Congruency and Users' Sharing on Social Media Platforms: A Novel Approach for Analyzing Content

Iman Ahmadi
Assistant Professor of Marketing
Warwick Business School, University of Warwick, United Kingdom
iman.ahmadi@wbs.ac.uk

Adrian Waltenrath
Doctoral Student
Faculty of Economics and Business Administration,
Goethe University Frankfurt, Germany
adrian.waltenrath@em.uni-frankfurt.de

Christian Janze
Ph.D., Independent Researcher,
Frankfurt am Main, Germany
christian.janze2@gmail.com

Abstract: With users increasingly spending time on social media platforms, firms expand their activity to more than one platform. Each has a unique vernacular—its popular communication style—increasing the need for firms to use platform-specific content optimization. This study distinguishes between textual and visual content intentions, depending on the degree of informative and affective appeals used. We examine how the congruency between visual content and the platform type and textual content affects users' sharing. We distinguish between hedonic platforms, such as Facebook, primarily used for entertainment and social interaction, and utilitarian platforms, such as Twitter, used for receiving timely information. We develop a new approach to examine how textual and visual content composition affects users' sharing behavior across platforms. Based on this new approach, we analyze posts by S&P 500 members operating on Facebook and Twitter. Our results show that posts with visual content congruent with the primary user intent of the platforms are more likely to be shared. Furthermore, Facebook users prefer affective textual and visual content, while Twitter users are more inclined toward a combination of informative visual and affective textual content.

Keywords: congruency, content sharing, social media, visual analysis, textual analysis.

With one-third of the global population participating daily on social media such as Facebook and Twitter (Facebook 2021b; Twitter 2021), these platforms have gained considerable attention from firms worldwide. Social media platforms allow firms to communicate directly with users through their own media (i.e., the official social media page; Stephen and Galak 2012) and receive user responses through, for example, sharing or retweeting. This content by firms on social media platforms is referred to as *firm-generated content* (FGC) (Kumar et al. 2016; Colicev, Kumar and O'Connor 2019). This study considers FGC (textual, visual, or a combination of both) as unpaid content published by firms on their official social media pages to which users may respond.[1]

As growing numbers of users spend ever-increasing time and have omnipresence on social media platforms (Statista 2021; Appel et al. 2020), firms have become increasingly active on these platforms (Trackalytics 2021). Various firms follow practitioners' advice to expand their activities beyond a single platform to increase the reach of their marketing efforts (Business.com 2020). However, they need advice on how to disseminate their content on multiple platforms (Unnava and Aravindakshan 2021). More specifically, firms often lack clear guidelines on whether and how to optimize the textual and visual content of FGC on individual platforms.

Motivated by research findings and practitioners' advice (Unnava and Aravindakshan 2021; Business.com 2020), many companies face incentives to adopt cross-posting (i.e., reusing identical posts across their different profiles) to remain active on multiple platforms. The practice of cross-posting is further encouraged by platforms (e.g., Facebook promotes cross-posting across both Facebook and Instagram; Facebook 2021a) and third-party tools (Bloomberg 2021). However, firms adopting cross-posting or disseminating an original post with minor modifications across different platforms may achieve suboptimal marketing outcomes, because each social media platform has a different use and purpose and develops its own *vernacular* (Shahbaznezhad, Dolan and Rashidirad 2021; Voorveld et al. 2018; Reich and Pittman 2020; Gibbs et al. 2015). Platform vernacular refers to the communication style of the platform and is shaped over time, based on the platform's design and users' interactions. Some users participate on platforms like Facebook to satisfy hedonic needs, such as entertainment and social interaction. However, other platforms, such as Twitter, fulfill users' needs for updates and information about current events (Schweidel and Moe 2014; Smith, Fischer and Yongjian 2012; Voorveld et al. 2018; Zhu and Chen 2015). This study accounts for the platform vernacular by distinguishing between the platform types—hedonic and utilitarian platforms—according to their focus on satisfying users' needs.

Conceptually, previous studies have highlighted the importance of *congruency* between FGC and the platform type, aligning the message and platform, for example, by posting a new product update on a utilitarian platform such as Twitter. Congruency may lead to increased processing fluency and more favorable evaluations by users (Chae and Hoegg 2013). However, posts that are not congruent with the platform type may benefit from increased visibility (Moorman, Neijens and Smit 2002), generating uncertainty about the optimal strategy for firms.

Visual-centric content has recently become popular on social media platforms. Emerging visual-centric platforms (e.g., Snapchat, Instagram) have grown in popularity, while existing platforms (e.g., Facebook, Twitter) have noted the importance of visuals and adapted their design to increase space for visual content (Hatmaker 2021; Appel et al. 2020). Figure 1 presents examples of FGC on two popular social media platforms, Facebook and Twitter, revealing that visual content is one of the critical components of FGC, typically given the most screen space in the presentation. Although previous research has emphasized the critical role of visual content in attracting users' attention (Pieters and Wedel 2004; Underwood and Klein 2002; Madzharov and Block 2010), the increasing popularity of visual-centric social media platforms and content has introduced new challenges in designing FGC. Whether firms benefit from congruency by aligning visual and textual content perceived as either *informative* (i.e., providing information about a brand or product, for example, promoting discounts on a particular product) or *affective* (i.e., influencing emotions or feelings) remains unclear. In particular, users may perceive FGC in which textual and visual content are congruent as dull (Villarroel Ordenes et al. 2019; Kocielnik and Hsieh 2017; Batra and Keller 2016), generating lower users' sharing.

"Insert Figure 1 about here."

This gap in the literature leaves firms with no clear guidelines for optimizing visual content in their posts based on the platform type and textual content. Studies addressing the relationship between FGC and users' sharing do not differentiate between textual and visual content and their interaction (e.g., Shahbaznezhad, Dolan and Rashidirad 2021), do not conceptualize the platform type (Li and Xie 2019; Villarroel Ordenes et al. 2019), or do not consider the role of the platform type (Farace et al. 2019; Rietveld et al. 2020).

Utilizing the congruency principle, impression management, and platform vernacular (Berger 2014; Dahlén 2005; Kocielnik and Hsieh 2017 Gibbs et al. 2015), we examined how the congruency of visual content with the platform type and textual content is associated with users' sharing behavior on two profile-based social media platform, Facebook and Twitter, perceived and used differently by users.

We propose a new approach to examine the relationship between textual and visual content composition and users' sharing across platforms, considering the ever-increasing amount of visual-centric content. The proposed approach is *flexible* and *scalable* and enables the annotation of large samples in a semi-supervised way by employing seeded Latent Dirichlet Allocation (LDA). Our flexible approach consistently defines textual and visual content across any desired dimensions. Hence, it allows investigating the interplay between content intentions (textual and visual) and the types of social media platforms. Our approach is scalable because, in contrast to other methods that rely solely on human workers to classify FGC, it allows guiding topic estimation based on topic-specific sets of seeds derived from a human-annotated subsample. Scalability enables the extraction of information from large-scale social media datasets, a challenge recently highlighted by researchers and practitioners (Hayes et al. 2021; Lee 2018).

CONCEPTUAL FRAMEWORK

Relationship between FGC and Users' Responses

Most existing research initially expressed interest in the influence of various components of FGC on users' responses (e.g., liking, sharing, or commenting). These studies have noted that various basic features of the textual content of FGC (e.g., the length of textual content, or whether it contains questions, citations, hashtags, or URLs), conceptual characteristics of the textual content (e.g., valence), and overall intent (e.g., content that is perceived to be less similar to advertising) affect users' response levels (De Vries, Gensler and Leeflang 2012; Lee, Hosanagar and Nair 2018; Sabate et al. 2014; Jalali and Papatla 2019; Stephen, Sciandra and Inman 2015).

The introduction and rapid growth of visual-centric social media platforms have increased the popularity of visual content, including a new dimension in this stream of the literature. Table 1 presents an overview of studies addressing the visual content of FGC while examining the relationship between FGC and users' responses on social media platforms, and compares these studies' results with our research. For example, Farace et al. (2019) examined whether text conveying emotion, combined with a regular visual pattern, increases user responses.

"Insert Table 1 about here."

Distinguishing FGC Components into Informative and Affective

Firms publish content on their official social media platform pages to gain users' attention and responses. Hence, FGCs face challenges similar to those of print ads, which compete for users' attention before any action occurs further down the purchase funnel (Li and Xie 2019). We distinguish two types of appeals in the advertising literature: Informative and emotional (or persuasive) (Chandy et al. 2001; Macinnis, Rao and Weiss 2002). Informative appeals contain evaluative messages, such as product characteristics, features, factual data, and objective selling arguments. In contrast, emotional appeals are designed to elicit an affective response (Dolan et al. 2016; Janssens and Pelsmacker 2005; Resnik and Stern 1977).

We identified and differentiated FGCs based on the degree of informative and affective appeals used. Following Resnik and Stern (1977), we considered (textual or visual) content as more informative if it primarily contains appeals intended to provide information, such as price, quality/performance, availability/special offers, or packaging of the brand or product. In contrast, we considered content to be more affective if it primarily contains appeals intended to create emotions or feelings linked to love, family, friendship, nature or animals, or amusement (e.g., Pelsmacker and Geuens 1997).[2]

Visual Content and Congruency with Social Media Platform

Social media platforms have distinct features, such as the degree of self-disclosure they require, the type of self-presentation they allow, limitations in the length of posts, the customization level of the post, and whether or not platforms are profile-based (in contrast to more content-based platforms, such as Yahoo! Answers) (Kaplan and Haenlein 2010; Peters et al. 2013; Berger et al. 2020; Voorveld et al. 2018; Zhu and Chen 2015). Depending on the design of the social media platform and the interaction between users and the platform over time, each platform develops its "platform vernacular" (Gibbs et al. 2015). Following this notion, previous studies have differentiated platforms and classified them into two major *types*: Hedonic and utilitarian platforms (Reich and Pittman 2020). Furthermore, according to the uses and gratifications theory (Blumler and Katz 1974), users participate in social media platforms for intrinsic gratification and as a means of satisfying their needs (Ko, Cho and Roberts 2005; Ifinedo 2016). Although some platforms (e.g., Facebook) primarily meet hedonic needs, such as entertainment, pastime, and social exchange, other platforms (e.g., Twitter) mainly address utilitarian content satisfying the need for new, expedient, and timely information (Schweidel and Moe 2014; Smith, Fischer and Yongjian 2012; Voorveld et al. 2018; Zhu and Chen 2015).

A different but related need is the need for self-presentation. The so-called *impression management* is an essential motivation for users interacting on social media platforms (Berger 2014; Dhir et al. 2019), allowing them to present themselves in particular ways, achieving desired impressions. For example, users may share a post because it contains valuable information, helps them regulate their emotions, or makes them seem interesting. However, sharing informative or affective content also shapes other users' impressions about the focal user. More specifically, when users share a post, they face a choice between developing an informative impression (sharing more informative content) or creating an emotional impression (sharing more affective content).

Previous studies have emphasized the roles of the medium and ad in consumers' evaluations (Dahlén 2005; Reich and Pittman 2020; Germelmann et al. 2020). The overall context of a medium and the ad converge in the consumer's mind (Dahlén 2005; Moorman, Neijens and Smit 2002), as per the *congruency principle*, which translates into the fit between the type of platform and the FGC on users' sharing behavior in social media platforms. For example, a post with more affective content shared on a hedonic platform is congruent with the platform type (as opposed to the situation in which the same post is shared on a utilitarian platform).

Due to the enrichment capacity of social media platforms, firms may create combinations of informative (or affective) textual and visual content. Regarding users' responses to FGC, the literature has shown that textual content perceived as informative decreases user responses because users may interpret it as direct selling (Lee, Hosanagar and Nair 2018), persuasion, or advertisement (Stephen, Sciandra and Inman 2015; Muntinga, Moorman and Smit 2011). However, it is not clear whether findings related to textual content also apply to visual content. A critical component of FGC, visual content, may have a significant effect on consumer attention, and has a superior ability to capture attention (Pieters and Wedel 2007; Pieters and Wedel 2004).

The congruency between the visual content and platform type is crucial because it decreases intrusiveness and generates positive reactions toward the content (Zhu and Chen 2015; Edwards, Li and Lee 2002). Congruency also increases processing fluency, yielding more favorable evaluations in the user's mind (Chae and Hoegg 2013). Moreover, since sharing is socially observable on social media, users may feel more comfortable sharing visual content congruent with the platform type. Therefore, we propose the following hypothesis:

H_1: Users share more often FGC with visual content congruent with the type of social media platform; in other words, FGC with more affective (informative) visual content is associated with higher users' sharing on hedonic (utilitarian) platforms.

Visual Content and Congruency with Textual Content

Research has highlighted the importance of interdependencies between the textual and visual content of FGC beyond their individual effects (Villarroel Ordenes et al. 2019; Pieters and

Wedel 2004; Rietveld et al. 2020; Farace et al. 2019). Although we hypothesized that posts including visual content congruent with the type of social media platform are associated with increased users' sharing (see H_1), research has yet to determine whether posts with visual content congruent with the textual content—herein, posts wherein textual and visual content are both more affective or informative—are shared more often.

Posts with congruent textual and visual content may be perceived as boring, not surprising, and not novel (Villarroel Ordenes et al. 2019; Kocielnik and Hsieh 2017; Batra and Keller 2016). Therefore, such posts may not increase users' sharing. Posts wherein textual and visual content are incongruent (e.g., more affective textual content combined with more informative visual content) tend to intrigue users by presenting a problem (Meyers-Levy, Louie and Curren 1994), encouraging users' sharing. Users may perceive them as novel; thus, these posts may be associated with a further increase in users' sharing. Therefore, we propose the following hypothesis:

H_2: Users share more often FGC with visual content incongruent with the textual content.

DATA DESCRIPTION

We collected FGC data from the 146 constituents of the S&P 500 with an official page on Facebook and Twitter in the US. The S&P 500 comprises 500 of the largest firms in the US in terms of market capitalization, providing rich information. Our dataset covers firms from ten industries, defined by the Industry Classification Benchmark (operated and managed by FTSE Russell for categorizing companies and securities), increasing the generalizability of our conclusions. These firms include consumer goods (e.g., General Motors, Ralph Lauren), consumer services (e.g., Amazon, CBS), financial services (e.g., Nasdaq, Bank of America), health care (e.g., Humana, Pfizer, Waters Corporation), technology (e.g., Adobe, IBM), and telecommunications (e.g., AT&T, Frontier Communications). Table A1 of Web Appendix A provides extensive details about the industries and examples of firms in our dataset (see Figure A1 of Web Appendix A for the number of posts by firms on each platform).

Our dataset includes 36,490 Facebook posts from the selected firms.[3] We retrieved information on the extent to which users engaged with a post by collecting the number of shares received for each post within at least 15 days (in line with past studies, such as Lee, Hosanagar and Nair (2018), revealing that more than 99.9% users respond within 15 days of the initial posting). We focused on users' sharing due to its crucial role in effective social media marketing (Villarroel Ordenes et al. 2019). When a user shares a post, it appears on the news feeds of the respective user's network at no cost, increasing the reach of FGCs (Jalali and Papatla 2019).

We used the same approach to develop the Twitter dataset, which comprises 51,651 individual tweets over the same period from the same 146 firms with an official page on Twitter. Table 2 presents the descriptive statistics of the variables.

"Insert Table 2 about here."

DESCRIPTION AND OPERATIONALIZATION OF VARIABLES

Figure 2 illustrates a roadmap of our analysis and summarizes the steps needed for creating the variables used in the empirical research. For the two types of platforms examined in this study (Facebook and Twitter), we differentiated between the two main components of FGC, textual and visual content, and their composition, controlling for various variables.

"Insert Figure 2 about here."

As illustrated in Figure 2, we operationalized the platform type by considering two well-known platforms. As mentioned above, we considered Facebook a hedonic platform because studies have shown that it is more likely to be used for entertainment, pastimes, self-promotion, building and maintaining connections with friends and acquaintances, and social exchanges. In contrast, we considered Twitter a utilitarian platform that allows users to discover new information and provides them with expedient and timely information (Schweidel and Moe 2014; Smith, Fischer and Yongjian 2012; Voorveld et al. 2018; Reich and Pittman 2020; Zhu and Chen 2015; Piskorski 2011).[4]

Classification of Content

Classification of Textual Content

We estimated the degree to which the textual content is affective or informative by examining the latent topics within the textual content of a post. To this end, we applied numerous standard text processing techniques.[5] We used seeded LDA (Jagarlamudi, Daumé and Udupa 2012) to calculate the probability distributions of textual content over two identified topics.[6]

In contrast to unsupervised LDA, seeded LDA, a priori, allows for controlling the topics learned by the model by using topic-specific sets of seed stems (seeds, henceforth). These seeds guide topic estimation during the sampling process. For our topic estimation, we avoid relying on standardized dictionaries, which typically present words from a context-free perspective and may not align with our specific context (Berger et al. 2020). Moreover, in contrast to dictionary-based approaches, seeded LDA does not require the list of seeds to be complete (i.e., to contain all relevant words representing the intended meanings of topics), because seeded LDA can learn related terms from the data. Hence, seeded LDA helps overcome the limitations of top-down (e.g., dictionary-based) and bottom-up (e.g., LDA) approaches (see Humphreys and Wang 2018 for a review) by combining both.

To determine appropriate seeds for informative and affective topics, we relied on Amazon Mechanical Turk (MTurk) workers. Table 3 presents list of informative and affective seeds from the manual coding of 1,000 random posts (see Web Appendix B for more details). Before using our seeds to apply the proposed method to the entire dataset, we checked the validity of the proposed approach based on posts tagged by MTurk workers. To this end, we applied a five-fold cross-validation procedure (using 80% of the dataset as training and the remaining 20% as hold-out). We achieved an average accuracy of 74.56%, supporting our approach and construct validities (see Web Appendix B).[7]

"Insert Table 3 about here."

We labeled document-topic probabilities as *TEXT_AFFECTIVENESS* (representing the degree to which textual content is affective) and *TEXT_INFORMATIVENESS* (representing the degree to which the textual content is informative), where *TEXT_AFFECTIVENESS* + *TEXT_INFORMATIVENESS* = 1. To avoid multicollinearity, we only included affectiveness in the model, normalized to ensure better interpretation (*Z_TEXT_AFFECTIVENESS*). Table A2 of Web Appendix A presents examples of textual content from Facebook posts and Twitter tweets, indicating the degree to which they are affective or informative. Table A3 Web Appendix A presents the most relevant stems for both topics estimated by seeded LDA.

Classification of Visual Content

To estimate the degree to which visual content is affective or informative, we followed steps similar to those applied for textual content. We began by extracting a vector of image labels (i.e., objects and concepts embedded in the image) and treating those labels as the words of one document.

To extract features from the visual content of a post, we used Google's Cloud Vision (GCV) application programming interface (API). GCV uses deep learning, allowing object detection, text recognition, and emotion detection from images (Google 2018). The GCV API output is a vector of the image labels. Access to Google's extensive data allows GCV to achieve high model performance, making it a valuable tool for scholars (Li and Xie 2019; Klostermann et al. 2018; see Table A4 of Web Appendix A for an example of output from GCV API; in Web Appendix C, we checked the validity of the GCV by comparing a sample of its output with human judgment).

We relied on Amazon MTurk workers to find seeds for informative and affective (visual) topics. Similar to the analysis of textual content, we used seeds obtained from a survey with 1,000 observations to perform seeded LDA (see Table 3). In this survey, we asked MTurk workers to evaluate the degree to which they perceived each image as informative or affective (see Web Appendix B for more details).

Next, we estimated the degree to which the image within a post is affective (i.e., *IMAGE_AFFECTIVENESS*) or informative (i.e., *IMAGE_INFORMATIVENESS*), where *IMAGE_AFFECTIVENESS* + *IMAGE_INFORMATIVENESS* = 1 (see Table A5 of Web Appendix A for examples of postings on Facebook and Twitter, and the degree to which their images are estimated to be informative or affective; Table A3 summarizes the most common labels for both affective and informative visual topics assessed by seeded LDA). In the proposed empirical analysis, we used the normalized value of *IMAGE_AFFECTIVENESS* (i.e., *Z_IMAGE_AFFECTIVENESS*).

Finally, we checked the validity of the proposed method by applying the same five-fold cross-validation procedure described for the textual content. For visual content, we obtained an average prediction accuracy of 78.45% (see Web Appendix B).

Operationalization of Other Variables

We controlled for several characteristics of textual content considered relevant in the literature. These characteristics include knowing whether the post is posing a question, has an exclamation mark (indicative of surprising or astonishing content), contains a citation (i.e., “ ”), an emoji, a hashtag, a URL, and the number of words in the posts. Moreover, by using natural language processing, we calculated the valence of the textual content of posts (see Berger and Milkman 2012).[8]

We also controlled for the presence of human figures and faces since they are quickly recognized by users and might attract users’ attention, affecting their attitudes (Xiao and Ding 2014). Moreover, based on the literature on print advertising that emphasizes the potential of words and logos to call attention to the entire advertisement (Pieters and Wedel 2004), we used GCV to retrieve whether the image contained printed words or logos as essential components.

We used firm fixed effects to control unobserved characteristics of firms that might lead to differences in users’ sharing (De Vries, Gensler and Leeflang 2012; Stephen, Sciandra and Inman 2015). Moreover, we accounted for the timing of posts by breaking down a day into 24 hours and considering whether they were posted during the weekend (Rooderkerk and Pauwels 2016; Zhang et al. 2014). We also observed whether a post type on Facebook was of a special type “link.”

Correlation among Explanatory Variables

Table 4 shows the correlation among the explanatory variables used in our empirical analysis. We noted a low correlation among the explanatory variables on both platforms. We found no evidence of multicollinearity issues (see Table A6.1 and Table A6.2 of Web Appendix A for the stability of coefficients across various model specifications).

“Insert Table 4 about here.”

FORMAL DESCRIPTION OF THE MODEL

Most FGCs are shared at least once, while many are shared around ten times (see Figure A2 of Web Appendix A). Hence, we used negative binomial regression setups (Rooderkerk and Pauwels 2016; Villarroel Ordenes et al. 2019) to address our dependent variable (i.e., *POST_SHARES_N*) on each platform (i.e., Facebook and Twitter). Equation (1) describes the proposed baseline negative binomial regression setup for examining the association between users' sharing and various characteristics of a post, using the explanatory variables presented in Table 2:

$$\begin{aligned}
&\Pr(Y = y_i|\mu_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}, \\
&\mu_i = \exp[\beta_0 + \beta_1 \times \text{TEXT_WORDS_N}_i + \beta_2 \times \text{TEXT_HAS_QUESTION}_i + \beta_3 \times \text{TEXT_HAS_EXCLAMATION}_i \\
&+\beta_4 \times \text{TEXT_HAS_CITATION}_i + \beta_5 \times \text{TEXT_HAS_EMOJI}_i + \beta_6 \times \text{TEXT_HAS_HASHTAG}_i \\
&+\beta_7 \times \text{TEXT_HAS_URL}_i + \beta_8 \times \text{TEXT_POSITIVITY}_i + \beta_9 \times \text{TEXT_NEGATIVITY}_i \\
&+\beta_{10} \times \text{Z_TEXT_AFFECTIVENESS}_i + \beta_{11} \times \text{POST_HAS_IMAGE}_i \\
&+\beta_{12} \times \text{POST_HAS_IMAGE}_i \times \text{IMAGE_HAS_FACE}_i + \beta_{13} \times \text{POST_HAS_IMAGE}_i \times \text{IMAGE_HAS_LOGO}_i \\
&+\beta_{14} \times \text{POST_HAS_IMAGE}_i \times \text{IMAGE_HAS_TEXT} + \beta_{15} \times \text{POST_HAS_IMAGE}_i \times \text{Z_IMAGE_AFFECTIVENESS}_i \\
&+\beta_{16} \times \text{POST_PUBLISHED_WEEKEND}_i + \beta_{17} \times \text{POST_IS_LINK}_i \\
&+\sum_{k=1}^{23} \gamma_k \times \text{POST_PUBLISHED_HOUR}_{ik} + \sum_{p=1}^{145} \delta_p \times \text{FIRM}_{ip}],
\end{aligned} \tag{1}$$

where y_i is the number of shares of post i (= 1, 2, …, N), $POST\_PUBLISHED\_HOUR_{ik}$ is a dummy variable equal to one when post i is published during hour $k \in \{1, …, 23\}$, $FIRM_{ip}$ is a dummy variable equal to one when post i belongs to firm p, $\alpha^{-1} > 0$ is the scaling parameter, and $\Gamma(.)$ is the gamma distribution.

EMPIRICAL RESULTS

Empirical Findings from Content Topic Accordance

Columns (1) and (2) of Model (1) in Table 5 present the results obtained estimating Equation (1) with our Facebook and Twitter datasets.

"Insert Table 5 about here."

Posts with more affective textual content are associated with higher users' sharing on both platforms (as shown by the coefficients on *Z_TEXT_AFFECTIVENESS* in columns (1) and (2) of Model (1) in Table 5). More specifically, more informative textual content (in line with the definitions of affective and informative content provided to MTurk workers for seed generation; see Web Appendix B) is associated with lower users' sharing.

Unlike the case of textual content, posts with more affective visual content (i.e., *HAS_IMAGE×Z_IMAGE_AFFECTIVENESS*) are not always associated with higher users' sharing. In Table 5, the results in columns (1) and (2) of Model (1) show that although posts with more affective visual content are associated with higher users' sharing on Facebook, the opposite applies to Twitter. Our results indicate that tweets are shared more often if they include a more informative image (i.e., an image that is congruent with the platform type). These findings support H_1.

Interplay of Textual and Visual Content

The results in columns (1) and (2) of Model (1) in Table 5 address whether firms may further increase users' sharing levels by constructing sophisticated combinations of affective textual and visual content on social media platforms. We introduced an interaction term in Equation (1) representing the congruency of the textual and visual content (i.e., *Z_TEXT_AFFECTIVENESS× HAS_IMAGE×Z_IMAGE_AFFECTIVENESS*; interaction term, henceforth).

The coefficient on the interaction term is significant and negative for Twitter, in line with H_2. This result indicates that FGC with incongruent textual and visual content (e.g., more affective textual content and more informative visual content) is associated with a boost in users' sharing on Twitter. On Facebook, we noted a negative but insignificant relationship between FGC with incongruent textual and visual content and users' sharing. Therefore, our results partially support

H_2. In Table 6, we summarize our main results and hypotheses.

"Insert Table 6 about here."

Figure 3 illustrates the net effect of the degree to which the textual and visual content (and their interplay) are more affective on users' sharing on Facebook and Twitter for a typical post. As shown in Figure 3, Facebook posts with more affective visual content and more affective textual content are associated with higher users' sharing. In contrast, on Twitter, posts with more informative visual content being combined with more affective textual content are associated with higher users' sharing (compare panels A and B of Figure 3).

"Insert Figure 3 about here."

ROBUSTNESS AND VALIDITY CHECKS

We checked the robustness and validity of our results in several ways.

First, in Model (2) of Table 5, we replicated our primary analysis (i.e., those under Model (1) of Table 5) on a subset of the data that included only posts with visual content, and we confirmed our primary results. Moreover, we tested the robustness of the results presented in Table 5 by conducting a battery of sensitivity analyses (see Table A6.1 and Table A6.2 of Web Appendix A for different model specifications). Our results remain robust across various specifications, thereby supporting our main conclusions.

Second, we checked the robustness of the results presented in Table 5 by further testing the validity of our approach to derive affective and informative constructs. We investigated whether enriching our seeds with existing (context-free) dictionaries might affect our results. For the set of affective seeds, we followed the work of Pelsmacker and Geuens (1997), who operationalized emotional appeals. We used appropriate categories from the linguistic inquiry and word count (LIWC) (Pennebaker et al. 2015). Regarding the informative seeds, we followed the classifications proposed by Resnik and Stern (1977), and we used the latest version of the *HARVARD IV-4* dictionary (Stone, Dunphy and Smith 1966) to derive informative seeds for conducting a seeded LDA analysis.[9]

We added the seeds from established dictionaries to those derived from the surveys. Then, we estimated the same models employed to obtain the results reported in Table 5. Based on the enriched set of seeds, the results presented in Table A7 of Web Appendix A indicate that our primary conclusions remain unchanged, supporting the proposed approach.

Third, we relied on the propensity score matching method to investigate whether firms use Facebook and Twitter differently, "systematically" posting different content on these platforms (i.e., self-selection bias). In particular, by using the explanatory variables from Table 2, we implemented a 1:1 nearest-neighbor matching algorithm without replacement and a small caliper of 0.01 to match posts by similar firms on Facebook and Twitter (Li and Xie 2019; Stuart 2010). Using the matched samples of 11,507 posts, we estimated the same models employed for obtaining the results in Table 5 (see Table A8 of Web Appendix A) and confirmed the conclusion summarized in Table 6.

Fourth, the value of the estimated document-topic probabilities of visual content is contingent on the validity of our labels. Therefore, we examined the validity of the GCV API output by comparing a sample of its output with human judgment. To this end, we relied on Amazon MTurk workers and determined the following rates: Accuracy = 86.42%, precision = 97.64%, recall = 81.36%, and F1 = 88.76%, reflecting the overall good quality of labels used as input for our approach.

DISCUSSION

With the increased users' presence on social media, more firms maintain a presence on these platforms to communicate with users, keep them updated, and attract their attention (e.g., Business.com 2020; McLachlan and Newberry 2021; Reich and Pittman 2020). Although previous studies have examined the relationship between FGC and users' responses on different social media platforms (e.g., Villarroel Ordenes et al. 2019; Li and Xie 2019; Shahbaznezhad, Dolan and Rashidirad 2021), this stream of literature still demands insights into how the composition of FGC is associated with users' sharing on different types of platforms, with varying communication styles. In addition, the increased popularity of visual content and the rapid growth of visual-centric social media platforms (Li and Xie 2019; Rietveld et al. 2020) call for research on tailoring the visual content to the platform type and to the textual content in order to optimize marketing outcomes across platforms.

We addressed these gaps in research by examining posts from the S&P 500 stock index constituents with official pages on both Facebook and Twitter in the US using a newly proposed approach. The two platforms differ in their primary focus, with Facebook providing a hedonic gratification and Twitter emphasizing its utilitarian nature by providing up-to-date content. Our results show that depending on the type of social media platform, various characteristics of visual content in a post are associated with different and sometimes opposing users' sharing behavior.

Contributions

Theoretical Contributions

From a theoretical perspective, we highlighted the importance of FGC components and linked them to users' sharing on different platforms. This phenomenon is crucial for visual content, generally used to draw attention in offline (Pieters and Wedel 2004; Underwood and Klein 2002) and online environments (Li and Xie 2019). Our analysis reveals that more affective visual content is associated with higher users' sharing on Facebook, while users favor more informative visual content on Twitter. The congruency principle and impression management support this finding. Sharing is a socially observable behavior; therefore, users consider the impression they make on their audience before sharing content. For instance, users may feel more comfortable sharing visual content that fits the platform type (which results in more fluent processing), yielding more favorable evaluations. These findings add to works on thematic congruency (i.e., the congruency between the ad and context; e.g., Balasubramanian, Karrh and Patwardhan 2006; Moorman, Neijens and Smit 2002) by extending the findings from traditional media (e.g., newspapers and magazines) to newer types of media (i.e., social media platforms; e.g., Carlson et al. 2021; Unnava and Aravindakshan 2021). Our findings also relate to research on the benefits of advertising on multiple social media platforms (Unnava and Aravindakshan 2021), indicating that such benefits may be fostered by tailoring the FGC to the platform type.

Moreover, users often share posts with incongruent textual and visual content because they do not perceive them as dull, presenting a puzzle to be solved. These findings align with prior research, highlighting that repeated exposure to (the same) message appeals may lead to boredom (Kocielnik and Hsieh 2017). Hence, we join recent studies investigating the combined effects of textual and visual content on social media platforms (e.g., Villarroel Ordenes et al. 2019; Farace et al. 2019), adding a cross-platform perspective.

Methodological Contributions

We propose a new approach that allows an in-depth analysis of textual and visual content from a methodological perspective. Utilizing seeded LDA that allows for guiding topic estimation based on seeds derived from a human-annotated subsample, our approach combines deductive top-down and inductive bottom-up approaches (see Humphreys and Wang 2018).

The flexibility of our approach allows the classification of the textual and visual content along any desired dimensions (e.g., informative/affective content or more dimensions, depending on the research question). The consistent classification of textual and visual content also enables the investigation of their interactions. Although we use FGC in our empirical analysis, our approach is not limited to FGC and may be extended to UGC. In this regard, the proposed method may help firms understand what consumers communicate on social media platforms about brands or any other topics (e.g., Liu, Dzyabura and Mizik 2015; Klostermann et al. 2018).

Moreover, our approach (in comparison to other methods, such as hiring online workers to code all posts) allows scalability because the underlying seeds do not need to be complete. Scalability helps researchers and managers process extensive data (for example, from social media platforms) (Sridhar and Fang 2019; Hayes et al. 2021).

Managerial Implications

Our study has several implications for firms. First, our findings emphasize the importance of considering the platform type and its association with users' sharing for content creation. Companies should consider the fit between the visual content and the platform type when designing posts because users feel more comfortable sharing visual content congruent with the platform type. For example, in the case of Facebook, more affective (and less informative) content (both textual and visual) is associated with higher users' sharing. Such a relationship introduces a trade-off for managers between reaching a significant number of shares (i.e., communicating with a broader audience) and disseminating information about the product (at the expense of fewer shares).

Second, posts with incongruent textual and visual content may be shared more often on Twitter; this finding highlights the importance of jointly optimizing the textual and visual components. These insights allow firms to benefit from increased users' sharing by combining more affective textual content with greater informative visual content.

Third, social media marketing managers may apply our approach to their posts across different social media platforms (both existing and emerging ones). In this way, managers may observe whether visual content receiving higher users' sharing on a specific platform may replicate the results on other platforms, such as Snapchat and Pinterest, which are more oriented toward entertainment (Voorveld et al. 2018).

Our study demonstrates that textual and visual content composition may significantly impact users' sharing on various platforms. Although these platforms are commonly referred to as social media, users resort to them to satisfy different needs due to their fundamental differences, leading to different users' sharing behavior. Therefore, we suggest that firms must carefully tailor their content, consider congruency with the specific platforms, and avoid "copying and pasting" identical content across profiles on different platforms when communicating with users.

Limitations and Future Research

First, a natural extension of our study is the application of our framework to video content. Recent studies in this nascent stream of literature investigate videos on Kickstarter and Netflix to optimize the outcome of projects (Liu et al. 2018; Li, Shi and Wang 2019). Future studies may investigate whether our results may be extended to social media platforms focusing on video content (e.g., TikTok).

Second, our work follows an exploratory approach and does not assess causality. Practitioners should handle our findings cautiously, with this aspect in mind. Future studies may extend our results through large-scale experiments in a controlled setting.

Third, although our dataset comprises firms across different industries, future research may extend our findings by applying this framework to posts from other firms (beyond the S&P 500 stock index members), over more recent periods, or using different types of social media platforms (e.g., Instagram, which is even more visual-centric) or platforms that are primarily popular in specific countries (e.g., Weibo, considered the Chinese version of Twitter).

Finally, based on users' limited attentional resources, future studies may examine how increasing the attention provided to one element of visual content (e.g., through the area occupied by the respective element) affects users' sharing.

NOTES

1. Publishing on social media platforms is also called "posting." A single piece of FGC is called a "post." This study uses the terms "FGC" and "post" interchangeably.

2. We consider informativeness/affectiveness of (textual or visual) content as a continuum (rather than treating it as dichotomous; in other words, content is more informative when it contains more informative appeals than affective ones; see also Section Classification of Content).

3. We excluded notifications about changed profile/cover pictures and posts that show multiple images (i.e., photo albums).

4. Twitter claims to be the number one platform for discovery (visit: https://business.twitter.com/).

5. Before constructing document-term matrices (consisting of unigrams and bigrams), we applied stemming, converted the text to lower case, and removed stop words, punctuation, other special characters (e.g., §, $, %), numbers, URLs, infrequent words (0.5%), and firm-specific words.

6. For text processing, we relied on the R-packages *tm* and *qdap* (Feinerer and Hornik 2020; Rinker 2020). For constructing document-term matrices we used *text2vec* (Selivanov and Wang 2018). For seeded LDA, we used the implementation from Ramesh et al. (2015) that is available under https://github.com/artir/ramesh-acl15.

7. Our accuracy exceeds the accuracies of automated text classifications on Facebook and Twitter achieved in the literature (see Hartmann et al. 2019).

8. We employed *Sentistrength* (Thelwall et al. 2010), which is appropriate for analyzing short texts, such as those found on Facebook and Twitter posts.

9. We use the following categories from the LIWC related to emotion, feelings, and excitation: *Humor*, *Positive Emotion*, *Family*, *Friends*, *Nostalgia*, *Eroticism*, *Provocation*, and *Fear*. We chose the *Econ@* and *Exch* dictionaries as our informative seeds.

ACKNOWLEDGMENTS

We thank the review team for their insightful comments and suggestions in revising and strengthening our manuscript.

REFERENCES

Appel, Gil, Lauren Grewal, Rhonda Hadi, and Andrew T. Stephen (2020), “The Future of Social Media in Marketing,” *Journal of the Academy of Marketing Science*, 48 (1), 79–95.

Balasubramanian, Siva K., James A. Karrh, and Hemant Patwardhan (2006), “Audience Response to Product Placements: An Integrative Framework and Future Research Agenda,” *Journal of Advertising*, 35 (3), 115–41.

Batra, Rajeev, and Kevin L. Keller (2016), “Integrating Marketing Communications: New Findings, New Lessons, and New Ideas,” *Journal of Marketing*, 80 (6), 122–45.

Berger, Jonah (2014), “Word of Mouth and Interpersonal Communication: A Review and Directions for Future Research,” *Journal of Consumer Psychology*, 24 (4), 586–607.

Berger, Jonah, Ashlee Humphreys, Stephan Ludwig, Wendy W. Moe, Oded Netzer, and David A. Schweidel (2020), “Uniting the Tribes: Using Text for Marketing Insight,” *Journal of Marketing*, 84 (1), 1–25.

Berger, Jonah, and Katherine L. Milkman (2012), “What Makes Online Content Viral?,” *Journal of Marketing Research*, 49 (2), 192–205.

Bloomberg (2021), “Six Apps to Help Small-Business Owners Build Their Brands Online,” https://www.bloomberg.com/news/articles/2021-09-29/small-business-six-social-media-tools-to-save-some-time, 5 October 2021.

Blumler, Jay G., and Elihu Katz (1974), *The Uses of Mass Communications: Current Perspectives on Gratifications Research*, Beverly Hills, London: Sage Publications.

Business.com (2020), “Why Every Business Should Be Using Multiple Social Media Accounts,” https://www.business.com/articles/why-every-business-should-be-using-multiple-social-media-accounts/, 5 May 2021.

Carlson, Jeffrey R., Sara Hanson, Joseph Pancras, William T. Ross, and Jacqueline Rousseau-Anderson (2021), “Social Media Advertising: How Online Motivations and Congruency Influence Perceptions of Trust,” *Journal of Consumer Behaviour*.

Chae, Boyoun, and JoAndrea Hoegg (2013), "The Future Looks "Right": Effects of the Horizontal Location of Advertising Images on Product Attitude," *Journal of Consumer Research*, 40 (2), 223–38.

Chandy, Rajesh K., Gerard J. Tellis, Deborah J. Macinnis, and Pattana Thaivanich (2001), "What to Say When: Advertising Appeals in Evolving Markets," *Journal of Marketing Research*, 38 (4), 399–414.

Colicev, Anatoli, Ashish Kumar, and Peter O'Connor (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), 100–16.

Dahlén, Micael (2005), "The Medium as a Contextual Cue: Effects of Creative Media Choice," *Journal of Advertising*, 34 (3), 89–98.

De Vries, Lisette, Sonja Gensler, and Peter S. Leeflang (2012), "Popularity of Brand Posts on Brand Fan Pages: An Investigation of the Effects of Social Media Marketing," *Journal of Interactive Marketing*, 26 (2), 83–91.

Dhir, Amandeep, Ashraf Khalil, Puneet Kaur, and Risto Rajala (2019), "Rationale for "Liking" on Social Networking Sites," *Social Science Computer Review*, 37 (4), 529–50.

Dolan, Rebecca, Jodie Conduit, John Fahy, and Steve Goodman (2016), "Social Media Engagement Behaviour: A Uses and Gratifications Perspective," *Journal of Strategic Marketing*, 24 (3-4), 261–77.

Edwards, Steven M., Hairong Li, and Joo-Hyun Lee (2002), "Forced Exposure and Psychological Reactance: Antecedents and Consequences of the Perceived Intrusiveness of Pop-Up Ads," *Journal of Advertising*, 31 (3), 83–95.

Facebook (2021a), "Facebook for Media," https://www.facebook.com/formedia/, 5 May 2021.

------ (2021b), *Facebook Reports Fourth Quarter and Full Year 2020 Results*.

Farace, Stefania, Anne Roggeveen, Francisco Villarroel Ordenes, Ko D. Ruyter, Martin Wetzels, and Dhruv Grewal (2019), "Patterns in Motion: How Visual Patterns in Ads Affect Product

Evaluations," *Journal of Advertising*, 95 (2), 1–15.

Feinerer, Ingo, and Kurt Hornik (2020), "tm: Text Mining Package (0.7-8)," https://CRAN.R-project.org/package=tm.

Gibbs, Martin, James Meese, Michael Arnold, Bjorn Nansen, and Marcus Carter (2015), "# Funeral and Instagram: Death, Social Media, and Platform Vernacular," *Information, Communication & Society*, 18 (3), 255–68.

Google (2018), "Cloud Vision," https://cloud.google.com/vision/, 6 March 2020.

Hartmann, Jochen, Juliana Huppertz, Christina Schamp, and Mark Heitmann (2019), "Comparing Automated Text Classification Methods," *International Journal of Research in Marketing*, 36 (1), 20–38.

Hatmaker, Taylor (2021), "Twitter is Testing Better Image Previews and Fewer Cropped Photos," https://techcrunch.com/2021/03/10/twitter-cropped-image-previews-test/, 21 April 2021.

Hayes, Jameson L., Brian C. Britt, William Evans, Stephen W. Rush, Nathan A. Towery, and Alyssa C. Adamson (2021), "Can Social Media Listening Platforms' Artificial Intelligence Be Trusted? Examining the Accuracy of Crimson Hexagon's (Now Brandwatch Consumer Research's) AI-Driven Analyses," *Journal of Advertising*, 50 (1), 81–91.

Humphreys, Ashlee, and Rebecca J.-H. Wang (2018), "Automated Text Analysis for Consumer Research," *Journal of Consumer Research*, 44 (6), 1274–306.

Ifinedo, Princely (2016), "Applying Uses and Gratifications Theory and Social Influence Processes to Understand Students' Pervasive Adoption of Social Networking Sites: Perspectives from the Americas," *International Journal of Information Management*, 36 (2), 192–206.

Jagarlamudi, Jagadeesh, Hal Daumé, and Raghavendra Udupa (2012), "Incorporating Lexical Priors into Topic Models," in *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics:* Association for Computational Linguistics, 204–13.

Jalali, Nima Y., and Purushottam Papatla (2019), “Composing Tweets to Increase Retweets,” *International Journal of Research in Marketing*, 36 (4), 647–68.

Janssens, Wim, and Patrick D. Pelsmacker (2005), “Emotional or Informative? Creative or Boring?,” *International Journal of Advertising*, 24 (3), 373–94.

Kaplan, Andreas M., and Michael Haenlein (2010), “Users of the World, Unite! The Challenges and Opportunities of Social Media,” *Business Horizons*, 53 (1), 59–68.

Klostermann, Jan, Anja Plumeyer, Daniel Böger, and Reinhold Decker (2018), “Extracting Brand Information from Social Networks: Integrating Image, Text, and Social Tagging Data,” *International Journal of Research in Marketing*, 35 (4), 538–56.

Ko, Hanjun, Chang-Hoan Cho, and Marilyn S. Roberts (2005), “Internet Uses and Gratifications: A Structural Equation Model of Interactive Advertising,” *Journal of Advertising*, 34 (2), 57–70.

Kocielnik, Rafal, and Gary Hsieh (2017), “Send Me a Different Message: Utilizing Cognitive Space to Create Engaging Message Triggers,” in *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, Charlotte P. Lee, Steve Poltrock, Louise Barkhuus, Marcos Borges and Wendy Kellogg, eds., New York, NY, USA: ACM, 2193–207.

Kumar, Ashish, Ram Bezawada, Rishika Rishika, Ramkumar Janakiraman, and P. K. Kannan (2016), “From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior,” *Journal of Marketing*, 80 (1), 7–25.

Lee, Dokyun, Kartik Hosanagar, and Harikesh S. Nair (2018), “Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook,” *Management Science*, 64 (11), 1–27.

Lee, In (2018), “Social Media Analytics for Enterprises: Typology, Methods, and Processes,” *Business Horizons*, 61 (2), 199–210.

Li, Xi, Mengze Shi, and Xin Wang (2019), “Video mining: Measuring visual information using automatic methods,” *International Journal of Research in Marketing*, 36 (2), 216–31.

Li, Yiyi, and Ying Xie (2019), "Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement," *Journal of Marketing Research*, 57 (1), 1-19.

Liu, Liu, Daria Dzyabura, and Natalie Mizik (2015), "Visual Listening In: Extracting Brand Image Portrayed on Social Media," in *Workshops at the Thirty-Second AAAI Conference on Artificial Intelligence*.

Liu, Xuan, Savannah W. Shi, Thales Teixeira, and Michel Wedel (2018), "Video Content Marketing: The Making of Clips," *Journal of Marketing*, 82 (4), 86–101.

Macinnis, Deborah J., Ambar G. Rao, and Allen M. Weiss (2002), "Assessing When Increased Media Weight of Real-World Advertisements Helps Sales," *Journal of Marketing Research*, 39 (4), 391–407.

Madzharov, Adriana V., and Lauren G. Block (2010), "Effects of Product Unit Image on Consumption of Snack Foods," *Journal of Consumer Psychology*, 20 (4), 398–409.

McLachlan, Stacey, and Christina Newberry (2021), "22 Benefits of Social Media for Business," https://blog.hootsuite.com/social-media-for-business/, 4 January 2022.

Meyers-Levy, Joan, Therese A. Louie, and Mary T. Curren (1994), "How Does the Congruity of Brand Names Affect Evaluations of Brand Name Extensions?," *Journal of Applied Psychology*, 79 (1), 46–53.

Moorman, Marjolein, Peter C. Neijens, and Edith G. Smit (2002), "The Effects of Magazine-Induced Psychological Responses and Thematic Congruence on Memory and Attitude toward the Ad in a Real-Life Setting," *Journal of Advertising*, 31 (4), 27–40.

Muntinga, Daniël G., Marjolein Moorman, and Edith G. Smit (2011), "Introducing COBRAs," *International Journal of Advertising*, 30 (1), 13–46.

Pelsmacker, Patrick D., and Maggie Geuens (1997), "Emotional Appeals and Information Cues in Belgian Magazine Advertisements," *International Journal of Advertising*, 16 (2), 123–47.

Pennebaker, James W., Ryan L. Boyd, Kayla Jordan, and Kate Blackburn (2015), *The Development and Psychometric Properties of LIWC2015*.

Peters, Kay, Yubo Chen, Andreas M. Kaplan, Björn Ognibeni, and Koen Pauwels (2013), "Social Media Metrics — A Framework and Guidelines for Managing Social Media," *Journal of Interactive Marketing*, 27 (4), 281–98.

Pieters, Rik, and Michel Wedel (2004), "Attention Capture and Transfer in Advertising: Brand, Pictorial, and Text-Size Effects," *Journal of Marketing*, 68 (2), 36–50.

------ (2007), "Goal Control of Attention to Advertising: The Yarbus Implication," *Journal of Consumer Research*, 34 (2), 224–33.

Piskorski, Mikołaj J. (2011), "Social Strategies that Work," *Harvard Business Review*, 89 (11), 116-22.

Ramesh, Arti, Shachi H. Kumar, James Foulds, and Lise Getoor (2015), "Weakly Supervised Models of Aspect-Sentiment for Online Course Discussion Forums," in *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers),* 74–83.

Reich, Brandon J., and Matthew Pittman (2020), "An Appeal to Intimacy: Consumer Response to Platform-Appeal Fit on Social Media," *Journal of Consumer Psychology*, 30 (4), 660–70.

Resnik, Alan, and Bruce L. Stern (1977), "An Analysis of Information Content in Television Advertising," *Journal of Marketing*, 41 (1), 50–53.

Rietveld, Robert, Willemijn van Dolen, Masoud Mazloom, and Marcel Worring (2020), "What You Feel, Is What You Like Influence of Message Appeals on Customer Engagement on Instagram," *Journal of Interactive Marketing*, 49, 20–53.

Rinker, Tyler W. (2020), "qdap: Quantitative Discourse Analysis Package (2.4.2)," https://github.com/trinker/qdap.

Rooderkerk, Robert P., and Koen H. Pauwels (2016), "No Comment?! The Drivers of Reactions to Online Posts in Professional Groups," *Journal of Interactive Marketing*, 35, 1–15.

Sabate, Ferran, Jasmina Berbegal-Mirabent, Antonio Cañabate, and Philipp R. Lebherz (2014), "Factors Influencing Popularity of Branded Content in Facebook Fan Pages," *European Management Journal*, 32 (6), 1001–11.

Schweidel, David A., and Wendy W. Moe (2014), "Listening in on Social Media: A Joint Model of Sentiment and Venue Format Choice," *Journal of Marketing Research*, 51 (4), 387–402.

Selivanov, Dmitriy, and Qing Wang (2018), "text2vec: Modern Text Mining Framework for R (0.5.1)," https://CRAN.R-project.org/package=text2vec.

Shahbaznezhad, Hamidreza, Rebecca Dolan, and Mona Rashidirad (2021), "The Role of Social Media Content Format and Platform in Users' Engagement Behavior," *Journal of Interactive Marketing*, 53, 47–65.

Smith, Andrew N., Eileen Fischer, and Chen Yongjian (2012), "How Does Brand-Related User-Generated Content Differ across YouTube, Facebook, and Twitter?," *Journal of Interactive Marketing*, 26 (2), 102–13.

Sridhar, Shrihari, and Eric Fang (2019), "New Vistas for Marketing Strategy: Digital, Data-Rich, and Developing Market (D3) Environments," *Journal of the Academy of Marketing Science*, 47 (6), 977–85.

Statista (2021), "Daily Time Spent on Social Networking by Internet Users Worldwide from 2012 to 2020," https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/, 5 March 2021.

Stephen, Andrew T., and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (5), 624–39.

Stephen, Andrew T., Michael R. Sciandra, and J. J. Inman (2015), "Is It What You Say or How You Say It That Matters? The Effects of Branded Content on Consumer Engagement with Brands on Facebook," *Working Paper*.

Stone, Philip J., Dexter C. Dunphy, and Marshall S. Smith (1966), *The General Inquirer: A Computer Approach to Content Analysis*, Oxford, England: M.I.T. Press.

Stuart, Elizabeth A. (2010), "Matching Methods for Causal Inference: A Review and a Look Forward," *Statistical Science*, 25 (1), 1–21.

Thelwall, Mike, Kevan Buckley, Georgios Paltoglou, Di Cai, and Arvid Kappas (2010), "Sentiment Strength Detection in Short Informal Text," *Journal of the American Society for Information Science and Technology*, 61 (12), 2544–58.

Trackalytics (2021), "Total Tweets from Coca-Cola on Twitter," https://www.trackalytics.com/, 19 September 2021.

Twitter (2021), *Q4 and Fiscal Year 2020 Letter to Shareholders*.

Underwood, Robert L., and Noreen M. Klein (2002), "Packaging as Brand Communication: Effects of Product Pictures on Consumer Responses to the Package and Brand," *Journal of Marketing Theory and Practice*, 10 (4), 58–68.

Unnava, Vasu, and Ashwin Aravindakshan (2021), "How Does Consumer Engagement Evolve when Brands Post Across Multiple Social Media?," *Journal of the Academy of Marketing Science*, 49 (5), 864–81.

Villarroel Ordenes, Francisco, Dhruv Grewal, Stephan Ludwig, Ko D. Ruyter, Dominik Mahr, and Martin Wetzels (2019), "Cutting through Content Clutter: How Speech and Image Acts Drive Consumer Sharing of Social Media Brand Messages," *Journal of Consumer Research*, 45 (5), 988–1012.

Voorveld, Hilde A. M., Guda van Noort, Daniël G. Muntinga, and Fred Bronner (2018), "Engagement with Social Media and Social Media Advertising: The Differentiating Role of Platform Type," *Journal of Advertising*, 47 (1), 38–54.

Xiao, Li, and Min Ding (2014), "Just the Faces: Exploring the Effects of Facial Features in Print Advertising," *Marketing Science*, 33 (3), 338–52.

Zhang, Lun, Tai-Quan Peng, Ya-Peng Zhang, Xiao-Hong Wang, and Jonathan J. Zhu (2014), "Content or Context: Which Matters More in Information Processing on Microblogging Sites," *Computers in Human Behavior*, 31, 242–49.

Zhu, Yu-Qian, and Houn-Gee Chen (2015), "Social Media and Human Need Satisfaction: Implications for Social Media Marketing," *Business Horizons*, 58 (3), 335–45.

TABLES

Table 1. Summary of Research Examining FGC on Social Media Platforms and Users' Responses

Study	Villarroel Ordenes et al. (2019)	Farace et al. (2019)	Li and Xie (2019)[a]	Rietveld et al. (2020)	Shahbaznezhad, Dolan and Rashidirad (2021)	Current study
Objective	Examined textual intentions (i.e., assertive, expressive, or directive) and their interplay with informative or action-calling images on users' sharing.	Examined how the composition of visual patterns (i.e., regular versus irregular) and textual information affects users' attitudes toward products (measured by the number of likes and retweets).	Examined the effect of text (e.g., sentiments) and image characteristics (e.g., image quality, colorfulness, presence of human faces) on users' responses (i.e., likes and retweets on Twitter and likes on Instagram).	Examined how the composition of visual content (i.e., emotional and informative) affects users' responses (i.e., likes and shares) on Instagram.	Examined the role of social media platform types on the relationship between different content types and users' responses (e.g., likes and comments)	Examines how congruency between visual content and (i) platform type and (ii) textual content is associated with users' sharing on Facebook and Twitter.
Platform(s)	Facebook; Twitter	Twitter	Twitter; Instagram	Instagram	Facebook, Instagram	Facebook; Twitter
Method(s)	Negative-Binomial regression	Poisson regression	Bivariate zero-inflated Negative-Binomial model; log-linear regression	Negative-Binomial regression	Regression analysis	Negative-Binomial regression
No. of firms	Facebook: 7 Twitter: 8	1	Instagram: 10 Twitter: 19	59 (6 industries)	Facebook: 2 Instagram: 2 (1 industry)	Facebook: 146 Twitter: 146 (10 industries)
No. of posts	Facebook: 12,374 Twitter: 29,413	832	Instagram: 2,044 Twitter: 33,749	46,900	Facebook: 456 Instagram: 582	Facebook: 36,490 Twitter: 51,651
Approach for analyzing visuals	Online workers annotated images according to how each image adds information or demands response.	Online workers coded whether the image included regular, irregular, or no visual pattern.	Utilized GCV API to extract features from images; Amazon MTurk workers coded for picture quality, source, and whether the image fits the text content.	Utilized MVSO model to extract emotional appeals; utilized GCV API to extract brand and product appeals.	Conducted qualitative content analysis, wherein online workers categorized posts.	Utilized GCV API to extract features from images; employed seeded LDA based on seeds derived from human judgment sample to classify textual and visual content across platforms consistently.
Examination of congruency between visual content and platform type on users' responses	×	×	×	×	(✓)[b]	✓
Examination of congruency between textual and visual content on users' responses	✓	✓	✓	×	×	✓

Notes: [a] The authors used a combination of FGC and user-generated content (UGC) created by users on social media platforms for their study; [b] the authors did not differentiate between textual and visual content; GCV: Google Cloud Vision; API: Application Programming Interface; MVSO: Multilingual Visual Sentiment Ontology.

Table 2. Description and Summary of Variables

Variable	Description	Facebook Mean	Facebook SD	Facebook Min.	Facebook Max.	Facebook N	Twitter Mean	Twitter SD	Twitter Min.	Twitter Max.	Twitter N
Users' sharing											
POST_SHARES_N	Number of times a post was shared	65.74	558.35	0.00	70,787.00	36,490	24.35	128.49	0.00	8,620.00	51,651
Textual content											
TEXT_WORDS_N	Number of words in the post	24.79	21.90	1.00	2,315.00	36,490	13.82	3.73	1.00	29.00	51,651
TEXT_HAS_QUESTION	If the post contains a question	0.21	0.40	0.00	1.00	36,490	0.15	0.36	0.00	1.00	51,651
TEXT_HAS_EXCLAMATION	If the post contains an exclamation	0.21	0.41	0.00	1.00	36,490	0.20	0.40	0.00	1.00	51,651
TEXT_HAS_CITATION	If the post contains a citation	0.01	0.09	0.00	1.00	36,490	0.00	0.02	0.00	1.00	51,651
TEXT_HAS_EMOJI	If the post contains an emoji	0.02	0.13	0.00	1.00	36,490	0.00	0.04	0.00	1.00	51,651
TEXT_HAS_HASHTAG	If the post contains a hashtag	0.27	0.45	0.00	1.00	36,490	0.64	0.48	0.00	1.00	51,651
TEXT_HAS_URL	If the post contains a URL	0.42	0.49	0.00	1.00	36,490	0.74	0.44	0.00	1.00	51,651
TEXT_POSITIVITY	Post's positive sentiment score	1.67	0.80	1.00	5.00	36,490	1.46	0.71	1.00	5.00	51,651
TEXT_NEGATIVITY	Post's negative sentiment score	−1.44	0.76	−5.00	−1.00	36,490	−1.22	0.54	−5.00	−1.00	51,651
Topic accordance											
Z_TEXT_AFFECTIVENESS	Normalized TEXT_AFFECTIVENESS (i.e., the degree to which the textual content is affective)	0.00	1.00	−5.47	2.89	36,490	0.00	1.00	−2.45	3.88	51,651
Visual content											
POST_HAS_IMAGE	If the post has an image	0.40	0.49	0.00	1.00	36,490	0.63	0.48	0.00	1.00	51,651
IMAGE_HAS_FACE	If the image contains a human face	0.23	0.42	0.00	1.00	14,571	0.23	0.42	0.00	1.00	32,630
IMAGE_HAS_LOGO	If the image contains a logo	0.48	0.50	0.00	1.00	14,571	0.42	0.49	0.00	1.00	32,630
IMAGE_HAS_TEXT	If the image contains printed words	0.77	0.42	0.00	1.00	14,571	0.67	0.47	0.00	1.00	32,630
Topic accordance											
Z_IMAGE_AFFECTIVENESS	Normalized IMAGE_AFFECTIVENESS (i.e., the degree to which the visual content is affective)	0.00	1.00	−2.49	1.40	14,571	0.00	1.00	−2.56	1.38	32,630
Controls											
POST_PUBLISHED_WEEKEND	If the post was sent during the weekend	0.17	0.37	0.00	1.00	36,490	0.16	0.36	0.00	1.00	51,651
POST_IS_LINK	If the post's type on Facebook is a link	0.59	0.49	0.00	1.00	36,490	–	–	–	–	–

Notes: SD: standard deviation; Min.: minimum; Max: maximum; N indicates the number of observations for which we may calculate their value—for example, N = 14,571 (underlined in the table) shows the number of Facebook posts that contain an image.

Table 3. Seeds under Affective and Informative Topics

Textual Content	Affective	happi, photo, shop, hope, mondaymotiv, comment, chanc, feel, nyc, proud_support, sunday, motiv, pet, kick, magic, …
	Informative	learn, make, work, check, year, read, custom, home, report, digit, busi, find, dont, data, global, …
Visual Content	Affective	person, man, vehicle, event, clothing, woman, sky, top, building, photography, pants, job, car, shoe, wheel, …
	Informative	line, diagram, electronics, banner, parallel, screenshot, website, mobile_phone, document, multimedia, laptop, map, plot, slope, web_page, …

Notes: Seeds ranked by the number of times a seed was categorized into the respective topic; underscore ("_") is used if two words describe a (single) object.

Table 4. Correlation between Explanatory Variables on Facebook (Lower Triangle) and Twitter (Upper Triangle)

	POST_SHARES_N	TEXT_WORDS_N	TEXT_HAS_QUESTION	TEXT_HAS_EXCLAMATION	TEXT_HAS_CITATION	TEXT_HAS_EMOJI	TEXT_HAS_HASHTAG	TEXT_HAS_URL	TEXT_POSITIVITY	TEXT_NEGATIVITY	Z_TEXT_AFFECTIVENESS	IMAGE_HAS_FACE	IMAGE_HAS_LOGO	IMAGE_HAS_TEXT	Z_IMAGE_AFFECTIVENESS	POST_PUBLISHED_WEEKEND
POST_SHARES_N	1.00	-0.02	-0.01	0.03	0.00	0.02	0.00	-0.02	0.01	0.00	0.06	-0.03	-0.04	-0.02	0.04	0.02
TEXT_WORDS_N	-0.07	1.00	0.00	0.01	0.21	-0.01	0.02	0.06	0.18	-0.14	-0.32	0.13	0.00	0.02	0.01	-0.05
TEXT_HAS_QUESTION	-0.03	0.12	1.00	0.03	-0.02	-0.02	0.05	0.10	-0.01	0.04	0.01	-0.09	0.00	-0.03	-0.06	0.03
TEXT_HAS_EXCLAMATION	0.00	0.09	-0.03	1.00	-0.02	0.05	0.06	-0.03	0.17	0.11	0.15	0.04	-0.01	-0.01	0.09	0.03
TEXT_HAS_CITATION	0.00	0.01	0.01	-0.01	1.00	0.00	-0.03	0.01	0.05	-0.04	-0.07	0.03	-0.01	0.00	0.00	0.00
TEXT_HAS_EMOJI	0.03	0.00	-0.01	0.00	0.00	1.00	0.03	-0.03	0.01	0.03	0.08	-0.02	-0.03	-0.02	0.02	0.00
TEXT_HAS_HASHTAG	-0.02	0.05	0.03	0.09	0.00	-0.01	1.00	0.14	0.01	0.07	-0.07	0.04	0.06	0.07	-0.01	-0.01
TEXT_HAS_URL	-0.06	-0.28	-0.02	-0.22	0.00	-0.01	-0.17	1.00	-0.02	0.08	-0.35	-0.13	0.00	-0.06	-0.15	-0.04
TEXT_POSITIVITY	0.00	0.04	0.02	0.06	-0.01	0.00	0.02	-0.06	1.00	0.00	0.05	0.12	-0.02	-0.04	0.11	0.02
TEXT_NEGATIVITY	0.02	0.01	0.00	0.03	0.00	0.00	0.03	-0.02	0.05	1.00	0.00	-0.03	0.01	0.00	0.03	0.00
Z_TEXT_AFFECTIVENESS	0.11	-0.15	0.05	0.23	0.00	0.00	0.03	-0.21	0.07	0.02	1.00	-0.05	-0.11	-0.11	0.15	0.12
IMAGE_HAS_FACE	-0.01	0.04	-0.07	0.02	-0.01	0.01	0.01	-0.10	0.01	-0.01	0.01	1.00	-0.06	-0.05	0.37	0.00
IMAGE_HAS_LOGO	-0.02	0.01	-0.02	0.02	0.00	0.00	0.06	-0.03	-0.04	-0.01	-0.15	-0.03	1.00	0.44	-0.21	-0.03
IMAGE_HAS_TEXT	-0.02	0.04	0.00	0.04	0.00	0.00	0.06	-0.09	-0.04	0.00	-0.18	-0.01	0.47	1.00	-0.29	-0.05
Z_IMAGE_AFFECTIVENESS	0.02	0.04	-0.03	0.07	0.00	-0.01	0.02	-0.14	0.06	0.02	0.23	0.35	-0.22	-0.32	1.00	0.04
POST_PUBLISHED_WEEKEND	0.02	-0.03	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.08	-0.01	0.00	-0.02	0.04	1.00

1

0

-1

Table 5. Results for Association Between Users' Sharing and FGC on Facebook and Twitter

	Model (1)				**Model (2)**			
Dependent variable	**POST_SHARES_N**				**POST_SHARES_N**			
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Platform	Facebook	Twitter	Facebook	Twitter	Facebook	Twitter	Facebook	Twitter
Textual content variables								
TEXT_WORDS_N	0.006**	0.019**	0.006**	0.019**	0.003**	0.024**	0.003**	0.024**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TEXT_HAS_QUESTION	−0.281**	−0.114**	−0.281**	−0.113**	−0.345**	−0.101**	−0.345**	−0.101**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TEXT_HAS_EXCLAMATION	0.117**	−0.112**	0.117**	−0.110**	−0.117**	−0.088**	−0.117**	−0.085**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TEXT_HAS_CITATION	0.048	0.119	0.047	0.128	0.366*	0.266	0.366*	0.279
	(0.582)	(0.520)	(0.582)	(0.485)	(0.026)	(0.245)	(0.026)	(0.222)
TEXT_HAS_EMOJI	0.081	0.172	0.081	0.178	0.144	0.009	0.143	0.018
	(0.194)	(0.108)	(0.193)	(0.097)	(0.055)	(0.949)	(0.055)	(0.893)
TEXT_HAS_HASHTAG	−0.031	0.013	−0.031	0.010	0.014	0.037**	0.014	0.034**
	(0.170)	(0.196)	(0.169)	(0.281)	(0.625)	(0.002)	(0.625)	(0.004)
TEXT_HAS_URL	−0.161**	−0.187**	−0.161**	−0.187**	−0.333**	−0.215**	−0.333**	−0.216**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TEXT_POSITIVITY	0.033**	0.006	0.033**	0.006	0.093**	0.009	0.093**	0.009
	(0.002)	(0.270)	(0.002)	(0.270)	(0.000)	(0.164)	(0.000)	(0.158)
TEXT_NEGATIVITY	−0.052**	−0.005	−0.052**	−0.005	−0.018	−0.009	−0.018	−0.008
	(0.000)	(0.465)	(0.000)	(0.514)	(0.354)	(0.305)	(0.354)	(0.342)
Z_TEXT_AFFECTIVENESS	0.027*	0.042**	0.027*	0.046**	0.069**	0.052**	0.069**	0.058**
	(0.029)	(0.000)	(0.029)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Visual content variables								
POST_HAS_IMAGE	0.927**	0.341**	0.927**	0.354**	–	–	–	–
	(0.000)	(0.000)	(0.000)	(0.000)				
POST_HAS_IMAGE×IMAGE_HAS_FACE	−0.475**	−0.057**	−0.475**	−0.062**	−0.379**	−0.047**	−0.379**	−0.051**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
POST_HAS_IMAGE×IMAGE_HAS_LOGO	0.043	−0.007	0.043	−0.006	0.090**	0.018	0.090**	0.018
	(0.157)	(0.576)	(0.158)	(0.605)	(0.002)	(0.135)	(0.002)	(0.119)
POST_HAS_IMAGE×IMAGE_HAS_TEXT	0.114**	0.102**	0.114**	0.098**	0.067*	0.084**	0.067*	0.081**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.043)	(0.000)	(0.043)	(0.000)
POST_HAS_IMAGE×Z_IMAGE_AFFECTIVENESS	0.153**	−0.050**	0.153**	−0.049**	0.095**	−0.055**	0.095**	−0.054**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Z_TEXT_AFFECTIVENESS×POST_HAS_IMAGE× Z_IMAGE_AFFECTIVENESS	–	–	−0.001	−0.038**	–	–	0.000	−0.040**
			(0.935)	(0.000)			(0.986)	(0.000)
Control variables								
POST_PUBLISHED_WEEKEND	−0.120**	0.041**	−0.120**	0.042**	−0.033	0.010	−0.033	0.010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.308)	(0.426)	(0.308)	(0.419)
POST_IS_LINK[a]	0.890**	–	0.890**	–	–	–	–	–
	(0.000)		(0.000)					
Controls for an hour of the post	yes	yes	yes	yes	yes	yes	yes	yes
Controls for firm	yes	yes	yes	yes	yes	yes	yes	yes
Constant	−0.945**	2.296**	−0.944**	2.302**	4.155**	1.945**	4.155**	1.971**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	36,490	51,651	36,490	51,651	14,571	32,630	14,571	32,630
Log likelihood	−144,546	−164,497	−144,546	−164,471	−59,702	−113,461	−59,702	−113,434

Notes: *p*-values are in parentheses; $^{*}p < 0.05$, $^{**}p < 0.01$; [a] applies to Facebook.

Table 6. Summary of Main Results and Hypotheses

Hypotheses	Platform		
	Facebook (hedonic platform)	**Twitter** (utilitarian platform)	**Overall**
H$_1$: Users share more often FGC with visual content congruent with the type of social media platform. (effect associated with more affective visual content)	**Supported** (higher users' sharing)	**Supported** (lower users' sharing)	**Supported** (opposite)
H$_2$: Users share more often FGC with visual content incongruent with the textual content. (effect associated with incongruent visual and textual content)	**Not Supported** (-)	**Supported** (higher users' sharing)	**Partially supported** (not lower)

Notes: Higher affective (textual or visual) content indicates lower informativeness.

FIGURES

Panel A: Example of FGC on Facebook and Twitter	Panel B: Decomposition of FGC into Textual and Visual Content

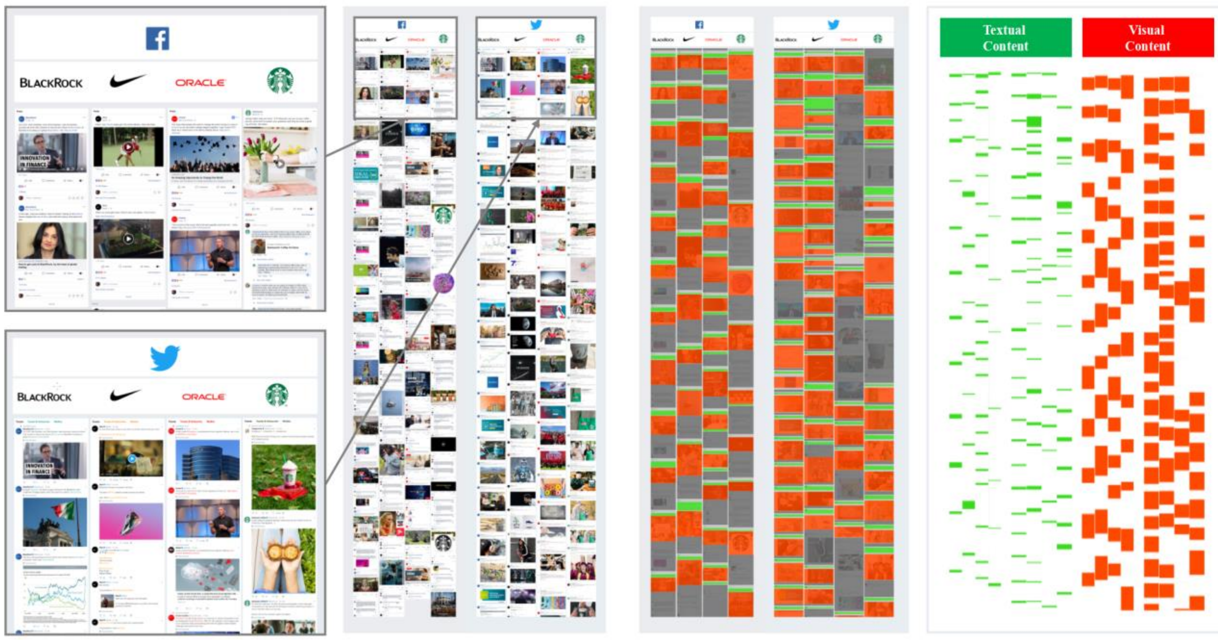

Figure 1. Examples of FGC and Its Components on Facebook and Twitter

Notes: In Panel B, the textual content and visual content of FGCs in Panel A are color-coded in green and red, respectively; the area colored in gray in Panel B contains non-original content (e.g., retweeted content) and control elements of the respective platforms.

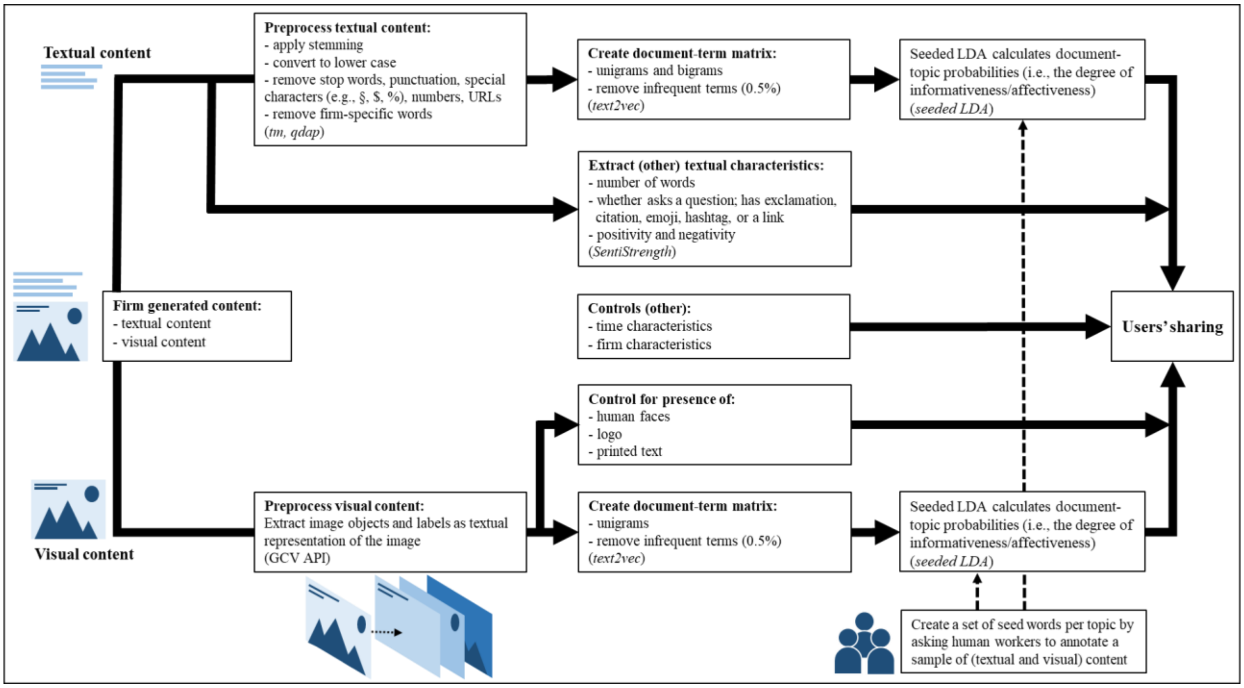

Figure 2. Road Map for our Analysis

Notes: For packages (in italics) *tm*, *qdap*, *text2vex*, *seeded LDA*, and *SentiStrength* see Feinerer and Hornik (2020), Rinker (2020), Selivanov and Wang (2018), and Thelwall et al. (2010), respectively; LDA: Latent Dirichlet Allocation; GCV: Google Cloud Vision; API: Application Programming Interface; content is more informative if it primarily contains appeals intended to provide information, such as price, quality/performance, availability/special offers, or packaging of the brand or product; content is more affective if it primarily contains appeals intended to create emotions or feelings linked to love, family, friendship, nature or animals, or amusement.

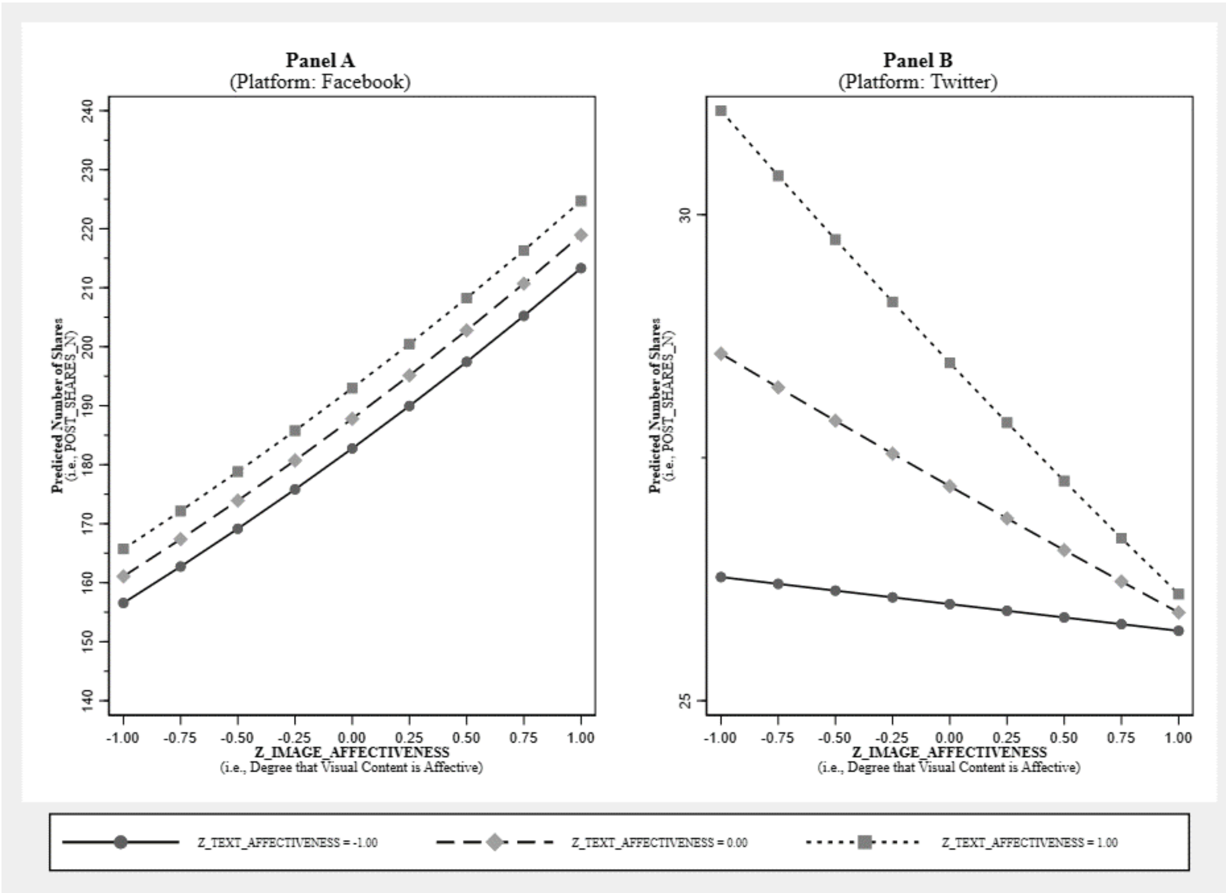

Figure 3. Values of Users' Sharing for Different Degrees of Affective Textual and Visual Content

Notes: Values are estimated for a post with typical textual and visual content (i.e., the respective explanatory variables in Table 2 are set at their median).