

HOW SOCIAL MEDIA IMPACTS BRAND VALUE: THE MEDIATING ROLE OF CUSTOMER SATISFACTION

CÓMO LAS REDES SOCIALES IMPACTAN EL VALOR DE LA MARCA: EL PAPEL MEDIADOR DE LA SATISFACCIÓN DEL CLIENTE

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Abstract

The growing popularity of social media platforms has increased brand investments in social media marketing. However, it is not clear whether and how social media marketing leads to the creation of value for consumers and brands; therefore, we investigate how marketer and user-generated content on social media affects consumer and brand metrics. Based on the marketing productivity chain, we propose that customer satisfaction, a leading consumer metric, mediates the link between social media content and brand value. To test such assertions, we use a sample of 87 brands from 17 industries and collect a unique dataset that combines social media data from Facebook, Twitter, and YouTube with customer satisfaction, brand value, and advertising expenses. We find that user-generated content has a stronger effect on customer satisfaction than marketer-generated content. We also find that YouTube is the most effective platform for user generated content. Interestingly, we find that the effects of marketer-generated content depend on the brand's corporate reputation. In other words, more reputable brands can leverage their marketer-generated content more effectively.

Keywords: Social media marketing, user-generated content, marketer-generated content, brand value, customer satisfaction, corporate reputation.

Resumen

La creciente popularidad de las plataformas de redes sociales ha estimulado el aumento de las inversiones de marca en el marketing de redes sociales. Aun así, no está claro cómo el marketing en redes sociales conduce a la creación de valor para los consumidores y las marcas. A este respecto, investigamos cómo el marketing y el contenido generado por el usuario en las redes sociales afecta las métricas de los consumidores y las marcas. Con base en la cadena de productividad del marketing, proponemos que la satisfacción del cliente, una métrica de consumo líder, medie el vínculo entre el contenido de las redes sociales y el valor de la marca. Para probar tales afirmaciones, utilizamos una muestra de 87 marcas en 17 industrias y recopilamos un conjunto de datos único que combina datos de redes sociales de Facebook, Twitter y YouTube con la satisfacción del cliente, el valor de la marca y la inversión en publicidad. Encontramos que el contenido generado por el usuario tiene un efecto más fuerte en la satisfacción del cliente que el contenido generado por el vendedor. También encontramos que YouTube es la plataforma más efectiva para el contenido generado por el usuario. Curiosamente, encontramos que los efectos del contenido generado por el

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vendedor dependen de la reputación corporativa de la marca. En otras palabras, las marcas más acreditadas pueden aprovechar su contenido generado por el vendedor de manera más efectiva.

Palabras clave: marketing en redes sociales, contenido generado por el usuario, contenido generado por el vendedor, valor de la marca, satisfacción del cliente, reputación corporativa.

Introduction

U.S. brands now spend an average 17% of their marketing budgets on social media (The CMO Survey, 2020). A large part of these investments are dedicated to the creation of Marketer Generated Content (MGC) (Colicev, Kumar, & O'Connor 2019; Meire, Hewett, Ballings, Kumar, & Van Den Poel, 2019), which is aimed at informing and persuading the consumer base; building trust; and developing customer engagement (Borah, Banerjee, Yu-Ting, Jain, & Eisingerich, 2020; Hewett, Rand, Rust, & Van Heerde, 2016; Lemon & Verhoef, 2016). For instance, marketers regularly post informative content such as tweets containing information on new product features and persuasive posts on Facebook aimed at attracting consumer attention. Such MGC is becoming the cornerstone of brand efforts on social media. However, social media also enables the creation of User Generated Content (UGC) (e.g. by 'tweeting' or 'retweeting' on Twitter), which is beyond marketers' direct control (Meire et al., 2019). While UGC is more credible, objective, and persuasive with respect to MGC (Borah et al., 2020; Zhang, Trusov, Stephen, & Jamal, 2017), it can also backfire if it contains negative brand evaluations. Thus, balancing MGC and UGC and their effect on brand performance has become a key managerial priority which has attracted a wealth of research over the past decade (Borah et al. 2020; Hanssens & Pauwels, 2016; Meire et al., 2019). For instance, previous research has documented the impact of social media on sales (Stephen & Galak, 2012), cash flows (Nam & Kannan, 2014), and stock returns (Colicev, Malshe, & Pauwels, 2018a).

However, besides affecting the tangible financial outcomes, social media also has the power to shift consumer minds and affect firms' intangibles. Indeed, there is a growing recognition that a significant proportion of firms' market value lies in intangible assets such as customer satisfaction and brand value (Bharadwaj, Tuli, & Bonfrer, 2011; Datta, Ailawadi, & van Heerde, 2017; Malshe, Colicev, & Mittal, 2019). This shifted the research focus towards assessing whether marketing activities can impact such intangible assets. This is important because, while the ultimate aim of a brand's social media efforts (e.g. MGC) is to boost sales, such efforts first need to affect customer metrics that can only later be reflected in sales. Similarly, the financial market seems to value those firms that have accumulated substantial intangible assets (e.g. brand value and customer satisfaction) (Fischer & Himme, 2016). Thus, to

have a more complete picture of the value-relevant outcomes of social media marketing, it becomes important to thoroughly assess the effects of social media on a firm's intangibles.

Accordingly, the goal of this study is to investigate whether, how, and to what extent social media affects customer satisfaction and brand value. Theoretically, the causality implied by the chain of marketing productivity (Colicev et al., 2018a; Rust, Ambler, Carpenter, Kumar, & Srivastava, 2004) suggests that the effects of social media marketing activities (MGC and UGC) are first reflected in consumer metrics (i.e. customer satisfaction) and only later in brand-related metrics (i.e. brand value). Thus, customer satisfaction mediates the effects of MGC and UGC on brand value. Next, to compare and contrast the effects of MGC and UGC on customer satisfaction, we rely upon previous research on the persuasive and informative effects of media (Goh, Heng, & Lin, 2013; MacInnis & Jaworski, 1989). In this respect, we argue that UGC is more persuasive than MGC and, accordingly, should have a stronger effect on customer satisfaction. Finally, we propose that, in order to mitigate the lower credibility of MGC, brands should first establish a good corporate reputation (Colicev et al., 2019; Erdem & Swait, 2004).

To test such assertions, we use a sample of 87 brands from 17 different industries and collect a unique dataset that combines data from multiple sources. We gather data on UGC and MGC from Facebook, Twitter, and YouTube, and then supplement this with data on customer satisfaction from YouGov Group, brand value data from Interbrand and Brand Finance, as well as traditional media data from the Kantar Media agency. We complement these data further using the corporate reputation from YouGov Group.

The rest of the paper is organized as follows. In the next section we provide the theoretical foundations of our study and motivate the four hypotheses. In section 3, we present the data while in section 4 we articulate the method. In section 5 we present the study's results which we then discuss in the last section.

Theoretical Foundations and Development of Hypotheses

To conceptualize the relationships between social media, customer satisfaction, and brand value we rely on three theoretical underpinnings. First, we build upon the the-

oretical logic detailed in the previous literature on the chain of marketing productivity (Colicev et al., 2018a; Rust et al. 2004). This literature postulates that the effects of any marketing-related activity (e.g. advertising and social media) are first reflected in consumer metrics (i.e. customer satisfaction) and only subsequently in brand-related metrics (i.e. brand value). In other words, customer satisfaction should play a mediating role between social media content (UGC and MGC) and brand value.

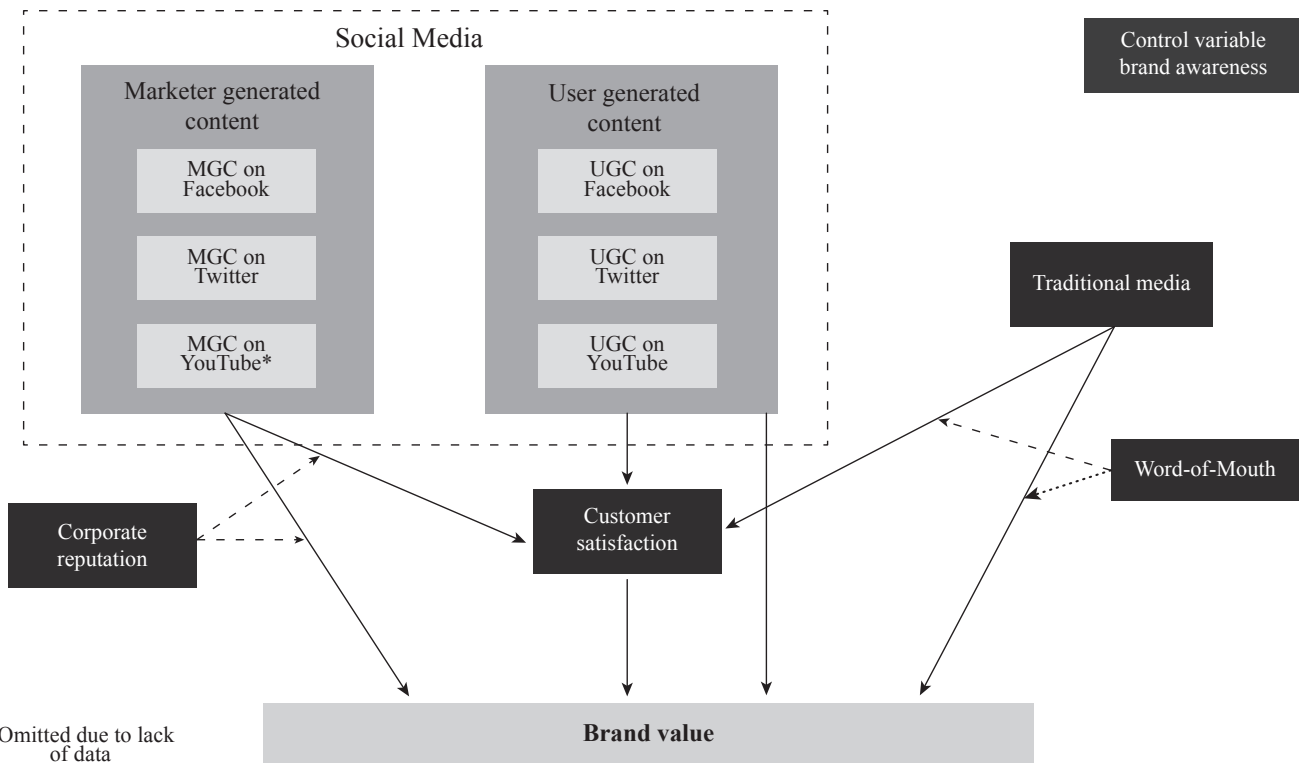
Second, to articulate the effects of UGC and MGC on customer satisfaction, and hence establish the first part of the mediation chain, we build upon the theory of persuasion. This theory shows that marketing actions can be used to persuade and/or inform consumers (Chevalier & Mayzlin, 2006; Goh et al., 2013). The informative effects are mostly related to how consumers discover relevant brand-related information from marketing communications. For example, UGC might contain relevant details (e.g. price or product characteristics) that could be useful for consumers to make informed decisions. The persuasive effects are based on the notion that marketing communications are not merely sources of information but rather creative tools that marketers can use to convince consumers to buy the brand's products. For instance, brand posts on social media typically contain positive and optimistic language about products and services. Thus, we postulate that both UGC and MGC can have informative and persuasive effects on consumers.

Third, we build upon the media credibility theory (Erdem & Swait, 2004; Riley, 1954) to argue how brands can offset the lower innate credibility of MGC (vs. UGC). Given that MGC comes from the brand itself, it encounters more resistance from consumers (Colicev, Malshe, Pauwels, & O'Connor, 2018b; Petty & Cacioppo 1986). However, we postulate that if brands can closely replicate the credibility of UGC, their MGC can be as effective. Accordingly, we posit that those brands with a high corporate reputation (i.e. are more reputable in the eyes of consumers) can enjoy a positive return on their MGC. In Figure 1, we summarise our conceptual model.

The Effects of MGC and UGC on Customer Satisfaction (Hypothesis 1)

Prior literature highlights how social media can be used by marketers to: a) persuade undecided consumers (*persuasive* effect) and b) provide information to help overcome uncertainties about product quality and characteristics (*informative* effect) (Chevalier & Mayzlin, 2006; Goh et al., 2013). The informative effects are based on the ways in which consumers access brand-related information (Abernethy & Franke, 1996), whilst the persuasive effects are based on the notion that (social media) content can contain persuasive cues that can impact consumer decisions. These two effects underlie the impact of social media on customer satisfaction. As social media allows

Figure 1. Conceptual Model



brands to more easily design and broadcast messages to wide audiences, we expect that MGC will affect customer satisfaction mostly through the informative route. Due to their expertise in content creation, marketers can generate high quality, informative, brand-related messages that inform customers about new products, offers, and corporate news about the brand. In other words, MGC shows consumers which brands are active on social media and educates people about brands' products, thereby creating top-of-mind recall and making consumers more likely to remember the brand (Risius & Beck, 2015). In addition, marketers can use MGC to engage with customers to get feedback and resolve product-related issues. For example, Delta Airlines uses Twitter to answer queries raised by passengers, thereby potentially increasing perceived brand quality. Thus, by being active on social media platforms, marketers can increase the perceived value and quality of their brand as well as set correct customer expectations, which ultimately affects customer satisfaction (Fornell & Johnson, 1996; Szymanski & Henard, 2001).

We expect UGC to impact customer satisfaction because it also delivers information (informative effect) about how many other people have experienced or used the product and how popular the product is in the market (Kübler, Colicev, & Pauwels, 2019; Meire et al. 2019), thus reducing cognitive dissonance after the purchase (Borah et al., 2020; Festinger, 1957). For example, UGC can reduce brand-related information asymmetry through relevant communication aimed at increasing the perceived value of the brand (Kirmani & Rao, 2000). In addition, UGC is typically broadcast throughout a social media user's network, spreading a powerful message that persists in consumer minds. This helps to enhance brand awareness (Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013) and persuade potential customers (persuasive effect). Indeed, the fact that there are consumers' opinions has an influence on other consumers, regardless of whether these opinions are positive or negative (Godes & Mayzlin, 2009). Furthermore, positive (negative) connotations of the content generates higher (lower) product sales by enhancing (lowering) customers' quality expectations and attitudes toward a product (Tang, Fang, & Wang, 2014).

As consumers, by default, trust other consumers more than the brand, they are more likely to be persuaded by UGC than MGC (Ho-Dac, Carson, & Moore, 2013). Indeed, previous empirical research supports this view by showing that the persuasive and informative effects of marketing communications vary based on source credibility (Erdem & Swait, 2004). For example, UGC in the form of, for example, product reviews, recommendations,

and / or Facebook Likes, provides trustworthy, objective signals to consumers and thus creates a strong persuasive cue. In contrast, MGC is likely to be perceived as less credible because it comes from the company itself with a clear commercial objective. Thus, overall, we expect that UGC will have a higher effect on customer satisfaction than MGC.

H1: The effect of UGC is higher than that of MGC on customer satisfaction

The mediating role of customer satisfaction in the social media-brand value link (Hypothesis 2)

Customer satisfaction is a key antecedent of firm performance (Gruca & Rego, 2005; Mittal, Anderson, Sayrak, & Tadikamalla, 2005; Otto, Szymanski, & Varadarajan, 2020; Tuli & Bharadwaj, 2009). The main rationale for this is that satisfied customers exhibit higher brand loyalty, which is reflected in their increased willingness to repurchase brand's products. Indeed, a wealth of studies has shown that higher customer satisfaction is related to intentions to repurchase and make product recommendations (Morgan & Rego, 2006). In turn, once satisfied customers purchase again from the brand, these transactions will be reflected in next quarter's sales and cash flows. Previous research demonstrates that firm-level positive changes in customer satisfaction lead to future sales (Grewal, Chandrashekar, & Citrin, 2010) and cash flows (Gruca & Rego, 2005). In turn, this affects how investors value the stocks with high customer satisfaction. In this respect, studies have successfully linked positive changes in customer satisfaction to firm risk (Tuli & Bharadwaj, 2009) and stock returns (Otto, Szymanski, & Varadarajan, 2020).

Since brand value is composed of market capitalization and financial reports as well as consumer side metrics (Interbrand, 2012), we expect that customer satisfaction will be directly reflected in higher brand value. In other words, we argue that firms with higher customer satisfaction will eventually experience a financial boost in sales and brand-building efforts that, in turn, will be reflected in more positive investor expectations about the stock price. Given that brand-value contains both the tangible and intangible aspects described in the methods section, we expect a significant and positive link between customer satisfaction and brand value. Once we establish that social media affects customer satisfaction in Hypotheses 1, and given that we argue above that customer satisfaction affects brand value, we expect customer satisfaction to be the mediating mechanism between social media and brand value.

H2: Customer satisfaction mediates the link between social media and brand value.

Boundary Conditions for MGC and Advertising (Hypotheses 3 and 4)

The extent to which different marketing communications can impact consumers largely depends on levels of credibility that consumers assign to such communication (Erdem & Swait 2004; Riley, Hovland, Janis, & Kelley, 1954). In the context of social media, UGC is, by default, the most credible as it is largely out of companies' control (Ho-Dac et al., 2013). As MGC comes from the brand itself, it enjoys a lower level of credibility among consumers (Herbig & Milewicz, 1993). However, previous studies have shown that lower default credibility of brand communications can be mitigated by higher brand reputation (e.g. Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016). For example, brands that enjoy a high corporate reputation are perceived as being more trustworthy and credible and encounter less resistance from consumers (Shu & Carlson, 2014). Based on these studies, we investigate whether corporate reputation moderates the effects of MGC on customer satisfaction.

H3: Corporate reputation moderates the effects of MGC on customer satisfaction

Previous studies on advertising effectiveness have highlighted the synergy between advertising and word-of-mouth (e.g. Onishi & Manchanda, 2012). Research has found that word-of-mouth often complements and extends the effects advertising has on sales (Hogan, Lemon, & Libai, 2004) and that WOM that is influenced by advertising is more likely to involve recommendations to buy a brand when compared with other WOM discussions (Keller & Fay, 2009). Other studies have argued that advertising and WOM have a positive synergistic impact on firm performance (Gopinath, Thomas, & Krishnamurthi, 2014). In sum, originating with the diffusion literature, research has demonstrated an interdependent relationship between traditional advertising and WOM.

H4: Word-of-mouth moderates the effects of traditional media on customer satisfaction

Data

We assemble a unique data set from multiple sources. We obtained access to unique data on MGC and UGC from a marketing research company that specializes in social listening. We further compliment these data with customer satisfaction information from the YouGov group. We use

Interbrand Top 100 Brands and Brand Finance databases to obtain data on brand values. Finally, we obtain traditional media expenditures from Kantar Media Agency. Table 1 provides a description of our key variables and the source of each item.

We use Interbrand's 100 most valuable brands as our sample. We had to remove certain brands due to age restrictions on social media pages (Budweiser, Corona Extra, Heineken, Jack Daniel's, Johnnie Walker, Moet & Chandon, Smirnoff), absence of an official Facebook presence (Kellogg's), differences in the composition of the 2012 and 2013 Interbrand brand value lists (Chevrolet, Discovery, and Duracell), and the absence of any social media data (MasterCard and Bank Santander). The final sample comprised 87 brands and over two years of data.

We merge the social media, brand value, YouGov, and Kantar data sets, and our final sample consists of 174 firm-year observations spanning a two-year period (2012-2013) for 87 brands for which all the relevant variables have non-missing values.

Social Media Data

We obtain data from three diverse and popular social media platforms: Facebook, Twitter, and YouTube. To collect the dimensions of MGC and UGC from these three platforms, we turned to a third-party data provider that archives publicly available social media data using a set of automated web tools. Historical social media data was collected twice. On both occasions, we paid for access to the archival social media data. The first data collection was carried out in July 2013 when we collected social media data for the first data point (December 2012). This data point is chronologically aligned with Interbrand's and Brand Finance reports on the brand value for 2012. The second data collection was carried out in January 2014 when we collected the social media data for the second data point (December 2013), and once again this corresponded to Interbrand's and Brand Finance reports on the brand value for 2013.

To ensure that the social media data provider correctly collects and archives the data, we undertook the following two-step validation process. Firstly, during the data collection periods (July 2013 and January 2014), over a period of ten days, we accessed each brand's social media page (Facebook, YouTube, Twitter) and manually collected our desired metrics (e.g., "number of brand posts", "user posts on brand wall"). In the second step, we compared the collected data with the data vendor's records. Finding no discrepancies suggested that the data provider reliably collects and archives data from the selected social media channels.

Table 1. The study's Measurements, Data sources, and Descriptions

Construct	Purpose	Source	Metrics	Description
Brand value	Main dependent variable	Interbrand and Brand Finance brand value databases	Interbrand brand value Brand Finance brand value	Latent variable underlying brand value
Customer satisfaction	Mediating variable	YouGov Group	Net promoter score of customer satisfaction	Measures brand's directly observed customer satisfaction
MGC on Facebook	Independent variable	Proprietary Data Source	No. photos posted No. videos posted No. status updates posted No. miscellaneous posted	Latent variable underlying brand actions on Facebook
MGC on Twitter	Independent variable	Proprietary Data Source	No. brand tweets	Latent variable underlying brand actions on Twitter.
UGC on Facebook	Independent variable	Proprietary Data Source	No. fans on brand page No. likes/brand posts No. comments/ brand posts No. shares/ brand posts No. people talking about this (PTAT)*	Latent variable underlying user actions on Facebook
UGC on Twitter	Independent variable	Proprietary Data Source	No. brand followers No. retweets on brand tweets	Latent variable underlying user actions on Twitter
UGC on YouTube	Independent variable	Proprietary Data Source	No. subscribers No. video views	Latent variable underlying user actions on YouTube
Traditional Media	Independent variable	Kantar Media	\$ amount spent on television \$ amount spent on newspapers \$ amount spent on outdoor	Latent variable underlying the traditional media.
Valence of user actions on Facebook	Independent variable	Proprietary Data Source	Polarity	Measure the directly observed UGC valence on Facebook as the ratio between the number of negative user posts divided by the total number of user posts.
Offline word-of-mouth	Moderator	YouGov Group	Offline word-of-mouth	Measures directly observed brand's word-of-mouth spread
Corporate Reputation	Moderator	YouGov Group	Corporate Reputation	Measures directly observed brand's corporate reputation
Awareness	Control Variable	YouGov Group	Percentage of people aware of the brand	Measures directly observed brand awareness

*The "PTAT" metric is defined by *Inside Facebook* as "the number of people who have created a story from a brand page post".

For UGC on Facebook, we collect the number of "Likes" on the brand page and the "Likes/ Comments/ Shares on brand posts" as well as in the "People Talking About This" metric ("PTAT"). For Twitter, we collect the "number of brand followers" and "number of user retweets". For YouTube, we collect the "number of channel subscribers" and "number of video views". Previous research has highlighted the importance of UGC valence (Babić Rosario, Sotgiu, De Valck, & Bijmolt, 2016). To capture the valence of UGC, we collected the textual user posts on each brand's Facebook page. To derive the UGC valence metric, we use the Naïve Bayes classifier algorithm. The probabilistic model of Naïve Bayes

classifiers is based on the Bayes' theorem, and it classifies posts into positive or negative valence categories based on the input training set of lexical words. Our valence metric is a composite volume-valence metric, which captures the number as well as the polarity of the user posts. We operationalize this UGC valence metric as the ratio of negative to total posts.¹

1 Note that such operationalization can also be reversed by taking the ratio of positive to total posts. In this case, the sign of the effects of UGC valence should be reversed. We check and find confirmation that when operationalizing the UGC valence as the ratio of positive to total user posts, the sign of the effect flips.

For MGC, we collect all brand activity on social media platforms. We collect the number of brand posts on Facebook in forms of photos, videos, and status updates to operationalize the MGC on Facebook. We collect the number of brand tweets to operationalize the MGC on Twitter. However, we were unable collect MGC statistics for YouTube as our data source only added this metric to their dashboard in May 2015.

Brand Value Data

We combine two commonly used metrics—the Interbrand and Brand Finance valuation approaches—to generate a comprehensive estimate of brand value. As previously discussed, Interbrand gathers the firm’s market capitalization from the stock market, reviews financial statements, and analyses market dynamics as well as the role of the brand in income generation (Kapferer, 2008). It then forecasts future earnings and discounts these on the basis of brand strength and risk, tabulating a yearly list of the 100 most valuable global brands; this has been widely used in previous research as a proxy for brand value (e.g. Torres, Bijmolt, Tribó, & Verhoef, 2012). Notwithstanding Interbrand’s reputation, in our study, we decided to supplement it with the Brand Finance brand value metric to give a more comprehensive estimate of brand value. Brand Finance’s metric is regarded as a valid alternative to Interbrand (Haigh & Gilbert, 2005); thus, combining both approaches helps us obtain a more complete estimate of brand value.

Customer Satisfaction Data

We have access to a unique database from the YouGov Group that offers a nationwide measurement of customer satisfaction. YouGov Group is a marketing research company that, through its BrandIndex panel (<http://www.brandindex.com>), monitors multiple brands by surveying 5,000 randomly selected consumers (from a panel of 5 million) on a daily basis, assuring representativeness by weighting the sample by age, race, gender, education, income, and region. YouGov data has been previously used in the marketing literature (Colicev et al., 2018a; Colicev et al., 2019).

YouGov collects the customer satisfaction metric as a single measurement by asking consumers whether they are satisfied/dissatisfied with a brand. At the aggregate brand level, YouGov’s scores fall within the range of -100 to +100, with the extremes only being reached if all respondents agree in their negative or positive

satisfaction with the brand relative to its competitors. For customer satisfaction, respondents are prompted with questions as to whether they are satisfied or dissatisfied with a certain brand. Those who answer “yes” to “satisfied” are counted as satisfied consumers for that day. Those who answer “yes” to “dissatisfied” are counted as dissatisfied consumers for that day. The aggregate brand measurement (Customer satisfaction) is calculated by counting the number of respondents who are dissatisfied, subtracted from the number of respondents who are satisfied, divided by the total number of respondents (see Equation 1).

$$\text{Customer satisfaction} = \frac{\text{Satisfied Respondents} - \text{Dissatisfied Respondents}}{\text{Total Number of Respondents}} \times 100 \quad (1)$$

Corporate Reputation and Word-of-Mouth

We also rely on the YouGov Group to collect the corporate reputation and word-of-mouth measurements. First, YouGov’s corporate reputations is a single measurement that captures the opinion of the crowd about the reputation of the brand (see Equation 2). Second, word-of-mouth captures the spread of brand-related word-of-mouth in the population (see Equation 3). Therefore, both measurements in YouGov Brandindex are a ratio-scaled variable that lie within the range of -100 to +100.

$$\text{Corporate Reputation} = \frac{\text{Nr. Positive Reputation Respondents} - \text{Nr. Negative Reputation Respondents}}{\text{Total Number of Respondents}} \times 100 \quad (2)$$

$$\text{Word-of-mouth} = \frac{\text{Nr. Positive WOM Respondents} - \text{Nr. Negative WOM Respondents}}{\text{Total Number of Respondents}} \times 100 \quad (3)$$

As brand awareness is an antecedent of both customer satisfaction and brand value (Hanssens & Pauwels, 2016), we collect the measurement of brand awareness from YouGov Group that captures whether the respondent knows or does not know about the brand (see Equation 4).

$$\text{Awareness} = \frac{\text{Nr. of Respondents who are aware} - \text{Nr. of Respondents who are not aware}}{\text{Total Number of Respondents}} \times 100 \quad (4)$$

Traditional Media Data

As a measurement of traditional media, we collect brand advertising expenditures from Kantar Media agency (Trusov, Bucklin, & Pauwels, 2009), expressing advertising expenditures as total yearly dollars spent on different media platforms (television, newspapers).

Method

We summarize our empirical strategy in Figure 2.

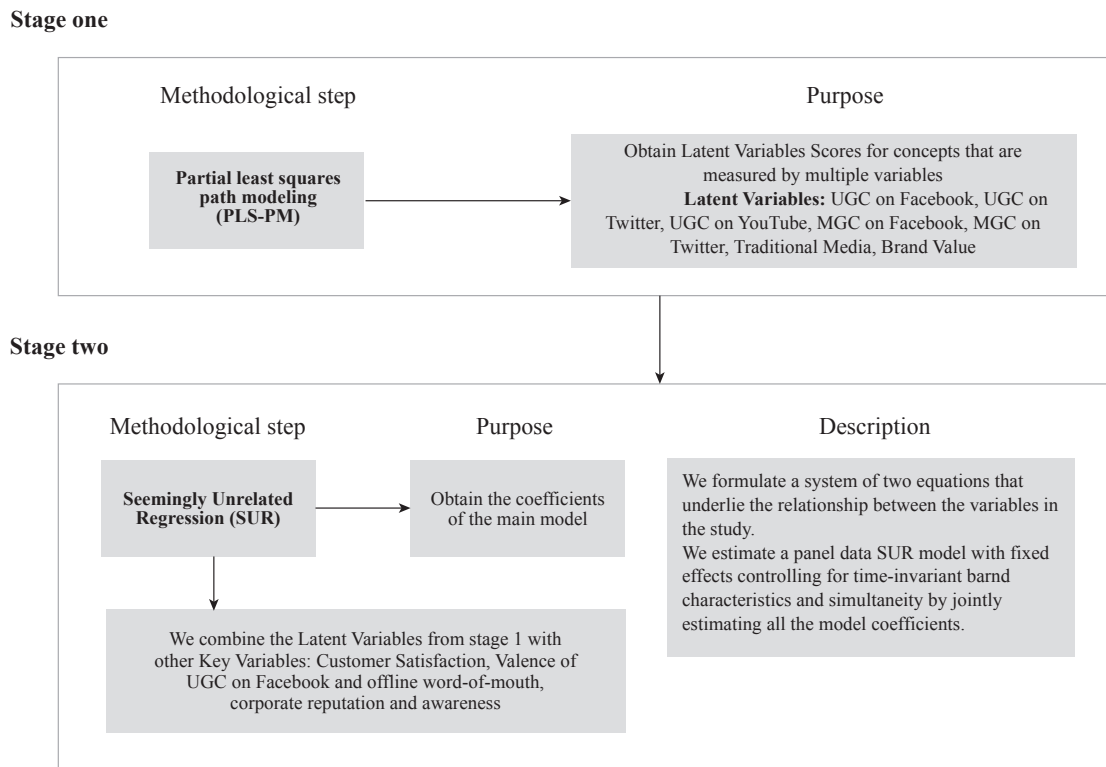
We group the social media metrics of UGC and MGC, traditional media, and brand value (see Table 1 for details) into latent variables by using Partial Least Squares Path Modelling (PLS-PM) (Tenenhaus, Esposito Vinzi, Chatelin, & Lauro, 2005). This model estimates latent variables' scores by ensuring that each is well related to its indicators by considering the correlations between latent variables in the model. We note that this approach, in contrast to Principal Component Analysis, takes into account the interrelationships among variables when estimating the constructs (Tenenhaus et al., 2005), offering higher precision and lower measurement error as the variables are postulated to affect each other. The standard errors in the estimates of the latent scores in PLS-PM are obtained through bootstrapping (e.g. 5000 resamples).

As we have two time periods in our data (2012 and 2013), we estimate the model for both time periods,

with both models achieving good convergent and discriminant validity with the constructs well related to their indicators. To check whether the loadings and path coefficients are time-invariant (Jöreskog, 1971), we use multiple group analysis (PLS-MGA) to compare the model in 2012 (group 1) to the model in 2013 (group 2). We used the distribution-free approach, using a random permutation procedure with 500 permutations, to assess the differences among groups. We found no significant differences between the two groups in terms of loadings and path coefficients. Thus, we conclude that the PLS-PM models are indeed time-invariant (results available upon request). Consequently, we obtain the latent variables of UGC on YouTube, Facebook, and Twitter and MGC on Facebook, Twitter, traditional media, and brand value. Other variables in this study are directly observed (customer satisfaction, valence of UGC on Facebook, brand awareness, corporate reputation, and offline word-of-mouth) and do not require the PLS-PM estimation.

Next, we use Seemingly Unrelated Regression (SUR) estimation that jointly estimates all the model coefficients by modelling the correlated error-terms across equations. We estimate a fixed effects model estimation to remove unobserved time invariant variables such as firm size, which could influence both social and traditional media variables as well as brand value and customer satisfaction. In addition, we simultaneously

Figure 2. Summary of the Methodology



estimate two equations to account for correlated errors across two equations. In addition, our model included a robust option for estimating the standard errors using the Huber-White sandwich estimators, which account for meeting assumptions such as normality and heteroscedasticity (White, 1980). Note that this option does not change coefficient estimates but instead provides a more reasonable set of p-values. Accordingly, we formulate the following system of two equations that underlies the relationship between these variables:

$$\begin{aligned}
 BV_{it} = & \alpha_0 + \beta_1 UGC_Y_{it} + \beta_2 UGC_F_{it} \\
 & + \beta_3 UGC_T_{it} + \beta_4 MGC_F_{it} \\
 & + \beta_5 MGC_T_{it} + \beta_6 TM_{it} + \beta_7 CS_{it} \\
 & + \beta_8 SM_VAL_{it} + \beta_9 OFFWOM_{it} \\
 & + \beta_{10} AWA_{it} + \beta_{11} CorpRep_{it} \\
 & + \beta_{12} OFFWOM_{it} \times TM_{it} \\
 & + \beta_{13} MGC_F_{it} \times CorpRep_{it} \\
 & + \beta_{14} MGC_T_{it} \times CorpRep_{it} \\
 & + FE_{1it} + \varepsilon_{1it}
 \end{aligned} \tag{5}$$

$$\begin{aligned}
 CS_{it} = & \beta_0 + \beta_1 UGC_Y_{it} + \beta_2 UGC_F_{it} + \beta_3 UGC_T_{it} \\
 & + \beta_4 MGC_F_{it} + \beta_5 MGC_T_{it} + \beta_6 TM_{it} \\
 & + \beta_7 SM_VAL_{it} + \beta_8 OFFWOM_{it} \\
 & + \beta_9 AWA_{it} + \beta_{10} CorpRep_{it} \\
 & + \beta_{11} OFFWOM_{it} \times TM_{it} \\
 & + \beta_{12} MGC_F_{it} \times CorpRep_{it} \\
 & + \beta_{13} MGC_T_{it} \times CorpRep_{it} + FE_{2it} + \varepsilon_{2it}
 \end{aligned} \tag{6}$$

Where, for each firm, I , and year t , BV_{it} is latent variable brand value, UGC_Y_{it} is latent variable UGC on YouTube, UGC_F_{it} is latent variable UGC on Facebook, UGC_T_{it} is latent variable UGC on Twitter, MGC_F_{it} is latent variable MGC on Facebook, MGC_T_{it} is latent variable MGC on Twitter, TM_{it} is latent variable traditional media expenditure, CS_{it} is customer satisfaction, VAL_{it} is valence metrics of user actions on Facebook, $OFFWOM_{it}$ is offline word-of-mouth, $CorpRep_{it}$ is the corporate reputation of the brand, and three interaction effects (MGC on Twitter and MGC on Facebook with corporate reputation and offline WOM with traditional media). FE_{1it} - FE_{2it} are brand specific fixed effect parameters and α and β are vectors of slope parameters. The error terms ε_{1it} - ε_{2it} are distributed $MVN(0,E)$.

Addressing Endogeneity Concerns

To alleviate endogeneity concerns due to potential omitted variables and simultaneity, we used a fixed effects

estimation to remove unobserved time invariant variables such as firm size, that could influence both social and traditional media variables as well as brand value and customer satisfaction. Secondly, we use (SUR) estimation that jointly estimates all model coefficients by modelling the correlated error-terms across equations. In addition, in the presence of endogeneity, we have to use instrumental variables that we gathered from the YouGov Group (product quality, product value, and brand impressions). We find that the statistic for the overidentifying restrictions Hansen-Sargan test is non-significant ($\chi^2(1) = 3.162$, $p = 0.075$), suggesting that the instruments are exogenous.

Results

In Table 2 we provide the main results of our model.

We find that MGC on Twitter has a negative significant effect on customer satisfaction (-0.120 , $p < 0.05$). We also find that UGC on Facebook has a negative significant effect on customer satisfaction (-0.321 , $p < 0.01$), UGC on Twitter has a positive significant effect (0.114 , $p < 0.05$). In support of H1, we find that the overall effect of UGC (0.57 in absolute value) is larger than that of MGC (0.13) on customer satisfaction ($t = 6.508$, $p < 0.001$). To verify whether the mediating role of customer satisfaction established in H2 is supported, we follow the methodology in Zhao, Lynch, and Chen (2010). Customer satisfaction has a significant and positive impact on brand value ($b = 0.223$, $p < 0.01$) thereby fulfilling Condition 1 of mediation. As reported above, we also satisfy Condition 2 for some of the effects of social media on customer satisfaction. Finally, we investigate Condition 3 regarding whether the Sobel's test on the product of the coefficients shows significant results. The product of the coefficients of the MGC on Twitter produces significant results ($b = -0.027 = 0.223 \times 0.120$, $t = -2.09$, $p < 0.05$). In addition, the product of the coefficients of the UGC on Facebook produces significant results ($b = 0.072 = 0.223 \times -0.321$, $t = -2.27$, $p < 0.05$), and the product of the coefficients of the UGC on Twitter also produces significant results ($b = 0.025 = 0.223 \times 0.114$, $t = 1.86$, $p < 0.1$) ($t = 1.86$, $p < 0.1$). Finally, the product of the coefficients of the traditional media produces significant results ($b = -0.146 = 0.223 \times -0.655$, $t = -2.24$, $p < 0.05$). Thus, these results suggest that customer satisfaction mediates the relationship between social media and brand value.

We find that social media has significant direct effects on brand value even after accounting for the effect of customer satisfaction, which supports partial mediation. Specifically, both MGC on Facebook and MGC on Twitter

Table 2. Results of the Main Model SUR estimation (Equations 5 and 6)

	Customer Satisfaction	Brand Value
Customer Satisfaction		0.223*** (4.48)
MGC on Facebook	-0.008 (-0.21)	0.075*** (2.95)
MGC on Twitter	-0.120** (-2.37)	0.105*** (3.10)
UGC on Facebook	-0.321*** (-2.64)	-0.187** (-2.30)
UGC on Twitter	0.114** (2.05)	-0.072* (-1.95)
UGC on YouTube	0.116 (0.78)	0.373*** (3.79)
Valence of UGC on Facebook	-0.019 (-0.97)	-0.046*** (-3.57)
Traditional Media	-0.655*** (-2.60)	0.299* (1.77)
Offline WOM	-0.025 (-0.17)	-0.195** (-2.08)
Awareness	1.176*** (5.39)	0.255* (1.65)
Constant	-0.920*** (-3.07)	0.278 (1.37)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Notes: t statistics in parentheses.

ter have a positive and significant direct effect on brand value (0.075, $p < 0.01$ and 0.105, $p < 0.01$, respectively). Next, UGC on Facebook and UGC on Twitter both have a negative and significant direct effect on brand value (-0.187, $p < 0.05$ and -0.072, $p < 0.1$, respectively), while UGC on YouTube has a positive and significant direct effect (0.373, $p < 0.01$). In addition, the negative valence of UGC on Facebook has a significant negative direct effect on brand value (-0.046, $p < 0.01$). Finally, traditional media has a positive and significant direct effect on brand value (0.299, $p < 0.1$). Summing up, customer satisfaction partially mediates the relationship between social media and brand value as we find direct significant effects of social media on brand value above and beyond the effect of customer satisfaction.

In Table 3 (Model B and C) we report the results of the interaction effects hypothesized in H4 and H5. First, we find that the interaction effect between MGC on Facebook and Corporate Reputation is significant (0.098, $p < 0.01$), providing support for H3. Second, we find that the interaction effect between MGC on Twitter and Corporate Reputation is significant (0.121, $p < 0.01$), providing support for H4. To graphically represent these results, we take the 25th, 50th, and 75th percentiles of the variables and plot them in Figure 3 (a, b, and c). For example, in Figure 3a, we present the interaction effects of MGC on

Facebook and corporate reputation. Note how, at low values of corporate reputation (25th percentile of corporate reputation in the x axis), the impact of MGC on Facebook on customer satisfaction is negative. However, at the higher levels of corporate reputation (75th percentile), MGC on Facebook has a positive effect on customer satisfaction. We note a similar pattern for MGC on Twitter (Figure 3b). Finally, in Figure 3c, we represent the interaction effect of traditional media and WOM on customer satisfaction. Note how at low levels of WOM (25th percentile of WOM in the x axis) the impact of traditional media on customer satisfaction is negative. However, at high levels of WOM (75th percentile of WOM), the impact of traditional media becomes positive.

As we find that customer satisfaction only partially mediates the relationship between social media and brand value, we can calculate the sum of direct and indirect (through customer satisfaction) effects of social media on brand value. We find that within different media, UGC (YouTube) has the highest total positive effect on brand value (0.399, $p < 0.01$), followed by traditional media (0.152, $p < 0.05$), MGC on Twitter (0.078, $p < 0.01$), and MGC on Facebook (0.073, $p < 0.01$).

Discussion

The findings from this study provide robust empirical support for the positive impact of social media marketing on customer satisfaction and brand value. We tested a conceptual model that links marketer generated content (MGC) and user generated content (UGC) to two metrics of firm's intangibles: customer satisfaction (more relevant for marketers) and brand value (more relevant for finance) that are precursors of sales and shareholder value (Fischer & Himme, 2016; Hanssens et al., 2014; Srinivasan & Hanssens, 2009).

Although marketing and finance executives have different objectives and focus on different stakeholder groups, both need to demonstrate relevant outcomes based on performance metrics. On the one hand, traditionally the primary objective of marketers was to maximize sales impact. However, since the immediate impact of social media on sales is hard to measure, it becomes imperative to show the effects of social media on consumer-related performance metrics (Colicev et al. 2018a; Colicev et al., 2019; Hanssens, Pauwels, Srinivasan, Vanhuele, & Gokhan, 2014). Based on the theory of the persuasive and informative effects of media, we propose and find that both MGC and UGC possess valuable information relevant for future consumer decisions and, thus, affect customer satisfaction.

Table 3. Results of additional models with interaction effects

	Model B (Interaction effects 1)		Model C (Interaction effects 2)	
	Customer satisfaction	Brand value	Customer satisfaction	Brand value
Customer satisfaction		0.181*** (3.05)		0.203*** (4.16)
MGC on Facebook	-0.008 (-0.25)	0.027 (1.08)	-0.009 (-0.23)	0.074*** (3.00)
MGC on Twitter	0.037 (0.90)	0.129*** (3.93)	-0.126** (-2.49)	0.095*** (2.89)
UGC on Facebook	-0.158* (-1.67)	-0.182** (-2.44)	-0.343*** (-2.83)	-0.220*** (-2.76)
UGC on Twitter	-0.036 (-0.76)	-0.139*** (-3.75)	0.121** (2.20)	-0.061* (-1.68)
UGC on YouTube	0.058 (0.51)	0.376*** (4.21)	0.073 (0.49)	0.322*** (3.32)
Valence of UGC on Facebook	0.022 (1.32)	-0.048*** (-3.75)	-0.014 (-0.74)	-0.041*** (-3.24)
Traditional Media	-0.668*** (-3.48)	0.307** (1.97)	-0.848*** (-3.09)	0.050 (0.27)
Offline WOM	-0.094 (-0.86)	-0.186** (-2.17)	0.008 (0.06)	-0.156* (-1.69)
Awareness	1.326*** (7.56)	0.529*** (3.33)	1.239*** (5.64)	0.356** (2.31)
Corporate Reputation	0.574*** (9.95)	-0.055 (-0.97)	--	--
MGC on Facebook x Corporate Reputation	0.098*** (3.95)	0.118*** (5.82)	--	--
MGC on Twitter x Corporate Reputation	0.121*** (3.03)	-0.007 (-0.23)	--	--
Traditional Media x Offline WOM	--	--	0.233* (1.71)	0.283*** (3.21)
Constant	-0.189 (-0.80)	0.285 (1.53)	-1.230*** (-3.53)	-0.123 (-0.53)

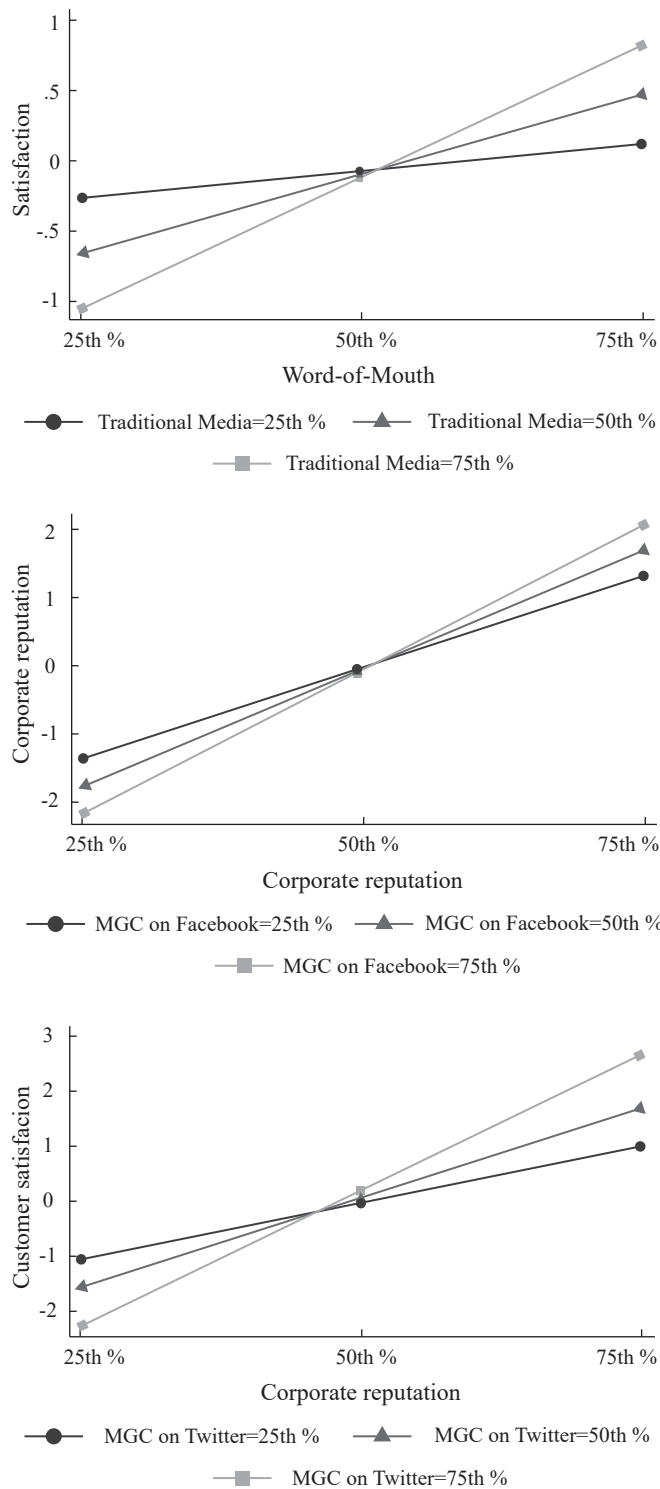
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Notes: t statistics in parentheses.

Moreover, finance executives are mostly concerned about the economic health of the firm. We find that customer satisfaction affects brand value, orienting the financial executives towards customer-related objectives. Interestingly, we find that customer satisfaction only partially mediates the social media to brand value link. Thus, social media affects brand value above and beyond its effect on customer satisfaction, implying that not all of the effects of social media go through consumers. As the value of the brand is also comprised of the brand's market capitalization, we speculate that social media can affect brand value directly, through its effect on investors. Previous research argued that social media possesses valuable information for investor decisions (Borah et al., 2020; Colicev et al., 2018a; Tirunillai & Tellis, 2012). Thus, we speculate that investors also react to MGC and UGC, anticipating the delayed effects of social media on customer satisfaction and affecting brand value. Consumer behaviour exhibits inertia (Bawa, 1990),

implying that customer satisfaction may take some time to fully take into account data communicated through UGC and MGC. Our results suggest that brands need to consider both the direct and indirect effects (through customer satisfaction) of social media to fully evaluate the consequences on brand value.

In terms of platform-specific effects, we find that UGC on YouTube has the greatest impact on brand value. This implies that marketers should focus on increasing the number of YouTube subscribers by, for example, designing high quality content (e.g. video tutorials) that increases channel visibility. Furthermore, we highlight the power of the negative consumer voice, demonstrating that the negative valence of UGC on Facebook negatively impacts brand value. This finding provides some explanation for why many brands heavily moderate, or in some cases even prohibit, UGC on their official Facebook presence. In contrast, some studies argue that brands, rather than moderating the UGC, should develop good

Figure 3. Interaction plots



intervention strategies for successful service recovery on social media (Balaji, Khong, & Chong 2016; Herhausen, Ludwig, Grewal, Wulf, & Schoegel, 2019). Similarly, findings about the valence of UGC explain why we also find that the volume of UGC on Facebook and Twitter can potentially be harmful if users posts and retweets portray brands in a negative light.

Finally, we find that UGC dominates the effects of MGC on customer satisfaction and brand value, echoing the research on the increasing importance of consumer voice (Borah et al., 2020; Colicev et al., 2019; Meire et al., 2019). However, based on media credibility theory, we show that brands with a good corporate reputation have more leverage on social media. In addition, by understanding the specific relationship between traditional advertising and word-of-mouth, managers can more adequately allocate resources to traditional media because of their ability to exploit the “multiplier” effect of traditional media and WOM. Researchers have found that word-of-mouth often complements and extends the effects of advertising on sales (Hogan et al., Therefore, our recommendation for managers is to create buzz around their brand before using traditional advertising.

The study’s main limitations are related to data availability. While we focus on Facebook, YouTube, and Twitter that are, to date, the largest social media platforms, future studies could analyse other social media platforms such as Snapchat, Flickr, and Instagram. In addition, future research might consider implementing our framework in an international context and/or for emerging economies. For instance, the growing popularity of social media marketing in Latin America has the potential to spur interest in the effectiveness of social media for brands in this region.

As brands and consumers continue to co-exist in the social media space, we hope that our study shows which social media metrics are most effective to achieve a satisfied customer base as well a high brand value.

References

- Abernethy, A. M. & Franke, G.R. (1996). The information content of advertising: A meta-analysis. *Journal of Advertising*, 17, 1-17.
- Babić Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, 53(3), 297-318.
- Balaji, M. S., Khong, K. W., & Chong, A. (2016). Determinants of negative word-of-mouth communication using social networking sites. *Information & Management*, 53(4), 528-40.
- Bawa, K. (1990). Modeling Inertia and variety seeking tendencies in brand choice behavior. *Marketing Science*, 9(3), 263-278.
- Bharadwaj, S., Tuli, K. R., & Bonfrer, A. (2011). The impact of brand quality on shareholder wealth. *Journal of Marketing*, 75(September), 88-104.

- Borah, A., Banerjee, S., Yu-Ting, L., Jain, A., & Eisingerich, A. (2020). Improvised marketing interventions in social media. *Journal of Marketing*, 84(2), 69-91.
- Chevalier, J.A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3), 345-54.
- Colicev, A., Kumar, A., & O'Connor, P. (2019). Modeling the relationship between firm and user generated content and the stages of the marketing funnel. *International Journal of Research in Marketing*, 36(1), 100-116.
- Colicev, A., Malshe, A., & Pauwels, K. (2018a). Social media and customer-based brand equity: An empirical investigation in retail industry. *Administrative Sciences*, 8(3), 55.
- Colicev, A., Malshe, A., Pauwels, K., & O'Connor, P. (2018b). Improving consumer mindset metrics and shareholder value through social media: The different roles of owned and earned media. *Journal of Marketing*, 82(1), 37-56.
- Datta, H., Ailawadi, K. L., & Van Heerde, H. (2017). How well does consumer-based brand equity align with sales-based brand equity and marketing-mix response?. *Journal of Marketing*, 81(3), 1-20.
- Erdem, T., & Swait, J. (2004). Brand credibility, brand consideration, and choice. *Journal of Consumer Research*, 31(1), 191-198.
- Festinger, L. C. (1957). *A theory of cognitive dissonance*. Stanford, CA: Stanford University Press.
- Fischer, M., & Himme, A. (2016). The financial brand value chain: How brand investments contribute to the financial health of firms. *International Journal of Research in Marketing*, 34(1), 137-153.
- Fornell, C., & Johnson, M.D. (1996). The American customer satisfaction index: Nature, purpose, and findings. *Journal of Marketing*, 60(October), 7-18.
- Godes, D., & Mayzlin, D. (2009). Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Science*, 28(4), 721-739.
- 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(1), 88-107.
- Gopinath, S. Thomas, J., & Krishnamurthi, L. (2014). Investigating the relationship between the content of online word of mouth, advertising, and brand performance. *Marketing Science*, 33(September), 241-58.
- Grewal, R., Chandrashekar, M., & Citrin, A. (2010). Customer satisfaction heterogeneity and shareholder value. *Journal of Marketing Research*, 47(4), 612-626.
- Gruca, T. S., & Rego, L. L. (2005). Customer satisfaction, cash flow, and shareholder value. *Journal of Marketing*, 69(July), 115-130.
- Haigh, D., & Gilbert, S. (2005). Valuing not-for-profit and charity brands—real insight or just smoke and mirrors. *International Journal of Nonprofit and Voluntary Sector Marketing*, 10(2), 107-119.
- Hanssens, D., & Pauwels, K. (2016). Demonstrating the value of marketing. *Journal of Marketing*, 80(November), 173-190.
- Hanssens, D., Pauwels, K., Srinivasan, S., Vanhuele, M., & Gokhan, Y. (2014). Consumer attitude metrics for guiding marketing mix decisions. *Marketing Science*, 33(4), 534-550.
- Herbig, P. & Milewicz, J. (1993). The relationship of reputation and credibility to brand success. *Journal of Consumer Marketing*, 10(3), 18-24.
- Herhausen, D., Ludwig, S., Grewal, D., Wulf, J., & Schoegel, M. (2019). Detecting, preventing, and mitigating online firestorms in brand communities. *Journal of Marketing*, 83(3), 1-21.
- Hewett, K., Rand, W., Rust, R., & Van Heerde, H. (2016). Brand Buzz in the echoverse. *Journal of Marketing*, 80(3), 1-24.
- Ho-Dac, N. N., 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(November), 37-53.
- Hogan, J., Lemon, K., & Libai, B. (2004). Quantifying the ripple: Word-of-mouth and advertising effectiveness. *Journal of Advertising Research*, 44(3), 271-280.
- Interbrand, (2012). *Interbrands: Most valuable brands 2012*. <https://www.interbrand.com/best-brands/best-global-brands/2012/ranking/>
- Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika*, 36(4), 409-426.
- Kapferer, J. N. (2008). *Strategic brand management, new approaches to creating and evaluating brand equity*. New York: Free Press.
- Keller, E., & Fay, B. (2009). The role of advertising in word of mouth. *Journal of Advertising Research*, 49(2), 154-158.
- Kirmani, A., & Rao, A. R. (2000). No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of marketing*, 64(April), 66-79.
- Kübler, R., Colicev, A., & Pauwels, K. (2019). Social media's impact on the consumer mindset: When to use which sentiment extraction tool?. *Journal of Interactive Marketing*, 50, 136-155.
- 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(1), 7-25.
- Lemon, K., & Verhoef, P. (2016). Understanding customer experience and the customer journey. *Journal of Marketing*, 80(6), 69-96.

- MacInnis, D., & Jaworski, B. (1989). Information processing from advertisements: Toward an integrative framework. *Journal of Marketing*, 53(4), 1.
- Malshe, A., Colicev, A., & Mittal, V. (2019). How main street drives Wall Street: Customer satisfaction, short sellers, and shareholder value. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3021327
- 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(6), 21-42.
- Mittal, V., Anderson, E., Sayrak, A., & Tadikamalla, P. (2005). Dual emphasis and the long-term financial impact of customer satisfaction. *Marketing Science*, 24(4), 544-555.
- Morgan, N., & Rego, L. (2006). The value of different customer satisfaction and loyalty metrics in predicting business performance. *Marketing Science*, 25(5), 426-439.
- Nam, H., & Kannan, P. K. (2014). The informational value of social tagging networks. *Journal of Marketing*, 78(4), 21-40.
- Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. *International Journal of Research in Marketing*, 29(3), 221-234.
- Otto, A., Szymanski, D., & Varadarajan, R. (2020). Customer satisfaction and firm performance: Insights from over a quarter century of empirical research. *Journal of the Academy of Marketing Science*, 48(3), 543-564.
- Peters, K., Chen, Y., Kaplan, A., Ognibeni, B., & Pauwels, K. (2013). Social media metrics — A framework and guidelines for managing social media. *Journal of Interactive Marketing*, 27(4), 281-298.
- Petty, R., & Cacioppo, J. T. (1986). *The elaboration likelihood model of persuasion, advances in experimental social psychology*. New York: Academic Press.
- Riley, M., Hovland, C., Janis, I., & Kelley, H. (1954). Communication and persuasion: Psychological studies of opinion change. *American Sociological Review*, (1954), 355-357.
- Risius, M., & Beck, R. (2015). Effectiveness of corporate social media activities to increase relational outcomes. *Information & Management*, 52, 824-839.
- Rust, R., Ambler, T., Carpenter, G., Kumar, V., & Srivastava, R. (2004). Measuring marketing productivity: Current knowledge and future directions, *Journal of Marketing*, 68(4), 76-89.
- Shu, S. B., & Carlson, K. A. (2014). When three charms but four alarms: Identifying the optimal number of claims in persuasion settings. *Journal of Marketing*, 78(1), 127-139.
- Srinivasan, S., & Hanssens, D. (2009). Marketing and firm value: Metrics, methods, findings, and future directions. *Journal of Marketing Research*, 46(3), 293-312.
- Stephen, A., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a micro-lending marketplace. *Journal of Marketing Research*, 49(5), 624-639.
- Szymanski, D., & Henard, D. (2001). Customer satisfaction: A meta-analysis of the empirical evidence. *Journal of the Academy of Marketing Science*, 29(1), 16-35.
- Tang, T., Fang, E., & Wang, F. (2014). Is neutral really neutral? the effects of neutral user-generated content on product sales. *Journal of Marketing*, 78(4), 41-58.
- Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, 48(1), 159-205.
- The CMO Survey. (2020). *CMO survey report: Highlights and insights February 2020*. <https://cmosurvey.org/results/february-2020/>
- Tirunillai, S., & Tellis, G. J. (2012). Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science*, 31(2), 198-215.
- Torres, A., Bijmolt, T., Tribó, J., & Verhoef, P. (2012). Generating global brand equity through corporate social responsibility to key stakeholders. *International Journal of Research in Marketing*, 29(1), 13-24.
- Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. *Journal of Marketing*, 73(September), 90-102.
- Tuli, K. R., & Bharadwaj, S. G. (2009). Customer satisfaction and stock returns risk. *Journal of Marketing*, 73(6), 184-197.
- White, H. (1980). A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. *Econometrica*, 48, 817-138.
- Zhang, Y., Trusov, M., Stephen, A., & Jamal, Z. (2017). Online shopping and social media: Friends or foes?. *Journal of Marketing*, 81(6), 24-41.
- Zhao, X., Lynch, J., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), 197-206.