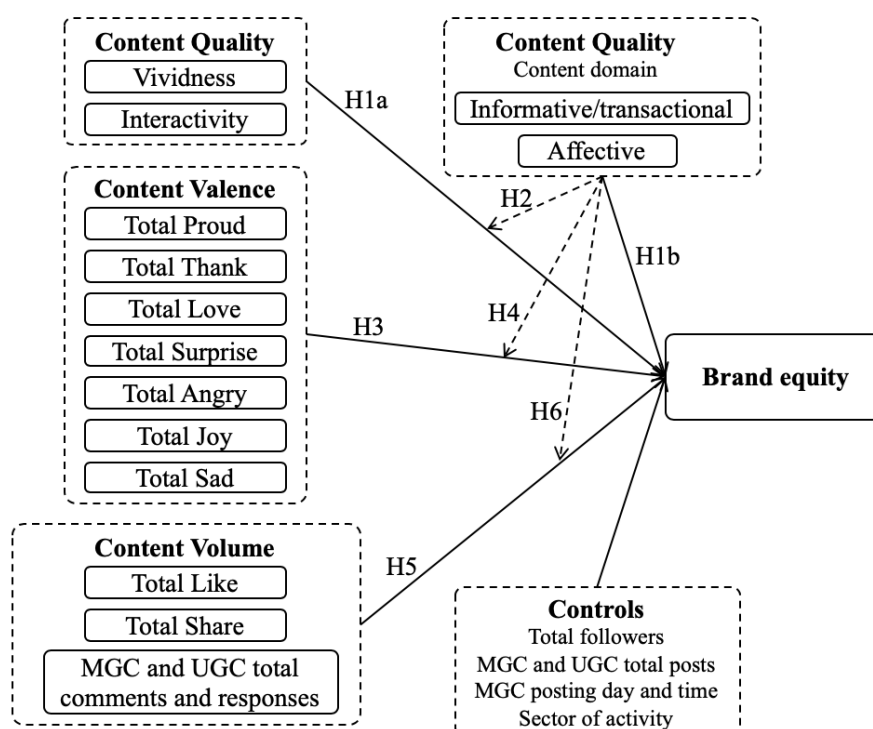
Social networks have become an additional marketing channel that can be integrated with the traditional ones as part of the marketing mix (Cvijikj and Michahelles, 2013); they are highly related to the *integrated marketing communication* strategy of companies (Šerić, 2017) and foster relationships with customers, especially through corporate Facebook brand pages (de Vries et al., 2012). All these characteristics make social media quite popular and relevant for companies. However, despite their popularity and relevance, empirical research investigating their economic value to companies is still quite limited.

From a management perspective, understanding what is happening on social media and how it interacts with marketing inputs to produce the desired marketing outcomes is a requisite to properly manage this channel (Peters et al., 2013). To shed light on this phenomenon, Peters et al. (2013) offer a theoretical research based on the *stimulus-organism-response* (SOR) framework (Mehrabian and Russell, 1974) and on Bandura's (1977; 2009) social learning theory—applied to social networks by Choi-Behm-Morawitz, (2017) and Nejad et al. (2014). The SOR model posits that the content published (stimulus) operates within social media (organism) to achieve managerial outcomes (response) at different levels.

Peters et al. (2013) regard social media as an organism itself, and four important elements emerged from their extensive literature review: motives, content, structure, and roles and interactions. They further devised a theoretical structure to characterise the content published on social networks (both MGC and UGC) on three content dimensions: quality, valence, and volume. The present work focuses on the three content dimensions identified by Peters et al. (2013) to empirically test their possible effects on a specific type of consumer response: brand equity. In addition, this research is based on the media richness theory to justify the inclusion of the vividness concept as MGC feature (Daft and Lengel, 1986). Finally, this research also draws upon the uses and gratifications theory (Katz et al., 1974; Muntinga et al., 2011)—which allows exploring people's motivations for brand-related,

social media use—to explain the differential effects on users of distinct content types (in terms of content domain) published on social media. The proposed research model is shown in Figure 1.

**Figure 1. Proposed Research Model**



## 2.1. Content quality

The first dimension, content quality, comprises the features, domain, and style of content published on social networks (Peters et al., 2013). The previous literature split content quality into three different aspects, namely interactivity (Luarn et al., 2015), vividness, and content domain (Coursaris et al., 2016). Content domain refers to what is being transmitted and may be subjectively interpreted (Sabate et al., 2014), whereas interactivity and vividness refer to how is information transmitted and are considered to be more dependent on the media type (Cvijikj and Michahelles, 2013).

On the one hand, interactivity represents “the degree to which two or more communication parties can act on each other, on the communication medium and on the messages, and the degree to which such actions are synchronised” (Luarn et al., 2015: p. 507). In general, higher levels of interactivity would be expected to generate more user engagement (Luarn et al., 2015). However, to the authors’ knowledge, little was known about the effect of interactivity on brand equity. Yet, interactive posts are more likely to empower users by offering them more opportunities for self-expression (so that users feel their opinion matters), thus positively affecting their image of the brand. In addition, interactive fan pages were viewed as likely to create stronger community ties. Following this, the overall effect of content interactivity was expected to be positive on most company/brand outcomes (de Vries et al., 2012), including brand equity.

On the other hand, vividness is defined as “the extent to which a brand post stimulates various

senses” (Luarn et al., 2015, p. 506), which is driven by the media type and richness of the content posted online (written text, picture, video). Media-richness theory proposes that media differ in their ability to capture and reproduce different contextual cues; hence, a medium’s capacity for more contextual cues should facilitate understanding of messages (Coursaris et al., 2016). More vivid content may also have a greater ability to create experiences that resemble the real world more closely (Tafesse, 2015). Hence, greater levels of post vividness can be expected to generate greater user engagement (Luarn et al., 2015), with findings supporting this contention (Cvijikj and Michahelles, 2013; Sabate et al., 2014). There is also suggestive evidence that vividness effects can differ across user response forms. For example, Tafesse (2015) found a significant effect of post vividness on shares, but not on likes. Considering that brand post shares can boost brand exposure, more vivid content should drive purchase value (Thornhill et al., 2017). Consequently, brand posts with greater vividness are expected to have a positive impact on brand value. Formally:

- **Hypothesis 1a (The Content Quality Hypothesis).** *On corporate Facebook fan pages, posts with higher levels of content quality (in terms of interactivity and vividness) will generate higher levels of brand equity.*

Previous research has established the influential role of content domain on different consumer responses (Luarn et al., 2015). Several authors have drawn upon the uses and gratifications theory to explain the differential effects on user of distinct content types (Muntinga et al., 2011). Following this theory, people are more likely to engage in social media when perceiving that it will serve their particular interests (Muntinga et al., 2011; Cvijikj and Michahelles, 2013). Since each type of content domain is best suited to achieving different objectives, users will engage more frequently with brand posts that fit their demands (Muntinga et al., 2011; Tafesse, 2015).

**Moderation.** Different classifications of content domain have been offered (de Vries et al., 2012; Luarn et al., 2015; Coursaris et al., 2016). Yet, the most important distinctions attend to the rational appeal (informative and transactional content) and emotional appeal (affective content) of the message. On the one hand, rational appeal (informative/transactional brand posts) highlights the functional attributes of products and services, or promote transactional behaviours (through promotions). Research has shown that information seeking is one of the main uses of social media (de Vries et al., 2012). When brands publish informative content, they offer fast, easy, and low-cost information enhancing decision-making processes (Muntinga et al., 2011). In addition, transactional content about product offers, promotions, and free trials may provide financial rewards that help individuals satisfy their remuneration goals (Cvijikj and Michahelles, 2013; Luarn et al., 2015). Based on the above, posts with rational appeal (informative/transactional content) are expected to exert a positive influence on user responses towards the company/brand (Luarn et al., 2015), and thus on brand equity.

On the other hand, brand posts with emotional appeal (affective content) are intended to evoke users’ emotions by using inspiring images, stories, or even jokes, with the goal of establishing an emotional connection with the brand (Coursaris et al., 2016). Posts containing such emotional content may



provide the audience with opportunities to distract, entertain and pastime (Luarn et al., 2015). In fact, entertainment is considered a key motivation for using social media (Muntinga et al., 2011). Empirical research has demonstrated that—with some exceptions (de Vries et al., 2012)—entertaining content (compared to informative content) can be expected to generate greater user responses (Cvijikj and Michahelles, 2013; Coelho et al., 2016; Tafesse, 2015). Thus, entertainment content type is more likely to transcend the fan page environment—through more sharing activity (Luarn et al., 2015). This is likely to improve brand image through its hedonic dimension (Bruhn et al., 2012) and to generate greater brand exposure (Thornhill et al., 2017). Consistent with this, brands that post more entertaining content on their fan page can achieve greater levels of brand equity. Therefore:

- **Hypothesis 1b (The Emotional Appeal Hypothesis).** *On corporate Facebook fan pages, posts with more emotional appeal (affective content) generate higher levels of brand equity than posts with rational appeal (informational/transactional content).*

**Moderation.** In addition, content domain is expected to operate as a moderator between other content features—interactivity and vividness—and brand equity. As for interactivity, when users seek information online, more interactive posts may serve to obtain customized information, as long as the company responds to their comments. However, such posts may be aimed simply at obtaining customer information and not at providing fast responses to information demands. The findings from Muntinga and colleagues (2011) provide support for this contention, given that users seeking for information tend to consume, but not create, branded content. Following this, less interactive posts may contain all the information required by users in a more direct way—they do not need to read all comments to find out relevant information or expect responses from the brand. Therefore, high interactivity can be expected to attenuate its impact on brand equity when the content domain is more rational (informative and transactional). On the other hand, individuals seeking for online entertainment through affective content may be willing to engage with the brand and other users, since it can be a pastime (Muntinga et al., 2011). Hence, the effect of more interactive posts may be more intense for such emotional/affective contents.

With regard to vividness, when users seek information online, more vivid posts may contain more informational cues and could provide more accurate knowledge about the branded product (Tafesse, 2015). However, given that users are investing time into a very specific activity—gathering information about the product, promotions, points of sale, etc.—and it may take longer for them to determine whether highly vivid content contains the required information, content with low-vividness features (but faster to understand) may be preferred. On the other hand, individuals seeking online entertainment through affective content may be more receptive to content vividness, since they may have more time to invest into the different activities required by the post—watching the video. This leads to the following hypothesis:

- **Hypothesis 2 (The Content Quality-Brand Equity Moderation and Emotionally Appealing Post Hypothesis).** *On corporate Facebook fan pages, the relationship between content quality (in terms of vividness and interactivity) and brand equity is stronger for posts with an*

*emotional appeal (affective content), than for posts with a rational appeal (informational/transactional content).*

## 2.2. Content Valence

Content valence captures tonality in terms of sentiments evoked by the published content (Smith et al., 2012), but also comprises subsuming emotions (Peters, et al., 2013) and reflects users' attitudes to the content (Chang and Wang, 2018). The existing literature on social media has mainly focused on the tonality dimension of content valence, by separating positive and negative content classes (Al-Obeidat et al., 2018; Wang et al., 2018). The present work moves the analysis of content valence from the meaning of content to the emotions it evokes in users. To do so, the authors consider the different ways users can respond to Facebook posts. Such reactions comprise positive emotions evoked in users (love, surprise, joy), or negative ones (sadness, anger). Users are likely to feel better when engaging in positive emotions in response to MGC (Berger and Milkman, 2010), thus contributing to brand image and value (Bruhn et al., 2012). There is consensus that positive content (such as positive e-WOM) motivates purchases, whereas negative content (such as negative e-WOM) inhibits purchases (Luo, 2009), with corresponding effects (positive or negative) on brand equity. Yet, there have been some mixed results regarding how the valence of users' posts on e-commerce websites affect different managerial outcomes (Floyd et al., 2014; You et al., 2015).

The literature has also demonstrated that two discrete emotions from the same valence can elicit different user responses (Ahmad and Laroche, 2016; Berger and Milkman, 2010). A possible explanation for this lies in the need to consider the psychological activation or arousal implicit in the emotion (Berger and Milkman, 2010). For example, although anger and sadness are both negative emotions, anger is characterized by high arousal, whereas sadness is characterized by low arousal. Likewise, love and joy are both positive emotions, but love has greater arousal connotations than joy. There is evidence that high-arousal emotions can lead to greater content virality (Berger and Milkman, 2010), which may leverage brand equity (Bruhn et al., 2012). Hence, this study proposes two alternative hypotheses to test how the two valence dimensions underlying the different discrete emotions that users assign to Facebook posts on fan pages relate to brand equity:

- **Hypothesis 3a (The Positive Emotion-Brand Equity Contribution Hypothesis).** *On corporate Facebook fan pages, posts with higher levels of positive valence emotions (assigned by users), such as pride, thankfulness, love, surprise, and joy, will contribute to brand equity, whereas posts with higher levels of negative valence emotions (assigned by users), such as anger and sadness, will lower brand equity.*
- **Hypothesis 3b (The High Arousal Emotion-Brand Equity Contribution Hypothesis).** *On corporate Facebook fan pages, posts with higher levels of arousal valence emotions (assigned by users), such as anger, surprise, and love, will contribute to brand equity, whereas posts with low arousal emotions (assigned by users), such as pride, thankfulness, sadness and joy, will lower brand equity.*

**Moderation.** Social media content drawing users' attention in terms of assigned emotions may signal relevance of the contents in the sense that they motivate individuals to make their emotions more visible. On Facebook fan pages, the emojis reflecting users' emotions appear right under the post

for which the response is intended, and thus can be understood at a glance (unlike comments). Users are likely to be more interested in the emotions reported by other users in an affective content domain, compared to an informational/transactional one. Informative content can be enough to satisfy users' needs by itself—for individuals searching for specific information (Muntinga et al., 2011), whereas affective content tends to be evaluated together with the emotions that it evokes. Emotions assigned by users to affective posts should be indicative of special interest that affective content can generate. Arguably, interactions on an emotional/affective level will be more valuable for social media users, and by extension, may contribute to brand value. Yet, it is hard to hypothesize which emotions will contribute more to brand equity, given that all may reflect users' interest in specific posts. Thus, the following hypothesis is proposed:

- **Hypothesis 4 (The Emotion-Brand Equity Moderation by Affective Post Content Hypothesis).** *On corporate Facebook fan pages, the relationship between emotions and brand equity is stronger for posts with an emotional appeal (affective content), than for posts with a rational appeal (informational/transactional content).*

### 2.3. Content Volume

Content volume is defined as the amount of content produced and published on social network sites (Peter et al., 2013). With exception of studies such as Colicev et al. (2016) or Luo et al. (2013), content volume has been very rarely considered as an antecedent to brand equity. Nevertheless, through social media content, users and companies have the power and opportunity to be co-involved in the creation of brand meaning (Pongsakornrunsilp and Schroeder, 2011). Following this way of thinking, previous research has found that brand actions on Facebook are positively related to brand value, whereas user actions on Facebook negatively relate to brand value (Colicev et al., 2016). However, in more general terms, higher amounts of users' responses, comments and other reactions (likes, shares) published on social networks generate more e-WOM, which help to spread brand messages among users (Lee and Hong, 2016) and can ultimately increase brand value (Schivinski and Dabrowski, 2015). Therefore:

**Hypothesis 5 (The Posts, Comments, and Responses Volume Impact on Brand Equity Hypothesis).** *On corporate Facebook fan pages, posts with higher volumes of likes, shares, MGC comments and responses, and UGC comments and responses, will generate higher levels of brand equity.*

**Moderation.** Drawing on the uses and gratifications theory, previous authors have found that the most important reasons or motivations for using Facebook are related to entertainment—considered here as affective content (Smock et al., 2011; Nadkarni and Hofmann, 2012). Users of Facebook brand fan pages have been found to respond and interact more when posts have entertainment goals, compared to other social networks (Zhang, 2010). This is likely because the hedonic character of affective and emotional messages aligns better with the inherently hedonic interests and motivations of consumers using Facebook brand fan pages (Coursaris et al., 2016). In fact, Facebook brand fan pages allow companies not only to provide entertainment to users, but also to communicate with current and future customers, and to establish and consolidate brand relationships with them (Zhang, 2010). There-

fore, users would be more engaged with brand fan pages (which implies more interaction with the page) when the published content includes entertainment (affective content in this research). Such affective content, at the same time, can increase brand awareness, stimulate online traffic, develop an adequate relationship with users, and increase brand equity (Moore and Rideout, 2007; Winkler and Buckner, 2006). These considerations allow formulating the following hypothesis:

- **Hypothesis 6 (The Posts, Comments and Responses Impact on Brand Equity Relationship Moderation Hypothesis).** *On corporate Facebook fan pages, the relationship between the number of likes, shares, MGC comments and responses, and UGC comments and responses, and brand equity is stronger for posts with an emotional appeal (affective content), than for posts with a rational appeal (informational/transactional content).*

### 3. METHODOLOGY

#### 3.1. Sampling and data collection

We empirically investigate data of 36 international brands that are actively posting content on their Facebook brand fan pages. To select the final sample, Facebook fan pages are chosen using the BrandZ ranking (BrandZ, 2017, 2018), which ranks the brands according to the following metrics: (1) financial information from annual reports and other sources, such as Kantar Retail; and (2) in-market and logistical factors, including price, availability, and distribution, through quantitative customer research. Previous e-marketing studies have also used the BrandZ ranking as a source of information for sampling (Ho-Dac et al., 2013). The selected brands in the sample have an official and global Facebook fan page (displaying a check mark but not displaying the option “change region” on the Facebook menu, respectively).

The selected brands cover 11 different product categories: banking (8 companies comprising 22.2% of the sample), technology (7 companies or 19.4% of the sample), telecom providers (5 companies, representing 13.9% of the sample), automotive industry (4 companies or 11.1% of the sample), retail (3 companies, comprising 8.3% of the sample), and other sectors (including fast food, alcohol, logistics, luxury, oil and gas, and personal care, comprising 9 companies or 25% of the sample).

To obtain relevant information for the present research, MGC and UGC data were collected in two time periods: (1) May 15, 2017 to June 15, 2017; and (2) November 15, 2017 to December 15, 2017. Following the procedure described in Sabate et al. (2014), the data collection is performed also in two additional time periods: (1) July 15, 2017 to September 15, 2017; and (2) December 15, 2017 to February 15, 2018. The delay between MGC and UGC publications and the data collection process is necessary to capture how users interact with the content already published. The time span (1 month) is enough for the purposes of this research because social networks are characterised for being extremely fast and dynamic communication channels; hence, content posted on a Facebook fan page for more than 30 days is not likely to receive more interaction (Sabate et al., 2014). Indeed, prior studies find that social media has a faster predictive value (or shorter “wear-in” time) than conventional online media (such as web traffic or internet searches) (Luo et al., 2013).

In the selected periods of time, 2,211 brand posts (MGC) were obtained for content quality, valence, and volume (969 brand posts were collected for period 1, and 1,242 brand posts are collected for period 2). In addition, the content volume dimension included comments to brand posts and responses to such comments by users and brands (UGC and MGC). It is worth noting here that posts are published directly on the wall (first level), whereas comments (second level) and responses (third level) are published in response to each first-level post, and located under the post for which the response is intended.

Collection of the data for this study was performed using NCapture, the Internet browser extension of the NVivo software, and manual codification. NCapture automatically collects data about each first-level post that contains the following information: (1) name of the user/brand that published the post; (2) post message; (3) if the message contains labels; (4) if the message contains images; (5) if the message contains links; (6) if the message contains videos; (7) post type; (8) number of likes; and (9) creation time. Additionally, NCapture also collects information about comments (second level) and responses to each post (third level): (10) name of the user/brand that published the comment; (11) comment message; (12) creation time; among other descriptive information about the user/brand that published the comment.

Given that NCapture does not automatically collect emotions and shares, such information was manually collected by checking all posts on each Facebook fan page included in our sample. Two coders manually collected the data for this research: an independent coder (without previous knowledge about the research hypotheses), and a member of the research team. Intercoder reliability, calculated using Holsti's (1969) reliability formula, was satisfactory (reliability = 0.85 > 0.80 minimum threshold). Any discrepancies between coders were examined and solved by a third member of the research team.

### **3.2. Operationalization of Variables**

The dependent variable of this study is the annual monetary value of brand equity, measured at the end of 2017 and 2018 in millions of dollars (\$M) for each of the companies included in the study sample. The BrandZ ranking is used to collect information about the brand value of each brand in the sample.

To facilitate the coding process of the independent variables—and following the procedure described in Tafesse (2016), a coding instrument was prepared based on previous research and on inductive examination of Facebook fan pages. The coding instrument was pretested on a sample of Facebook fan pages ( $n = 5$ ) not included in the final sample, which allowed for a clearer definition of the variables to be included in the final coding manual. The coding manual is shown in Table 1 and provides operational definitions and examples used during the coding process. In particular, independent variables are classified into three different categories, called content dimensions: content volume, content quality, and content valence (Peters et al., 2013).

**Table 1. Coding Manual of Independent Variables**

Content	Measure	Definition	Coding strategy and examples	Source/s
Quality	<i>Vividness</i>	Measures different levels of vividness (the extent to which a post stimulates various senses) of a brand post <i>i</i>	Several categories are coded: 0 for no vividness, including status posts 1 for low vividness, including photos and images 2 for medium vividness, considering links and hashtags (#) 3 for high vividness, mainly comprising videos (uploading a recorded video, sharing a link from YouTube or from other sources)	Coursaris et al. (2016) Jeon et al. (2016)
	<i>Interactivity</i>	Measures different levels of interactivity (the degree to which two or more communication parties can act on each other, on the communication medium and on the messages, and the degree to which such actions are synchronised) of a brand post <i>i</i>	Several categories are coded: 0 for no interactivity, considering status posts, photos, and videos (uploading a recorded video, sharing a link from YouTube or from other sources) 1 for low interactivity, comprising links, hashtags (#), and votes for alternatives 2 for medium interactivity, implying requests for users to interact, for example, visiting a website, liking the post, commenting, and entering contests 3 for high interactivity, including questions and quizzes	Luarn et al. (2015)
	<i>Content domain</i>	Informative/Transactional content (rational appeal)	Binary coding: 1 if the content of a post <i>i</i> is transactional, by including information about promotions, trials, coupons, contest, quizzes, special offers, deals, loyalty programs, distribution points, and other sales related activities 0 if the content of a post <i>i</i> is informational, comprising merely general information about the brand, such as product specifications, reviews, recommendations, practical tips, and corporate social responsibility	Coursaris et al. (2016) Taecharunroj (2017) Tafesse (2015)
Valence	<i>Total Proud</i>	Number of emotions that a brand post <i>i</i> has received from users	Binary coding: 1 if the content of a post <i>i</i> is affective by including entertainment content (humorous messages, witty messages, anecdotes, teasers, slogans, wordplays) or emotion-evoking content (artistic works, imagery, sentimental messages, storytelling, inspirational quotation, poems) 0 otherwise	Coursaris et al. (2016) Luarn et al. (2015) Tafesse 2015
	<i>Total Thank</i>		Continuous variable indicating the total number of proud emotions assigned to brand post <i>i</i>	
	<i>Total Love</i>		Continuous variable indicating the total number of thank emotions assigned to brand post <i>i</i>	
	<i>Total Surprise</i>		Continuous variable indicating the total number of love emotions assigned to brand post <i>i</i>	
	<i>Total Angry</i>		Continuous variable indicating the total number of surprise emotions assigned to brand post <i>i</i>	
	<i>Total Joy</i>		Continuous variable indicating the total number of angry emotions assigned to brand post <i>i</i>	
	<i>Total Sad</i>		Continuous variable indicating the total number of joy emotions assigned to brand post <i>i</i>	
	<i>Total Sad</i>		Continuous variable indicating the total number of sad emotions assigned to brand post <i>i</i>	
Volume	<i>Total Likes</i>	Number of likes that a brand post <i>i</i> has received from users	Continuous variable indicating the total number of likes assigned to a brand post <i>i</i>	Peters et al. (2013)
	<i>Total Shares</i>	Number of shares that a brand post <i>i</i> has received from users	Continuous variable indicating the total number of shares assigned to a brand post <i>i</i>	
	<i>MGC and UGC total comments</i>	Number of marketer's and users' comments assigned to a brand post <i>i</i>	Continuous variable indicating the total number of marketer's and users' comments assigned to a brand post <i>i</i>	
	<i>MGC and UGC total responses</i>	Number of marketer's and users' responses to MGC and UGC comments to a brand post <i>i</i>	Continuous variable indicating the total marketer's and users' responses to MGC and UGC comments assigned to a brand post <i>i</i>	Adapted from: Coehlo et al. (2016) de Vries et al. (2012)

With respect to the first group, content quality, three different measures are considered: vividness, interactivity, and content domain. On the second group of variables, content valence, the number of emotions that a brand post  $i$  has received from users has been collected. Finally, with regard to the last group of variables, content volume, data were collected about the number of likes and shares, total number of marketer's and users' comments assigned to a brand post  $i$  and total number of marketer's and users' responses to MGC and UGC comments.

Finally, we have also included some variables as controls. The *total followers* variable measures the number of users that follow the firm's Facebook fan page. This measure was captured at the end of 2017. We also consider as a control the total number of posts published by marketers and users on each Facebook fan page during the period of data collection; these are called *MGC and UGC total posts*, respectively (Peters et al., 2013). Additionally, we include *MGC posting day*, which identifies the day of the week when a specific brand publishes a post  $i$ . This variable takes the value of 0 for weekend (from Friday at 15:00 to Sunday at 23:59) and 1 for weekday (the remaining time) (Sabate et al., 2014). Additionally, we include *MGC posting time*, which identifies the time when a specific brand publishes a post  $i$ ; it takes the value of 0 for non-business hours (0:00-7:59 and 18:00-23:59, Monday through Thursday; 0:00-7:59 and 15:00-23:59 on Friday; Saturday and Sunday, all day); and 1 for business hours (8:00-17:59, on Monday through Thursday; 8:00-14:59 on Friday) (Sabate et al., 2014). We also include a set of dummy variables indicating sectors of activity of each company in the database (technology industry is selected as the baseline category and excluded from the models). All variables have been standardised to better fit a normal distribution and to improve the explanatory power of the model.

### 3.3. Statistical Analysis and Results

Bivariate correlation values and the *variance inflation factor* (VIF) are examined to test the absence of multicollinearity. Correlations with values above 0.8 indicate multicollinearity and individual VIF values greater than 10 indicate a multicollinearity problem (Neter et al., 1989). The relatively high correlations between some of the independent variables, in particular between total love and total surprise ( $r = 0.88, p < 0.05$ ), and between UGC total comments and UGC total responses ( $r = 0.86, p < 0.05$ )<sup>1</sup>, could make the results prone to multicollinearity. Therefore, the empirical analyses are performed using ridge regression, instead of *ordinary least squares* (OLS) regression. In the presence of multicollinearity in data, the estimation of parameters or regression coefficients in marketing models by means of OLS may give estimates, though unbiased, with absolute values tend to be inflated with a high variance and with signs may reverse with negligible change in data (Hoerl et al., 1970). In addition, under high multicollinearity the parameter estimates tend to be very unstable and can change drastically when different LS computer algorithms are used (Beaton et al., 1976) and/or new samples are used to validate the estimates (Farrar and Glauber, 1967). However, ridge regression overcomes

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<sup>1</sup> The complete correlation matrix is not reported here but is available upon request.

the multicollinearity problem through the production of estimates which are stable and closer to the true values of the coefficients the analyst is trying to develop.

In comparison with OLS estimates, which are unbiased with large variance, ridge estimates are biased but with a smaller variance (Mahajan et al., 1977). These smaller variances offset the bias of the ridge regression estimates, the mean square error of the estimates is reduced below that of OLS, and the  $R^2$  of the ridge regression was a bit lower than the OLS regression model due to the fact that this model accounted for multicollinearity (Verhoef, 2004). However, the ridge regression results are highly comparable with the OLS estimation results. In short, the advantage of ridge regression is that it penalizes the size of the coefficients and is insensitive to correlations (Malthouse, 1999).

Table 2 describes the correspondence between the hypotheses and models proposed in this research. In addition, Tables 3 and 4 report results of these models. In particular, Table 3 shows results at time period  $t$  (2017) and Table 4 shows analogous results on the dependent variable measured at time period  $t + 1$  (s2018). The purpose to test the proposed relationships at  $t$  and  $t + 1$  is related with the identification of the short-term effects, because independent variables are also measured at  $t$ , and long-term effects generated one year later of the considered publications.

Following the recommendations of Cohen et al. (2003) related to hierarchical models, variables are introduced in Models at  $t$  and  $t + 1$  in 4 steps (see more details in Table 2). First, the variables involved in the main effects and controls are included in the Baseline Model. Second, interaction terms between the independent variables and informational content are also included in Model 1. Model 2 adds the interaction terms between the independent variables and transactional content. Finally, Model 3 includes the interaction terms between the independent variables and affective content.

The proposed relationships are tested hierarchically because hypotheses H1a, H1b, H3a, H3b, and H5 are tested through the Baseline Model; H2 is tested through the comparison among Model 1, 2 and 3 for variables related to content quality (vividness and interactivity); H4 is tested through the comparison among Model 1, 2 and 3 for variables related to content valence (emotions); and finally, H6 is tested through the comparison among Model 1, 2 and 3 for variables related to content volume (number of likes, shares, MGC comments and responses, and UGC comments and responses).

**Table 2. Hypothesis and corresponding models**

Content Dimension	Hypotheses	Models
Quality	H1a Vividness and interactivity $\rightarrow$ brand equity	Baseline models for $t$ and $t + 1$
	H1b Content domain $\rightarrow$ brand equity	Baseline models for $t$ and $t + 1$
	H2 Moderating role of content domain on the relationships: vividness and interactivity $\rightarrow$ brand equity	Models 1, 2 and 3 for $t$ and $t + 1$
Valence	H3a Positive/negative tonality $\rightarrow$ brand equity	Baseline models for $t$ and $t + 1$
	H3b High/low arousal emotions $\rightarrow$ brand equity	Baseline models for $t$ and $t + 1$
	H4 Moderating role of content domain on the relationship: content valence $\rightarrow$ brand equity	Models 1, 2, and 3 for $t$ and $t + 1$
Volume	H5 Content volume $\rightarrow$ brand equity	Baseline models for $t$ and $t + 1$
	H6 Moderating role of content domain on the relationship: content volume $\rightarrow$ brand equity	Models 1, 2, and 3 for $t$ and $t + 1$



**Table 3. Hierarchical ridge regression results (time  $t = 2017$ )**

Independent variables	Baseline model	Model 1 -Informative-	Model 2 -Transactional-	Model 3 -Affective-
	$\beta$ coefficients (S.E.)	$\beta$ coefficients (S.E.)	$\beta$ coefficients (S.E.)	$\beta$ coefficients (S.E.)
<i>Content quality:</i>				
Vividness	0.080 (0.015)*	0.140 (0.025)*	0.100 (0.015)*	0.045 (0.020)*
Interactivity	0.020 (0.015)	0.033 (0.025)	0.012 (0.020)	0.020 (0.020)
Informative/transactional content	-0.022 (0.020)	-0.004 (0.020)	-0.100 (0.040)**	-0.023 (0.020)
Affective content	0.040 (0.015)**	0.044 (0.150)*	0.040 (0.015)*	0.100 (0.020)*
<i>Content valence:</i>				
Total Proud	-0.045 (0.020)*	0.700 (0.111)*	-0.050 (0.016)*	-0.052 (0.020)*
Total Thank	-0.005 (0.015)	-0.152 (0.070)**	-0.001 (0.015)	-0.005 (0.015)
Total Love	0.050 (0.034)	-0.100 (0.110)	0.041 (0.034)	0.043 (0.043)
Total Surprise	-0.040 (0.033)	-0.020 (0.100)	-0.032 (0.033)	-0.031 (0.043)
Total Angry	0.060 (0.020)*	0.300 (0.100)*	0.052 (0.020)*	0.054 (0.020)*
Total Joy	-0.030 (0.015)***	-0.100 (0.025)*	-0.040 (0.020)**	-0.012 (0.016)
Total Sad	-0.002 (0.015)	0.203 (0.112)***	-0.001 (0.015)	-0.010 (0.015)
<i>Content volume:</i>				
Total Like	0.011 (0.020)	-0.002 (0.032)	0.011 (0.020)	0.015 (0.021)
Total Share	-0.010 (0.022)	-0.015 (0.040)	-0.001 (0.023)	-0.013 (0.030)
MGC total comments	-0.020 (0.015)	-0.134 (0.100)	-0.014 (0.015)	-0.020 (0.015)
UGC total comments	-0.040 (0.040)	0.016 (0.052)	-0.056 (0.040)	-0.050 (0.050)
MGC total responses	-0.030 (0.020)	-0.090 (0.035)**	-0.003 (0.020)	-0.022 (0.020)
UGC total responses	0.055 (0.035)	0.100 (0.120)	0.100 (0.040)***	0.054 (0.044)
<i>Controls:</i>				
Total followers	-0.020 (0.020)	-0.030 (0.020)***	-0.020 (0.020)	-0.025 (0.020)
MGC total posts	-0.030 (0.022)	-0.030 (0.022)	-0.024 (0.022)	-0.030 (0.023)
UGC total posts	0.100 (0.020)*	0.064 (0.020)*	0.100 (0.020)*	0.100 (0.020)*
MGC posting day	-0.045 (0.020)*	-0.040 (0.016)**	-0.043 (0.020)*	-0.040 (0.020)**
MGC posting time	-0.030 (0.020)***	-0.031 (0.020)***	-0.030 (0.020)***	-0.030 (0.020)***
Banking sector	-0.040 (0.020)**	-0.044 (0.020)**	-0.050 (0.020)**	-0.041 (0.020)**
Telecom providers sector	0.700 (0.020)*	0.700 (0.020)*	0.700 (0.020)*	0.700 (0.020)*
Cars sector	0.110 (0.021)*	0.110 (0.020)*	0.110 (0.020)*	0.110 (0.021)*
Retail sector	-0.100 (0.022)*	-0.100 (0.022)*	-0.100 (0.023)*	-0.100 (0.022)*
Others sectors	0.010 (0.020)	0.010 (0.020)	0.007 (0.020)	0.020 (0.020)
<i>Interactions:</i>				
Vividness	-	-0.100 (0.031)*	-0.064 (0.075)	0.121 (0.033)*
Interactivity	-	-0.020 (0.031)	0.074 (0.050)	-0.020 (0.034)
Total Proud	-	-0.720 (0.112)*	-0.100 (0.454)	0.803 (0.130)*
Total Thank	-	0.153 (0.100)**	-0.200 (0.112)***	-0.100 (0.100)
Total Love	-	0.122 (0.114)	1.325 (0.700)***	-0.221 (0.133)***
Total Surprise	-	-0.015 (0.100)	-2.500 (0.933)*	0.100 (0.100)
Total Angry	-	-0.221 (0.100)*	0.600 (0.200)*	0.200 (0.100)***
Total Joy	-	0.100 (0.032)**	-0.020 (0.100)	-0.133 (0.042)*
Total Sad	-	-0.210 (0.113)***	-2.001 (0.900)**	0.300 (0.115)**
Total Like	-	0.020 (0.040)	0.130 (0.102)	-0.024 (0.042)
Total Share	-	0.011 (0.050)	1.300 (0.832)	0.022 (0.052)
MGC total comments	-	0.120 (0.100)	-0.200 (0.124)	0.122 (0.155)
UGC total comments	-	-0.102 (0.100)	0.255 (0.120)**	0.040 (0.100)
MGC total responses	-	0.100 (0.040)**	-0.115 (0.054)**	0.004 (0.105)
UGC total responses	-	0.010 (0.130)	-0.350 (0.300)	0.100 (0.200)
Goodness of fit:	$R^2 = 0.553$ $R^2 \text{ adj.} = 0.550$ $F = 99.960^*$	$R^2 = 0.570$ $R^2 \text{ adj.} = 0.562$ $F = 68.480^*$	$R^2 = 0.562$ $R^2 \text{ adj.} = 0.554$ $F = 66.340^*$	$R^2 = 0.570$ $R^2 \text{ adj.} = 0.561$ $F = 68.170^*$

\* $p < 0.01$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.1$

**Table 4. Hierarchical ridge regression results (time  $t + 1 = 2018$ )**

Independent variables	Baseline model	Model 1 -Informative-	Model 2 -Transactional-	Model 3 -Affective-
	Non-standardised $\beta$ coefficients (S.E.)	Non-standardised $\beta$ coefficients (S.E.)	Non-standardised $\beta$ coefficients (S.E.)	Non-standardised $\beta$ coefficients (S.E.)
<i>Content quality:</i>				
Vividness	0.100 (0.015)*	0.120 (0.025)*	0.100 (0.015)*	0.050 (0.020)*
Interactivity	0.025 (0.015)***	0.043 (0.025)***	0.022 (0.020)	0.024 (0.020)
Informative/transactional content	-0.020 (0.020)	-0.010 (0.020)	-0.100 (0.040)**	-0.020 (0.020)
Affective content	0.050 (0.015)*	0.054 (0.015)*	0.051 (0.015)*	0.100 (0.020)*
<i>Content valence:</i>				
Total Proud	-0.043 (0.020)*	0.602 (0.112)*	-0.050 (0.020)*	-0.053 (0.020) *
Total Thank	0.001 (0.015)	-0.140 (0.100)**	0.010 (0.015)	0.001 (0.015)
Total Love	0.100 (0.034)**	-0.065 (0.110)	0.100 (0.034)**	0.100 (0.043)**
Total Surprise	-0.055 (0.033)	-0.020 (0.100)	-0.050 (0.033)	-0.100 (0.043)
Total Angry	0.100 (0.020)*	0.300 (0.100)*	0.053 (0.020)*	0.054 (0.020)*
Total Joy	-0.030 (0.015)**	-0.100 (0.025)*	-0.040 (0.020)**	-0.020 (0.020)
Total Sad	-0.010 (0.015)	0.200 (0.112)	-0.004 (0.015)	-0.011 (0.015)
<i>Content volume:</i>				
Total Like	0.013 (0.020)	-0.002 (0.032)	0.014 (0.020)	0.020 (0.021)
Total Share	-0.010 (0.022)	-0.011 (0.040)	-0.005 (0.023)	-0.012 (0.030)
MGC total comments	-0.020 (0.015)	-0.130 (0.092)	-0.014 (0.015)	-0.020 (0.015)
UGC total comments	-0.040 (0.040)	0.010 (0.053)	-0.055 (0.040)	-0.054 (0.050)
MGC total responses	-0.030 (0.020)	-0.100 (0.035)**	-0.010 (0.020)	-0.020 (0.020)
UGC total responses	0.043 (0.035)	0.062 (0.120)	0.053 (0.040)	0.050 (0.044)
<i>Controls:</i>				
Total followers	-0.010 (0.020)	-0.020 (0.020)	-0.010 (0.020)	-0.020 (0.020)
MGC total posts	0.043 (0.022)**	0.044 (0.22)**	0.050 (0.022)**	0.042 (0.022)**
UGC total posts	0.080 (0.020)*	0.100 (0.020)*	0.100 (0.020)*	0.100 (0.020)*
MGC posting day	-0.040 (0.020)**	-0.031 (0.020)*	-0.035 (0.020)**	-0.030 (0.020)***
MGC posting time	-0.025 (0.020)	-0.030 (0.020)	-0.023 (0.020)	-0.025 (0.020)
Banking sector	-0.050 (0.20)**	-0.052 (0.020)*	-0.050 (0.020)*	-0.050 (0.020)*
Telecom providers sector	0.700 (0.020)*	0.700 (0.020)*	0.700 (0.020)*	0.100 (0.020)*
Cars sector	0.032 (0.021)	0.033 (0.021)	0.031 (0.020)	0.040 (0.021)***
Retail sector	-0.200 (0.022)*	-0.200 (0.022)*	-0.200 (0.023)*	-0.200 (0.022)*
Others sectors	0.060 (0.020)*	0.100 (0.020)*	0.100 (0.020)*	0.100 (0.020)*
<i>Interactions:</i>				
Vividness	-	-0.100 (0.031)**	-0.100 (0.100)	0.100 (0.033)*
Interactivity	-	-0.020 (0.031)	0.050 (0.050)	-0.003 (0.035)
Total Proud	-	-0.700 (0.113)*	-0.400 (0.455)	0.800 (0.130)*
Total Thank	-	0.015 (0.100)**	-0.200 (0.112)	-0.063 (0.100)
Total Love	-	0.200 (0.114)	1.600 (0.700)**	-0.310 (0.133)**
Total Surprise	-	-0.050 (0.100)	-2.420 (0.935)*	0.100 (0.100)
Total Angry	-	-0.220 (0.100)*	0.600 (0.200)*	0.140 (0.100)
Total Joy	-	0.100 (0.032)**	0.004 (0.070)	-0.132 (0.042)*
Total Sad	-	-0.181 (0.113)	-2.330 (0.900)*	0.300 (0.120)**
Total Like	-	0.020 (0.040)	0.122 (0.102)	-0.021 (0.042)
Total Share	-	0.010 (0.050)	1.100 (0.900)	0.032 (0.053)
MGC total comments	-	0.110 (0.100)	-0.200 (0.0124)	0.130 (0.200)
UGC total comments	-	-0.100 (0.100)	0.240 (0.120)**	0.013 (0.100)
MGC total responses	-	0.100 (0.040)**	-0.100 (0.054)	-0.120 (0.105)
UGC total responses	-	0.013 (0.130)	-0.400 (0.300)	0.223 (0.200)
Goodness of fit:	$R^2 = 0.552$ $R^2 \text{ adj.} = 0.550$ $F = 99.550^*$	$R^2 = 0.570$ $R^2 \text{ adj.} = 0.560$ $F = 67.420^*$	$R^2 = 0.560$ $R^2 \text{ adj.} = 0.552$ $F = 65.740^*$	$R^2 = 0.570$ $R^2 \text{ adj.} = 0.560$ $F = 67.290^*$

\* $p < 0.01$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.1$

The results regarding content quality are related to vividness, interactivity, and content domain (which comprises informative, transactional, and affective contents). First, with respect to vividness, the results indicate that more vivid posts lead to greater brand equity in the short term (see the short-term results in Table 3 when using the 2017 value for brand equity as the dependent variable) ( $\beta = 0.080, p < 0.01$ ), and also in the long term (see the long-term results in Table 4 when using the 2018 value for brand equity as the dependent variable) ( $\beta = 0.100, p < 0.01$ ). Second, with respect to interactivity, results show a positive relationship with brand equity, but only in the long term ( $\beta = 0.025, p < 0.10$ ); consequently, H1a is partially supported in the short term, but fully supported in the long term. These results mean that, on corporate Facebook fan pages, posts with higher levels of content quality, in terms of vividness, generate higher levels of brand equity in the short term, and similarly so in the long term, but in terms of vividness and interactivity.

Third, with respect to content domain, the results indicate that affective posts generate greater brand equity in the short term ( $\beta = 0.040, p < 0.05$ ) and even in the long term ( $\beta = 0.050, p < 0.01$ ); these results yield support for H1b. This means that, on corporate Facebook fan pages, posts with affective content generate higher levels of brand equity than those with informational/transactional content, both in the short and long term. Finally, with regard to the moderating role of content domain, the relationships between vividness and brand equity is stronger for posts with affective content than informational/transactional content in the short and long terms ( $\beta = 0.121, p < 0.01$  and  $\beta = 0.100, p < 0.01$  respectively). However, such a relationship is not observed for interactivity. Consequently, H2 is partially supported in the short and long terms for vividness.

The results related to content valence refer to the levels of emotions assigned by users to brand posts on Facebook; these emotions are pride, thankfulness (available during the period of data collection), love, surprise, anger, joy, and sadness. First, posts with higher levels of the pride emotion assigned by users exerted a negative effect on brand equity in the short term ( $\beta = -0.045, p < 0.01$ ) and in the long term ( $\beta = -0.043, p < 0.01$ ). Second, posts with higher levels of the anger emotion assigned by users exerted a positive effect on brand equity in the short term ( $\beta = 0.060, p < 0.01$ ) and even stronger in the long term ( $\beta = 0.100, p < 0.01$ ). Third, posts with higher levels of the joy emotion assigned by users exerted negative effect on brand equity in the short ( $\beta = -0.030, p < 0.1$ ) and in the long term ( $\beta = -0.030, p < 0.05$ ). Finally, love also exerted a positive effect on brand equity, but only in the long term ( $\beta = 0.100, p < 0.05$ ).

These results lend support for H3b for the anger and love emotions considered here to be high-arousal emotions, and pride and joy emotions, considered here to be low-arousal emotions. Consequently, on corporate Facebook fan pages, posts with high-arousal emotions assigned by users, such as anger and love, exert a greater effect on brand equity than posts with low-arousal emotions being assigned, such as joy and pride. Finally, with respect to the moderating role of content domain, the results indicate that posts with higher levels of the pride emotion assigned by users exerted a stronger

effect on brand equity for affective posts than for informational and transactional posts, both in the short ( $\beta = 0.803, p < 0.01$ ) and in the long term ( $\beta = 0.800, p < 0.01$ ); additionally, posts with higher levels of joy emotion being assigned exerted a stronger effect on brand equity for affective posts than for informational and transactional posts, both in the short ( $\beta = -0.133, p < 0.01$ ) and in the long term ( $\beta = -0.132, p < 0.01$ ); these results lend support to H4 for both the pride and joy emotions in the short and long term.

The last group of results, for content volume, show non-significant relationships between MGC and UGC total comments and responses and brand equity, thus not supporting H5. Similarly, regarding the moderating role of content domain, the relationships between MGC and UGC total comments and responses and brand equity are not stronger for posts with affective content than for posts with informational/transactional content, thus not supporting H6. However, the MGC total responses are positively related to brand equity when content is informative both in the short ( $\beta = 0.100, p < 0.05$ ) and in the long term ( $\beta = 0.100, p < 0.05$ ) and negatively related to brand equity when content is transactional only in the short term ( $\beta = -0.115, p < 0.05$ ). In addition, the UGC total comments are positively related to brand equity when content is transactional both in the short ( $\beta = 0.255, p < 0.05$ ) and in the long term ( $\beta = 0.240, p < 0.05$ ).

#### 4. DISCUSSION AND CONTRIBUTIONS

The findings of this research offer important theoretical and managerial contributions to the understanding of how to improve content on social networking sites. On the one hand, as regards the theoretical implications, the present work contributes to the social media research stream by empirically testing part of the theoretical SOR framework proposed by Peters et al. (2013). More specifically, the research model has analysed the effect of the three proposed content dimensions (quality, valence, and volume). In addition, both MGC and UGC data were included as potential levers of brand equity. By selecting brand equity as dependent variable, the present study also adds to the growing research stream examining the extent to which the social media efforts of brands have economically significant effects that reach beyond the online environment—that is, on brand equity as the overall business value expressed in currency units.

The first content dimension, quality, encompasses interactivity, vividness, and content domain (which can be split also into informative, transactional, and affective contents). Consistent with previous literature (de Vries et al., 2012), the overall effect of interactivity was beneficial for the brands, in terms of brand equity. This is reasonable because more interactive fan pages and posts on social media are likely to create stronger community ties with the brand, and to empower users by offering them more opportunities for self-expression (so that users feel their opinion matters), thus positively affecting their image of the brand. Similarly, the overall effect of vividness was also positive on brand equity; more vivid content may have a greater ability to create experiences that resemble the real world

more closely (Tafesse, 2015), thus generating greater user engagement (Luarn et al., 2015) and brand exposure (Thornhill et al., 2017).

With respect to content domain, as hypothesized, posts with affective content (emotional appeal) were found to generate higher levels of brand equity, compared to posts with informational/transactional content (rational appeal). This finding is in line with the consideration of entertainment as a key motivation for social media use (Muntinga et al., 2011). Further, brand posts with emotional appeal seems to provide users with more opportunities to distract, entertain and pastime (Luarn et al., 2015; Tafesse, 2015) than rational ones. Regarding the potential moderating role of content domain in the relationship between content vividness and brand equity, there was no support to the expectation that more interactive posts would influence brand equity more favourably for affective contents. Surprisingly, more vivid posts were negatively related to brand equity for informative contents. This unexpected result could signal users' preference for content with low-vividness features, which can be understood faster.

The findings obtained on the second content dimension, valence, were supportive of previous research showing that high-arousal emotions, such as anger, can lead to greater content virality (Berger and Milkman, 2010), generating broader reach and brand awareness, which in turn may leverage brand equity (Bruhn et al., 2012). In this study, posts with high-arousal emotions assigned by users, such as anger and love, exerted greater effect on brand equity than posts with low-arousal emotions assigned, such as joy or pride (with were negatively related to brand equity).

With respect to the moderating role of content domain in the relationship between content valence and brand equity, the results show substantial differences between informative, transactional and affective content. First, the results for the pride and joy emotions are in line with previous literature indicating that, unlike informational content, affective content is more likely to be evaluated together with the emotions it evokes (Muntinga et al., 2011). This is an indication of the interest that emotional content can generate, and by extension, of its stronger potential effect on brand equity. For the informative content, the impact of the specific assigned emotions was in the same direction than their valence (except for pride), that is, positively (negatively) valenced emotions exerted positive (negative) influence on brand value. On the other hand, for transactional content, positive effects on brand equity were exerted by high arousal emotions (love, anger), whereas lower arousal emotions (gratitude, sadness) negatively affected brand equity. Altogether, these results lend support for the analysis of discrete emotions on social media and indicate the adequacy of examining them by acknowledging several dimensions.

The effects of the third (and final) content dimension, volume, on brand equity did not corroborate the hypotheses proposed. However, with respect to the moderating role of content domain, the results indicate that posts with higher levels of MGC total responses positively affected brand equity when content was informative and negatively when content was transactional. Previous research demonstrated that when brands use Facebook for disseminating information (informative content), they gen-

erate favourable purchasing behaviour (Goh et al., 2013), as well as when brands respond promptly to users demands on social media, they help create a positive image, build trust and increase the perceived quality and value of the brand (Bruhn et al., 2012).

Hence, when brands content is directly related with the generation of transactions (transactional content), users can lose interest, negatively affecting brand value. This can be a consequence that remuneration motivations, which are more closely linked to transactional content, are less frequent in social media compared to information or entertainment ones (Muntinga et al., 2011). Such content is only relevant for a small part of the users. In addition, UGC total comments positively affect brand equity when content is transactional. Indeed, users' actions, such as commenting MGC posts, help in the dissemination of the brands' messages more widely (users' comments appear in news feeds of their friend network) (Colicev et al., 2016). Thus, users' comments ultimately affect brand equity, especially if the disseminated MGC content is transactional and encourage users buying products of these brands creating posts.

As for the managerial implications derived from this research, probably one of the most frequent questions surrounding firms' use of social media is whether and the extent to which their effects reach beyond the digital environment. The findings from this study indeed show significant relationships between different actions taken by companies on social media (Facebook) and brand equity. However, the identified effects were modest, and may become diluted over time (but should be expected to remain significant). This study delved into the separate influence of three content dimensions (quality, valence, and volume) on brand equity. Overall, the results show that variables from the three dimensions under study can influence brand equity, thus, signalling the importance of addressing quality, valence, and volume issues when developing asocial media content strategy. Yet, content quality and valence may have a stronger impact than content volume on brand equity, which warns practitioners against focusing only on publication frequency.

The three content dimensions under study are equally malleable by social media managers. For instance, it seems easier to manipulate the different content quality subdimensions (vividness, interactivity, and domain), as well as the volume variables controlled by brands (MGC responses), compared to users' social media actions (UGC posts and responses, and assigned emotions). The findings suggest that more vivid, interactive, and affective posts can generate greater brand equity. Therefore, social media managers can schedule posts with videos, or post questions on topics not directly related to the brand. Yet, such content may conflict with other company goals, such as informing about the company's products (informative content) or promoting sales (transactional content). Importantly here, content domain moderates many of the analysed influences MGC and UGC influences on brand equity. For example, for informative content, positive emotions (thank, joy) appear to exert a positive effect on brand equity, whereas negative emotions (anger, sadness) negatively influence brand equity. These patterns are opposite to those of general model and the affectively-framed model.

Moreover, these results are different from the ones obtained in the transaction-framed model, where anger has a positive impact, and sadness has a negative impact on brand equity. The volume dimension also indicates that company reactions that provide brand value under a certain framing, such as MGC responses for the informational and transactional framings, results in positive and negative brand equity respectively, but no effect with an affective framing. Although the above-described pattern of relationships may seem complex, it highlights the importance of carefully framing messages, not only before publishing but also afterwards. Interestingly, the most-widely known measure of success on Facebook (“likes”) did not show significant influences on brand equity in any of the tested models and conditions. Similar, non-significant results were obtained for “shares”, MGC comments and UGC responses.

## **5. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH**

To date, limited empirical research has been devoted to understanding how the effort put into social media by brands reach beyond the online environment. This work aims to fill this gap by analysing the effect of different content characteristics of Facebook posts on brand equity. Following the conceptualization and structure of social media content proposed by Peters et al. (2013), three content features were proposed and tested as antecedents of brand equity: quality, valence, and volume. It should be acknowledged here that Facebook brand pages are one of the many (online and offline) tools used by marketers, which may help to understand the extent of explanatory power captured by the analyses. However, the results provided partial support for the content quality hypotheses in the short term (more vivid and affective posts lead to greater brand equity), and large support for the content quality hypotheses in the long term (more vivid, more interactive, and affective posts lead to greater brand equity). The results also provided support for some content valence hypotheses (both in the short and long term), involving high- and low-arousal emotions (anger and joy, respectively). Pride and joy emotions exert also a stronger effect on brand equity when posts are affective (in the short and long term).

Finally, although the content volume hypotheses were not supported, the amount of companies’ and users’ reactions can affect brand equity under certain circumstances. More specifically, MGC responses positively affect brand value for informational contents and negatively affect brand value for transactional contents; UGC comments positively affect brand value when content is transactional. Overall, the results of this study provide support for the notion that what happens on Facebook does not only stay on Facebook. Rather, depending on content quality, valence, and volume, it can be concluded that what (and how it) happens on Facebook will affect brand equity.

This paper has some limitations, which call for future research. First, although Facebook is the most-widely used social network worldwide, previous literature has shown that consumers may behave differently on different social media platforms, even when reacting to similar content types (Coelho et al., 2016). Hence, future research should consider the study of additional social media plat-

forms to extend the proposed model and its effects on brand equity. Other potential predictors of brand equity could be considered, such as non-digital marketing strategies implemented by companies, as well as users' cognitive and affective variables (beyond the behavioural ones included in this study's models). Moreover, the measurement of users' reactions to branded content could be refined. This study measured only users' active behaviours (clicking on reaction buttons and commenting), but not passive ones, such as reading content, which can also affect brand value through message comprehension and internalization (Muntinga et al., 2011; Zhang et al., 2017). Consequently, qualitative analysis (text and visual mining) of the specific content discussed in each comment and response is a promising research stream. Future research could also account for personal, socio-demographic traits (such as culture, gender, age, among others) to better profile users who find branded content more valuable.

Finally, this study was based on a large dataset extracted from several corporate Facebook fan pages, but manual codification of some variables had a limiting effect on the final sample. Although intercoder reliability was high, it would have been less of an issue by using automated classification methods. As a final consideration, extracting data throughout the whole year would provide a more detailed analysis of the antecedents of brand equity on social networks.

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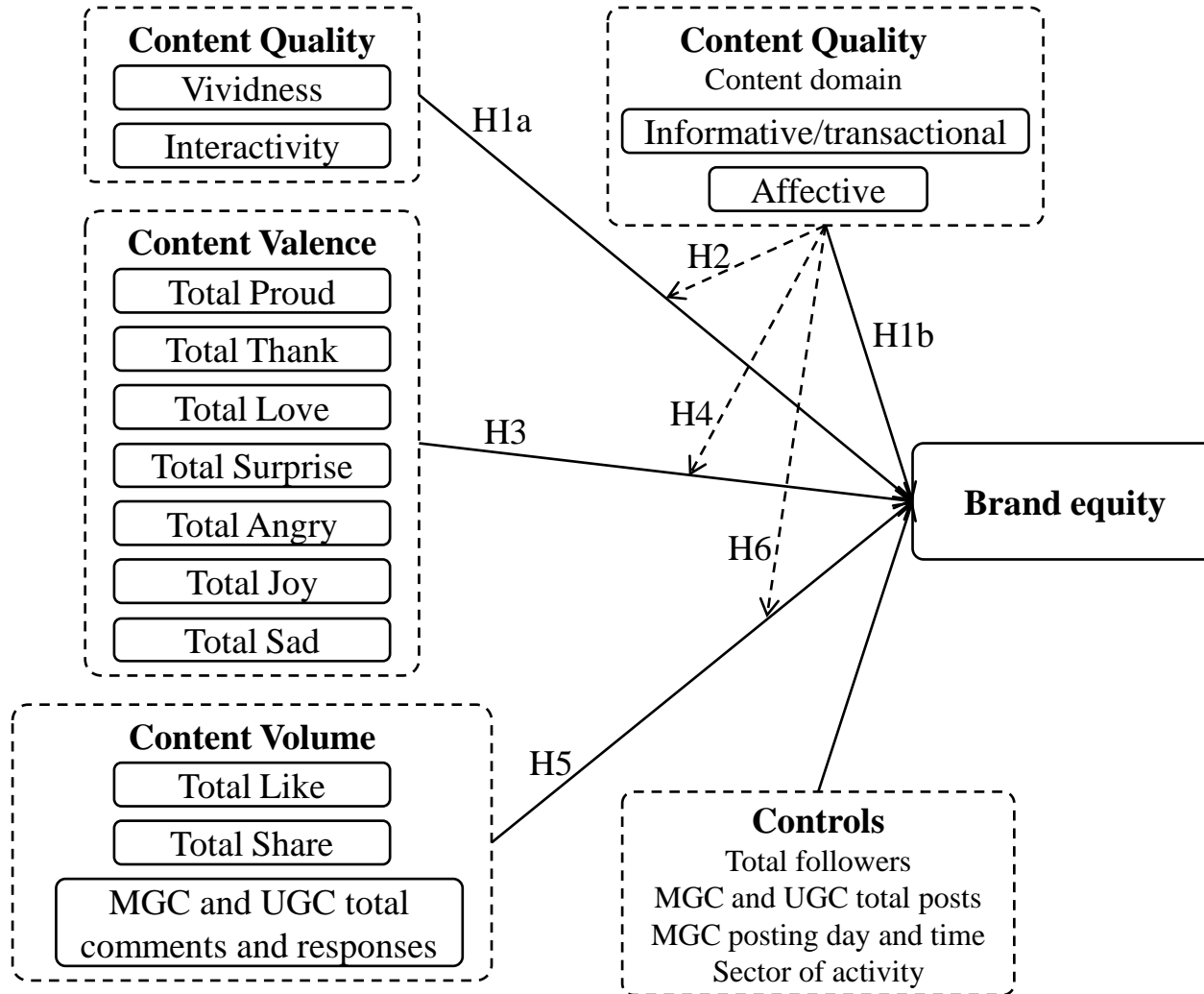


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Figure



## Conflict of Interest and Authorship Conformation Form

Please check the following as appropriate:

- ✓ All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.
- ✓ This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.
- ✓ The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript
- ✓ The following authors have affiliations with organizations with direct or indirect financial interest in the subject matter discussed in the manuscript:

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