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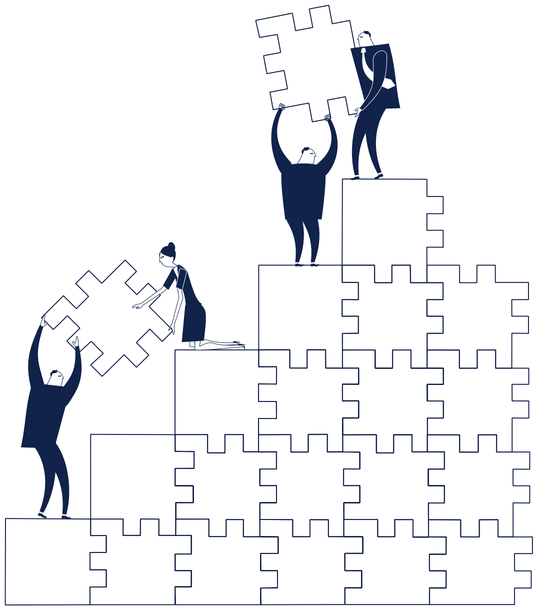

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Is It What You Say or How You Say It? How Content Characteristics Affect Consumer Engagement with Brands on Facebook

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Contribution Statement

This research shows how consumer engagement with brands in social media is affected by various characteristics of the content that marketers create and disseminate on social media platforms. We build on the limited prior literature on this topic by considering a broader set of content characteristics (fourteen types), a more comprehensive set of social media engagement behaviors reflecting meaningfully different types of engagement (six), and investigate the response of different types of consumers. We use a novel dataset of brands' Facebook posts over 18 months, covering nine different brands from four distinct industries, and find that many social media content characteristics have little influence on consumer engagement with branded content. The characteristics that are important are predominantly associated with how brands communicate their messages with respect to a post's persuasive elements (e.g., the extent to which a branded Facebook post feels like an advertisement, and how clear the communicated message is). Interestingly, however, persuasive elements result in *less* engagement. Our findings suggest that branded content that is less like advertising is more likely to engage members of a brands' social media audience. Thus, core principles of traditional advertising may not apply in social media, at least not directly. In general, this research advances our understanding of how consumers process and interact with brands in social media.

Abstract

The popularity of social media has led to many brands using platforms such as Facebook for marketing communications, typically whereby brands post content (text, images, and/or videos) on their social media pages for their consumer "fans" to see and, hopefully, engage with. Despite the widespread use of social media marketing, relatively little is known about how various characteristics of branded social media content affect different types of consumer engagement (e.g., liking, commenting, sharing) with brands on social media. The authors analyze 4,284 Facebook posts made by nine brands during an 18-month period. A theory-based typology of fourteen content characteristics covering aspects of what brands say and how they say it is developed and these are linked to different types of consumer engagement with brands' posts. Various drivers of engagement are found, with the most important being those associated with persuasion. Contrary to traditional marketing communications, persuasive content characteristics are found to *lower* engagement in the social media context. This research sheds light on how consumers process and interact with branded content in social media, and has implications for how marketers should design content to maximize consumer engagement with their brands.

The popularity of social media has led to many brands using platforms such as Facebook for marketing communications. The most common approach typically involves brands designing and then posting content (text, images, and/or videos) on their social media pages for their consumer "fans" to see and, hopefully, interact with. This is often referred to as social media content marketing, and has become a very common part of major brands' media mixes (e.g., approximately 80% of Fortune 500 companies use Facebook for this purpose; Barnes and Lescault 2014). Using content, marketers strive to pique the interest of consumers and engender higher levels of consumer engagement with their brands. Increasing consumer engagement is desirable because it is thought to be associated with positive consequences such as stronger consumer-brand relationships and brand affinity, increased satisfaction and loyalty, and more purchasing (e.g., Brodie, Ilic, Juric, and Hollebeek 2013; Calder, Malthouse, and Schaedel 2009; van Doorn et al. 2010; Laroche, Habibi, and Richard 2013; Sprott, Czellar, and Spangenberg 2009). Additionally, due to the socially networked nature of social media platforms such as Facebook and Twitter, encouraging consumers to share branded content with friends by clicking "Share" or "Retweet" can help amplify marketing messages through word-of-mouth (WOM) communications.

Despite the prevalence of branded content on major social media platforms such as Facebook, Instagram, and Twitter, little is known about why consumers respond to some types of content but not to others. For example, does content that possesses characteristics similar to those present in traditional communications channels (e.g., persuasive and/or informative messages in advertising) work well in social media? Or does the two-way, interactive, and informal nature of social media require brands to rethink the types of content that will be effective in engaging consumers in that channel? In this research we consider how various characteristics of the content created and then disseminated by brands on social media are related to different types of consumer engagement with brands, as indicated by standard social media metrics such as "liking" a post, "commenting" on it, or "sharing" it with others. We are particularly interested in whether *what* branded content says or *how* it is said plays a bigger role in driving consumer engagement in this context. Specifically, we focus on understanding how different content characteristics, all of which are under the control of marketers and include informative and persuasive elements, influence consumer engagement with brands' social media posts.

To address this, we develop a comprehensive typology of content characteristics for branded social media posts and use it to classify a unique set of 4,284 branded Facebook posts made over an 18-month period by nine brands from four distinct industries (consumer-packaged goods, restaurants, retail, and sports), and with Facebook audiences at the time of data collection ranging from approximately 130,000 to 30 million people. Using this post-level data, we estimate the effects of the classified content characteristics on Facebook-provided metrics for consumer engagement. Post-level engagement metrics are used as indicators of consumers' *attitudinal responses* to content (e.g., positive responses indicated by "likes") and meaningful *marketing outcomes* triggered by content that are stronger and more volitional indicators of underlying consumer-brand engagement and interest (e.g., website traffic referrals indicated by "clicks" and WOM indicated by "shares").

To preview our findings, we find that *how*—more than *what*—brands communicate to consumers through Facebook posts influences consumer engagement in the form of consumers' attitudinal responses (e.g., likes) as well as actions associated with meaningful marketing outcomes (e.g., sharing, clicks). Persuasive characteristics of branded content are particularly important. Interestingly, however, the presence of persuasive characteristics in posts tends to *decrease* engagement, and messages conveyed in a *less* clear and *less* formal manner—which is uncommon in traditional advertising—engender *greater* engagement. We argue that this is because, on social media, brands tend to communicate mostly with consumers who are already relatively highly interested in the brand because of the opt-in nature of following brands on platforms such as Facebook (i.e., they chose to follow the brand and receive advertising-like messages). Accordingly, content that is more informal and feels less like conventional marketing communications may resonate more with this already-interested consumer type, which leads to higher engagement. These findings contribute to the nascent literature on consumer behavior in social media settings by developing a more comprehensive understanding of how different types of content characteristics affect consumers' engagement actions toward brands in social media. Additionally, this research follows recent calls for more research on consumer responses to social media marketing actions (Lamberton and Stephen 2015; Stephen 2016).

BACKGROUND AND CONCEPTUAL DEVELOPMENT

Prior Research on Content Effects in Marketing Communications

Which types of content—or content characteristics—influence if and how consumers engage with brands on social media platforms such as Facebook? Prior research in the context of social media platforms offers only a limited perspective on how *different types* of branded social media content (i.e., content characteristics: *what* is said and *how* it is said) affect *different forms* of consumers' engagement behaviors in response to that content. Previous studies in the social media marketing literature tend to consider limited, narrow sets of content characteristics and/or engagement. However, two recent studies are important for the current research. First, De Vries, Gensler, and Leeflang (2012) show how content vividness, interactivity, page position, and valence affect the popularity of Facebook posts as measured by the numbers of likes and comments received. Among other things, they find that vividness plays an important role in affecting the two engagement behaviors they observed. Second, Lee, Hosanagar, and Nair (2015) test how branded Facebook posts' numbers of likes and comments are influenced by two linguistic characteristics of the text of brands' posts (informativeness and persuasiveness) that are identified with machine learning techniques. They find that both general linguistic characteristics matter. Their findings are limited, however, because they do not consider the non-textual characteristics of posts—images and/or videos—that, following from De Vries et al.'s (2012) vividness finding, should be relevant and important to consider (the presence or absence of non-textual characteristics is instead merely controlled for).

Two other recent studies also warrant discussion in light of the current research. Kumar, Bhaskaran, Mirchandani, and Shah (2013) discuss the importance of marketing messages in social media campaigns, however they focus primarily on social influence-related factors in a framework for measuring the value of social media marketing. They therefore do not closely examine the role of various types of content or specific content characteristics with respect to driving consumer engagement with brands in social media. Finally, although not in the context of social media per se, Berger and Milkman (2012) consider how certain content characteristics are associated with word-of-mouth sharing (i.e., one particular type of engagement with content). This is considered in a different context to ours, however (newspaper articles published in the *New York Times*). They show that the arousal generated by a newspaper article can be positively associated with article sharing popularity measured by whether or not an article makes a "most emailed" list. It is unclear, however, if this finding generalizes beyond news articles on a newspaper's website to our broader context of branded content on a social media platform where consumers can engage with content in a variety of ways, not only by sharing via email.

Despite limited prior research on how marketers communicate with consumers in social media, understanding marketers' attempts to communicate with consumers through various forms of content or messaging (including advertising) is a well-researched topic. The content of a marketing communication, which refers to what is said and/or shown in a marketing message and how the message is conveyed, has been linked to persuasion-related outcomes in prior work (e.g., Frazier and Summers 1984; Mohr and Nevin 1990). Traditionally, researchers have taken conventional marketing communications such as television commercials, classified them on various dimensions, and then linked those dimensions or content characteristics to marketing outcomes. For example, Resnik and Stern (1977) focused on the information contained in advertising messages, specifically for television ads, and attempted to measure the informational value of these messages using a typology of 14 types of "informational cues" that could be present in a television ad. They found that only half of the 378 ads they assessed contained these cues and were thus deemed to have some informational value. Hence, brands' marketing messages are not purely informational, and other characteristics therefore need to be considered.

If informational cues in the tradition of Resnik and Stern (1977) reflect *what* is conveyed in branded content, then *how* it is said may be encapsulated by other dimensions related to affective and tonal qualities of the communication. Prior research such as Olney, Holbrook, and Batra (1991) and Singh and Cole (1993) studied how the emotional aspects of television ads (in addition to informational cues) impact effectiveness and consumer engagement with the advertising (e.g., Olney and colleagues test how ad content characteristics ultimately affect ad viewing time as a measure of consumer attention). Similar work has been done for other types of advertising media, such as print advertisements (e.g., Turley and Kelley 1997) and, more recently, for digital advertising in both website display and mobile settings (e.g., Bart, Stephen, and Sarvary 2014; Danaher, Smith, Ranasinghe, and Danaher 2015; Drossos et al. 2007; Goldfarb and Tucker 2011; Lohtia, Donthu, and Hershberger 2003). In general, advertising research outside the social media context finds that what is said (informational cues, calls to action, specific claims) and how it is said (arousal-, emotion-, and persuasion-related elements) both affect how consumers engage with advertising. Beyond this, research also links traditional advertising message characteristics to consumers' purchasing behaviors (e.g., Bertrand et al. 2010; Liaukonyte et al. 2014).

In sum, although research on social media content marketing by brands is scant, the literature on advertising content and brand messaging in marketing communications provides a useful foundation for the current research. We do not presume that advertising content effects on consumer engagement with brands found for traditional media will be the same in social media. However, the general set of findings indicating that marketing message characteristics—what is said and how it is said—are important provides a basis for the current study. Additionally, classic studies such as Resnick and Stern (1977) and Olney et al. (1991) provide an important foundation because they consider branded content (in their case, television ads) as a bundle of characteristics or dimensions. We adopt this perspective, and note that it is distinct from recent related work such as Lee et al. (2015) that focuses on more abstract and general characterizations of social media posts (e.g., informativeness and persuasiveness) determined by automated machine learning algorithms instead of decomposing posts into their underlying attributes according to a typology of branded social media content characteristics.

A Typology of Content Characteristics for Branded Content in Social Media

Our conceptual framework has two parts. First, in this section, we develop a typology of content characteristics that we use for decomposing brands' posts along various dimensions. We draw these dimensions from prior research on advertising content and from reviewing brands' social media (Facebook) posts to identify common recurring characteristics. Second, in the next section, we argue how the content characteristics in this typology are related to consumer engagement with branded content in social media.

Because of the flexibility afforded to marketers when designing branded social media content for platforms such as Facebook, content can take on many forms and, thus, there are many content characteristics that could be considered. As we mentioned earlier, the prior research on social media marketing content is limited and only a small set of content characteristics have been considered. For example, De Vries et al. (2012) consider factors such as vividness and valence, and Lee et al. (2015) consider the general use of words associated with informativeness and persuasiveness. Also, in related literature on social sharing, Berger (2011) and Berger and Milkman (2012) consider arousal and emotionality related to content (or pieces of information). Although these characteristics are relevant, they represent only a fraction of what could be considered. A more comprehensive typology of content characteristics for branded social media content is needed. Given that our empirical setting is branded posts on Facebook, we focus primarily on Facebook but expect that our typology of content characteristics is applicable to other social media channels where brands' posts can have textual and/or visual (images, videos) elements.

Some classic studies on advertising content provide a useful starting point for developing our typology (e.g., Olney et al. 1991; Resnick and Stern 1977). Based on that stream of literature, the recent work on social media content and social sharing, and our own observations of hundreds of branded Facebook posts, we advance a typology of content characteristics that considers six general categories, each with a set of more specific component characteristics (with a total of 14 components across the six categories). Generally, our typology incorporates both *what* is said in a branded post and *how* it is said. Thus, we include informational cues following work such as Resnick and Stern (1977), as well as cues that are more emotion-based in line with Olney et al. (1991) for television ads and Berger and Milkman (2012) for newspaper articles. Additionally, since branded posts are marketing messages intended to persuade or influence consumers, we also incorporate persuasion-related aspects. Persuasion-related aspects are important because a key question of this research lies in determining whether branded content on social media is effective in engaging consumers when messages are conveyed in a manner akin to conventional marketing communications (e.g., persuasive advertising messaging); that is, we assess whether the lack of certain hallmarks of persuasive marketing communications is better in this context. We now describe the dimensions of our typology.

Arousal-oriented. This category refers to the extent to which branded content possesses characteristics that may arouse positive affective responses from consumers. This includes generating positive emotional reactions (Berger and Milkman 2012), having positive valence (De Vries et al. 2012), or being humorous. We consider two components of arousal-oriented content: (1) positivity (how positive the post’s tone is), and (2) humor (how funny or humorous the post is). Note that it is also possible to consider negativity but for branded content it is unlikely that managers would intentionally develop content intended to arouse negative emotions in consumers. For this reason, we exclude it from this typology but acknowledge that it may have a place in a broader typology for branded and non-branded social media content. In sum, arousal-oriented characteristics relate to how a brand conveys its marketing messages to its social media audiences through the use of linguistic and visual devices designed to positively arouse or generate positive affect.

Persuasion-oriented. This category refers to the extent to which branded content possesses characteristics that may persuade or influence consumers' attitudes, opinions, or behaviors. While using persuasive language has been considered in prior work (Lee et al. 2015), our perspective is more specific and our typology includes three components related to the extent to which content is persuasion oriented: (1) relevance, or how appropriate the content is to, and fits with, the focal brand's image, (2) message clarity, or how clear and fluent the post's message appears to be, and (3) advertising tone, or how much the post feels like or comes across as an advertisement in the "traditional" sense of advertising. Conventional marketing communications (e.g., traditional advertising) are typically designed to be high on each of these components. Whether this works well for branded social media content, however, is unclear.

These components were selected because they are related to three key mechanisms through which persuasive messages can affect consumers' attitudes and/or behaviors: processing motivation and processing ability from the elaboration likelihood literature (e.g., Petty and Cacioppo 1979; Petty, Wells, and Brock 1976), and psychological reactance (Brehm 1966). First, relevance is important because content that seems to be incongruent with the focal brand could block information processing altogether (e.g., the message is ignored). This persuasion-oriented dimension is related to processing motivation (Petty and Cacioppo 1979, 1981) in the sense that messages that are apparently relevant to the associated brand likely engender higher processing motivation in consumers, which could result in higher attention and thus a greater chance of engagement actions taking place. Also, observations of branded Facebook posts suggests that there is high variance in message-brand relevance, thus also making it a practically important content characteristic.

Second, message clarity is important because in traditional advertising and marketing communications, messages that are clearer or more fluent tend to be more persuasive (Lee and Aaker 2004). This is related to processing ability (Petty et al. 1976; Petty and Cacioppo 1981) because messages that are easier to read, interpret, or understand increase a consumer's ability to process them (particularly along the "central route" to persuasion in the elaboration likelihood model) and thus require fewer cognitive resources for processing. On the other hand, less-clear messages, while being harder to process, might motivate consumers to actively process them and thus pay more attention (e.g., the point of the message is not immediately obvious so a consumer is motivated to "figure it out").

Additionally, whereas clear, easy-to-process marketing messages might be more persuasive and influential in one-way communications channels (e.g., television advertising), in newer two-way channels like social media where consumers interactively socialize with others, less-clear messages from brands might, paradoxically, be better because they are more consistent with the predominant style of communication taking place in the channel. In other words, to the extent that social-interpersonal communication on social media comprises relatively less clear and less polished messages than conventional marketing communication, it may be that clear messages from brands on social media appear inconsistent with the conversational norms of social media platforms. Thus, very clear messages from brands on social media platforms such as Facebook might stand out as persuasive marketing messages, which could activate persuasion knowledge (Friestad and Wright 1994) and possibly trigger a reactance-like response against the message and brand (Brehm 1966; Fitzsimons and Lehmann 2004).

Finally, the extent to which a post has an “advertising tone” or feels like a traditional advertisement is expected to be important for a similar reason. If a message comes across as overtly persuasive in the sense that it feels (and/or looks) like a traditional advertisement it might look out of place in the social media environment and violate the prevailing communication norms in the social media context. As with clear messages (which tend to be found in advertisements), content that feels like an ad or has an apparent “advertising tone” might activate persuasion knowledge and lead to reactance against the brand.

Information. This category refers to the extent to which branded content possesses characteristics associated with particular informational cues. Note that we focus on the presence of specific types of information (e.g., price information, details about a promotional campaign, or mentioning particular product attributes), similar to Resnick and Stern (1977), instead of a more general assessment of how “informative” a piece of content may or may not be (which is arguably less precise; cf. Lee et al. 2015). Prior work in advertising has considered very large sets of informational cues. In our case, three relatively general marketing-related informational components are considered: (1) product-related, or whether the post mentions product-related information such as how a product can be used, its benefits, and whether it is new, (2) value-related, or whether the post mentions value- or price-related information such as discounts or coupons, and (3) brand-related, or whether the post mentions brand-related promotional information such as general news about the brand or brand-related events. We note that in prior advertising research the norm has been to consider larger numbers of very specific informational cues (e.g., over ten informational cues are listed in Resnick and Stern’s exhibit 1). Our three components subsume many of the more specific components in prior work, and, from a more practical perspective, correspond to marketing mix elements (i.e., product, price, promotion).

Calls to action. The fourth category is *calls to action*. This refers to the extent to which branded content explicitly encourages consumers to undertake specific engagement actions such as “liking” a post, answering a question or leaving a comment, or following a link to a webpage. Social media marketers often use calls to action in their attempts to increase their post-level engagement metrics, and prior research has touched on certain types of calls to action by considering how asking questions affects engagement (De Vries et al. 2012). Whether calls to action are effective, however, is unclear. While asking consumers to take specific engagement actions could lead to compliance (i.e., positive effects), it seems equally plausible that consumers would instead either just ignore such calls or react against them. We consider two types of calls to action: (1) calls to engage (whether the post directly solicits engagement by requesting likes, comments, or shares, or by asking a question to be answered in the comment box), and (2) calls to enter a competition (whether the post asks consumers to enter into a competition or sweepstakes, which usually requires clicking a link to an external website). We consider calls to enter a competition separately because it is sufficiently common in practice to treat it as such, and, more importantly, because it requires more effort from consumers than the within-page calls to engage such as simply clicking on the like button or answering a question in the comment box.

References. The fifth category is *references*. This captures whether branded content refers to entities or events that are not central to the brand itself but are related to it in some way. References are common in practice and have been linked to purchase attitudes (Dean 1999) and memory (Johar and Pham 1999). We consider two types: (1) non-brand references (whether the post mentions non-brand entities such as charities or sponsored sporting teams), and (2) holidays (whether the post mentions a major holiday such as Thanksgiving or Christmas, or a pseudo-holiday such as International Talk Like A Pirate Day). Conventional wisdom among social media marketers is that references lift engagement because they allow brands to “piggyback” on current topics or causes of which their audiences are already aware or thinking about, thus making it more likely for audiences to pay attention to and engage with posts. Whether this logic is correct, however, is questionable because non-brand references could also dilute or obfuscate a post’s message, leading some consumers to find the message irrelevant or confusing.

Media elements. The final category is *media elements*. This refers to whether branded content is comprised of only text or also includes other types of media such as images, videos, and links to external webpages (Keller 2009; Venkatachari 2013). We consider two kinds of media elements: (1) rich media (whether a post includes an image/photo or video), and (2) URLs (whether a post includes one or more links to websites).

Linking Content Characteristics to Consumer Engagement with Branded Content

We now consider how the six categories of content characteristics in our typology are related to consumer engagement with branded content in social media. Figure 1 provides an overview of how we expect branded social media content characteristics to be related to various post-level engagement actions taken by consumers. These actions are grouped into two sets: those that reflect consumers’ attitudinal responses to content, and those that are more closely aligned with meaningful marketing outcomes.

Figure 1: Conceptual Framework

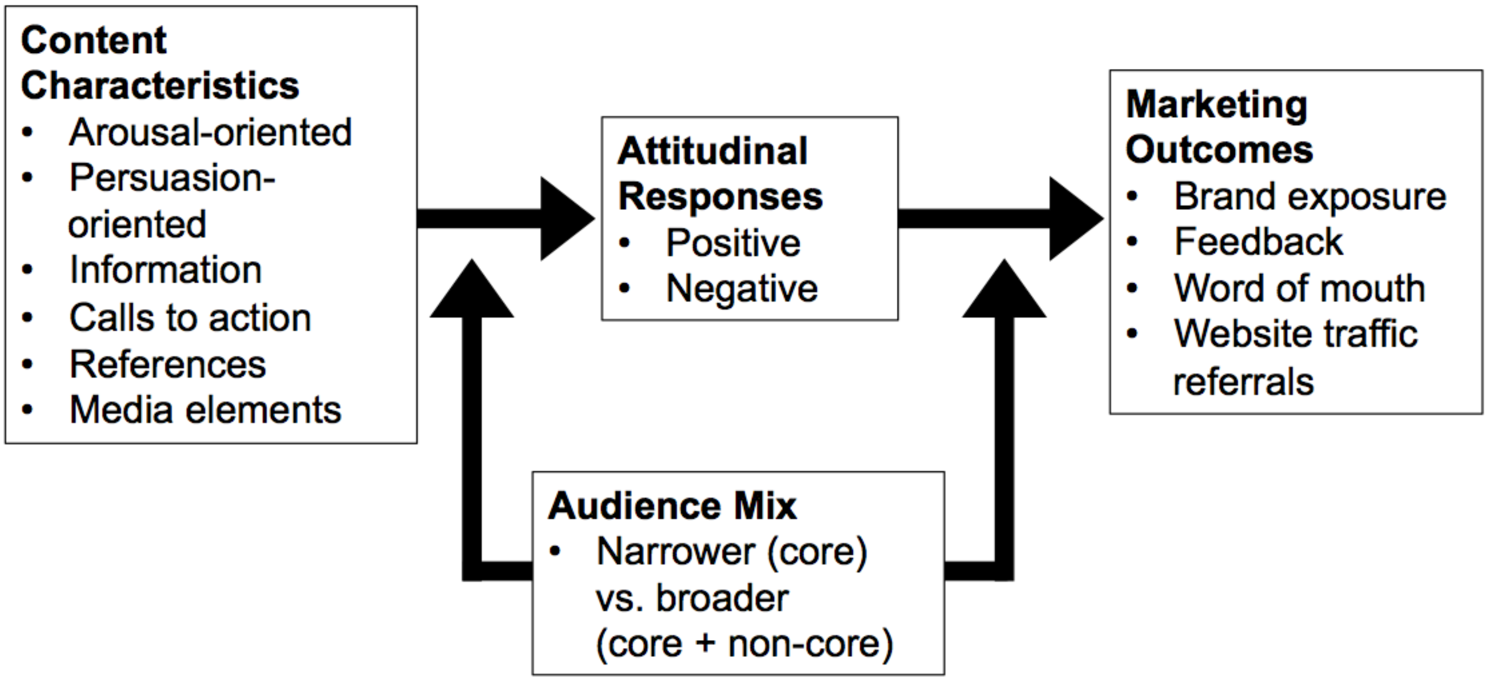


Figure 1 shows two sets of variables that are expected to be affected by content characteristics. Collectively, attitudinal responses and marketing outcomes in this framework are "engagement" outcomes with respect to branded posts. Engagement with content is an oft-stated objective for social media marketing (Dubois 2014; Hemley 2013; Leung 2014), and prior work has considered subsets of the variables considered here (e.g., both De Vries et al. [2012] and Lee et al. [2015] consider "likes" and "comments"). Conceptually, consumer-brand engagement in a social media context has been conceptualized as a multidimensional construct reflecting consumers' brand-related cognitive, affective, and behavioral actions (Hollebeek, Glynn, and Brodie 2014), with dimensions indicating various levels of intensity of consumers' interactions with brands (Vivek, Beatty, and Morgan 2012; Wang and Calder 2006).

Consistent with this perspective, we break engagement into multiple dimensions (and indicators). We categorize these dimensions in the manner shown in Figure 1 because some engagement actions taken by consumers in social media, particularly Facebook, are more attitudinal in nature, whereas others are more meaningful, particularly for marketers. We consider the measurable engagement actions taken by consumers in response to branded Facebook posts (e.g., likes, comments, shares) to be indicators of underlying constructs, attitudinal responses and marketing outcomes, which are posited to be consequences of marketers' content design decisions. We now discuss these consequences and how they are related to observed post-level actions.

Consumers' attitudinal responses to branded Facebook posts in general signal their thoughts and feelings about the content, both in terms of what is specifically communicated in the post, as well as more general concepts such as the associated brand. Attitudinal responses are valenced; that is, they can be positive or negative. On Facebook, two marketer-observable engagement metrics indicate, respectively, positive and negative attitudinal responses to content: the number of times a post has been liked (Likes), and the number of times a post has received negative feedback (Negatives). Although not as common as actions such as liking, Facebook users can mark a post as negative. Some users treat this as a way to "dislike" posts or signal a "thumbs down" reaction. On other social media platforms, related measures include the number of times a post has been "favorited" (e.g., Twitter), "loved" (e.g., Instagram), or "thumbed up" or "thumbed down" (e.g., Reddit). We posit that attitudinal responses occur in reaction to branded content, and in turn can influence other types of post-level engagement that we consider to be indicators of actual marketing outcomes.

An issue with attitudinal responses such as likes and negatives is that they convey only a small amount of information about what a consumer thinks. This is because it is very easy to click "like" on a post and it is thus a fairly low-level form of engagement. A number of other measurable engagement actions, however, are relatively less easy for consumers to take and also represent outcomes of interest to marketers. We consider four such outcomes. First, brand exposure, which is indicated by a post's total audience size (Reach). Second, feedback, which is indicated by the number of comments received by a post (Comments). Third, WOM, which is indicated by the number of times a post is shared with other people on Facebook (Shares). Finally, website traffic referrals, which is indicated by the number of times posts (including embedded links) are clicked on (Clicks).

We allow for the possibility that each of these outcomes could be influenced indirectly by content characteristics through consumers' attitudinal responses. Specifically, we argue that if content prompts consumers to take an action of interest to marketers such as spreading WOM or visiting a website, the content first will induce changes in consumers' attitudes. That is, at a conceptual level we hypothesize that marketers' content characteristic decisions influence marketer-desired behaviors (i.e., marketing outcomes) through consumers' attitudinal responses.

Finally, in our conceptualization we also consider the possibility that the effects of content characteristics on attitudinal responses and marketing outcomes depend on the type of consumer being reached. In Figure 1 this is represented by the audience mix (core vs. core + non-core consumers) construct, which may moderate the content-related effects on engagement with branded content. Audience mix refers to the extent to which a post's audience—the consumers who see a post—is comprised of core fans. For a given brand, its core fans are those consumers who actively follow the brand on social media, regularly engage with it, and most likely are actual customers. We allow for audience mix to moderate the effects of content on engagement because it is possible that content characteristics might affect engagement in different ways depending on whether the audience is mainly core fans (who know the brand well) or a wider audience that also includes non-core fans (who do not know the brand as well).

EMPIRICAL ANALYSIS OF BRANDED FACEBOOK POSTS

Data Collection and Variable Definitions

To empirically test how content characteristics affect consumer engagement with branded social media posts, we collaborated with nine brands to compile a unique dataset of branded Facebook posts made by these brands over an 18-month period from March 1, 2012 to August 31, 2013. The brands represent four industries (consumer packaged laundry goods, retail, quick-service restaurants, and sports). Our dataset includes 4,284 branded Facebook posts, which is all of the posts made by these nine brands during our observation window. Additional information is given in Appendix A, however confidentiality agreements limit the information we can provide. We now explain how each of the constructs in our conceptual framework were measured and the data collection process for each one.

Post-level engagement and reach. Facebook provides brands with a detailed set of post-level engagement and reach metrics through the “Facebook Insights” tool. We measure attitudinal responses by the numbers of likes (unique users clicking “like” under a post; Likes) and instances of negative feedback (unique users indicating they do not like a post; Negatives) received for each post. Marketing outcomes are measured for each post as follows. First, exposure is measured by a post’s total reach, which is the number of unique users that were shown a post (Reach). Second, feedback is measured by the number of comments received (unique users writing comments; Comments). Third, WOM is measured by the number of shares received (unique users clicking “share” under a post; Shares). Finally, website traffic referrals is measured by the number of clicks received (unique users clicking posts; Clicks).

Each of these measures is cumulative. This means that we do not have, for example, daily measures for each of these variables, per post. Instead, we have the total counts for each of these variables taken at the time the data were provided to us by the companies, which was a number of months after the end data of our data-observation window. Thus, we assume that each engagement or reach measure for each post is the “terminal” or final value of the underlying time series; i.e., each one is the maximum cumulative level reached for that post. Facebook does not provide time series data for post-level engagement and reach. Given that companies downloaded this data some time after the observation window for posts closed, it is reasonable to assume that our engagement and reach data represents the final levels of those variables achieved by each post during its run on Facebook. Although brands rarely remove posts in order to stop them from being seen in the future, Facebook's algorithms heavily prioritize recently posted content, and therefore the likelihood of a user being served older posts decreases with the time since posting.

Audience mix. As mentioned above, we use a post's reach as a measure of the marketing outcome of brand exposure. Facebook also decomposes the total reach metric into three components based on how people were reached (total reach = paid + organic + viral), which we use to measure audience mix (core vs. core + non-core fans). Paid reach is the number of unique users who saw a post because the brand paid to increase or "boost" the post's reach. Organic reach is the number of unique users who saw a post because Facebook's EdgeRank algorithm showed them the post based on their recent engagement (i.e., they have recently engaged with the brand on Facebook, and probably are fans of the brand's page). Viral reach is the number of unique users who saw a post because one of their "friends" engaged with that post by liking it, commenting on it, or sharing it. We use this decomposition of total reach, particularly paid reach, to construct a measure of audience mix. Paid reach is a direct consequence of a marketer's "boosting" decision (i.e., paying to increase reach) and is thus related to content dissemination with respect to audience mix (narrower vs. wider).

The audience mix for brand i's j^{th} post is equal to the proportion of a post's total reach that is due to boosting (i.e., paid): $AudienceMix_{ij} = PaidReach_{ij} / TotalReach_{ij}$. Paid reach is greater than zero only when a post is boosted, meaning that when a post is *not* boosted, $AudienceMix = 0$ and the post's audience is likely mostly be core fans who are organically reached (due to EdgeRank). We note that viral reach is also possible in the absence of paid boosting, meaning that some non-core consumers will also be reached when $AudienceMix = 0$, but, at least in our data, viral reach is very small relative to organic reach. Lower values of

AudienceMix (closer to 0) indicate a narrower audience of mostly core consumers, and higher values (closer to 1) indicate a wider audience that includes non-core consumers.

Given that more precise measures for the composition of a post's audience are not revealed to marketers by Facebook and are unavailable through third-party sources (e.g., analytics agencies), this measure is the best available indicator of audience mix. Note that an alternative measure would be a dummy variable indicating if a post was boosted (paid reach > 0) or not (paid reach = 0). Although possible, this would not account for the extent of boosting, which increases with increasing paid reach relative to total reach, and is a direct consequence of how much money a manager wishes to spend on post boosting (which is not revealed in data provided by these companies).

Content characteristics. The fourteen content characteristics defined earlier were measured for each post using a comprehensive content-coding undertaking involving human judges (as opposed to, for example, machine learning algorithms). Multiple human judges assessed each post and used a coding instrument with items designed to measure each specific content characteristic. This procedure had two stages.

The first stage involved developing the coding instrument. This was an iterative process in which we tested and retested question items for measuring each content characteristic. Our goal was to develop valid and reliable measures, while at the same time minimizing the length of the coding instrument as much as possible given the relatively large number of specific characteristics that judges needed to assess. To begin, we looked at a series of branded Facebook posts from major brands (some of which were in our dataset) in order to develop a list of potential content characteristics. We then refined this list with assistance from a group of marketing doctoral students who were heavy Facebook users. Following this, we constructed items to measure each characteristic on the refined list and tested this preliminary coding instrument on judges recruited from Amazon Mechanical Turk, who were shown 30 randomly selected posts from our dataset. Five judges coded each post and provided feedback on the instrument. Items with low inter-judge reliability were carefully scrutinized and either refined or replaced. Following this, we randomly selected another 30 posts and had three undergraduate research assistants code the posts using the updated instrument. The research assistants coded the posts independently and then met together with the authors to provide feedback. This identified redundant items that could be dropped and ambiguous items that required rewording or clearer instructions. At the conclusion of this process, we arrived at a final coding instrument that was then used in the second stage of this process for coding all posts, which resulted in the content characteristics data used in our analysis.

The list of variables for each content characteristic is shown in Table 1. Through the coding instrument, 38 variables were measured (note that some extra measures were captured but not used because those characteristics turned out to be very uncommon). We collapsed these into the 14 variables in Table 1. For the perceptual items measured on five-point scales (e.g., the extent to which a post feels like an advertisement), when the characteristic had multiple items we collapsed these into a single item by averaging (scale reliabilities were high; see Table 1). For items measured on binary (0/1) scales (e.g., whether or not a post mentioned a charity as an indicator of non-brand references), we grouped the component items and collapsed them into single binary items that took on a value of 1 if at least one of the underlying components was present in the post, and 0 if none of the underlying components were present (as a robustness check, we also tested an alternative specification averaging the multiple binary items and found no differences in our findings).

Table 1: Content Characteristics Used in Analysis

Variable	Description	Measurement	Mean (St. Dev.)
Arousal-oriented			
Positivity	Post is perceived as positive	6 items, 1-5, averaged, $\alpha = .91$	3.24 (.52)
Humorous	Post is perceived as humorous/funny	1 item, 1-5	2.21 (.66)
Persuasion-oriented			
Relevance	Post is perceived as being relevant to the brand	4 items, 1-5, averaged, $\alpha = .98$	4.05 (.60)
ClearMessage	Post is perceived as having a clear message	2 items, 1-5, averaged, r = .87	4.17 (.40)
AdvertisingTone	Post is perceived as feeling like an advertisement	1 item, 1-5	3.66 (.87)
Information			
Product	Post mentions product-related information, including uses (how or when), benefits, and new products or extensions	4 items, 0/1	.16 (.37)
Value	Post mentions value-related information, including pricing and discounts/coupons	2 items, 0/1	.08 (.27)
Brand	Post mentions news about the brand that promotes the brand in general and/or promotes brand-related events	2 items, 0/1	.39 (.49)
Calls to Action			
Engage	Post asks for engagement, including by asking a question or requesting likes/comments/shares/clicks/photos	5 items, 0/1	.38 (.49)
Competition	Post asks for entry into competition (contests/sweepstakes or giveaways)	2 items, 0/1	.09 (.28)
References			
NonbrandRefs	Post refers to non-brand entities, such as mentioning sponsorships or promoting/mentioning charities	3 items, 0/1	.09 (.29)
Holiday	Post refers to a major or minor holiday (Christmas, etc.)	2 item, 0/1	.12 (.33)
Media elements			
RichMedia	Post includes either an image or a video	3 items, 0/1	.66 (.47)
URLs	Post includes one or more links (URLs) to websites outside of Facebook	1 item, 0/1	.39 (.17)

The second stage used human judges to assess each post using the coding instrument. A combination of eleven undergraduate research assistants and thousands of members of Amazon Mechanical Turk handled this workload. Each post was coded by between two and five judges ($M = 3.04$, $SD = .52$). For any given post, if two judges completely agreed on the binary items (e.g., Does this post include a photo?) or inter-judge reliability (α) was greater than .70 for the interval-scaled items, we used only those two judges. If not, we added a third judge and in the vast majority of cases this resulted in sufficiently high levels of inter-judge agreement and reliability. In a small number of cases this did not, and we therefore added a fourth or (if needed) fifth judge. This incremental approach was taken for practical reasons; that is, we had a large number of posts to code, coding was costly, and we therefore wanted to use only the necessary number of judges for each post. To assess inter-judge reliability, we used Fleiss' Kappa for binary-scaled items (Fleiss 2003; Fleiss, Nee, and Landis 1979; Landis and Koch 1977) and Cronbach's Alpha for interval-scaled items. The average reliability across posts was good for the binary-scaled items ($M = .601$, $SD = .237$) and very good for the interval-scaled items ($M = .917$, $SD = .048$). For the binary items, when there was disagreement we used the majority opinion among the judges. For scale items, we averaged judges' scores.

Empirical Considerations and Model Specification

Modeling considerations. Our modeling effort focuses on testing the conceptual framework in Figure 1. Our goal is to estimate effects of content characteristics on attitudinal responses (Likes, Negatives) and marketing outcomes (Reach, Comments, Shares, Clicks), the effects of each attitudinal response on each marketing outcome, and audience mix interactions.

However, this cannot be achieved by estimating a set of basic regression models due to factors related to data characteristics and the possible underlying data-generation processes. The following five considerations are therefore accommodated in our empirical modeling approach.

First, the six dependent variables are counts with large variances (see descriptive statistics reported in Table 2). The ranges of the data and extreme values make the use of count distributions (e.g., Poisson, negative binomial) less appropriate. Instead, we use logarithmic transformations of these variables in our analysis. Specifically, for dependent variable y, the transformation is log(1 + y) where 1 is added to prevent taking logs of 0.

Table 2: Engagement and Reach Descriptive Statistics

Variable	Mean	St. Dev.	Median	Minimum	Maximum
Engagement:					
Likes	2,752.63	11,134.07	122.00	0	314,112
Negatives	270.29	1,369.24	10.00	0	37,248
Comments	205.37	945.48	26.00	0	24,378
Shares	139.15	864.09	6.00	0	32,896
Clicks	200.26	1,520.62	2.00	0	39,066
Reach:					
Total	486,510.11	2,620,272.46	24,011.00	1	49,874,776
Organic	140,466.75	369,632.71	21,615.50	0	6,560,693
Paid	340,273.53	2,492,608.58	0.00	0	49,214,580
Viral	5,769.83	57,430.64	94.50	0	1,444,352

Second, the dependent variables are likely to be interdependent, i.e., correlated. Thus, we model them jointly in a system-of-equations multivariate model. Interdependence among them not directly captured by effects specified in the model is captured through correlated errors.

Third, because of Facebook’s EdgeRank algorithm, we need to control for effects of previous posts’ outcomes on current posts. Facebook does not reveal the details of how EdgeRank works, but it is known that the engagement and reach a brand receives for previous posts can affect the reach and engagement of subsequent posts. We accommodate this with state-dependent effects; i.e., each equation includes lags of all dependent variables.

Fourth, a brand's social media marketing prowess or the ability and expertise of its social media marketing team plausibly could affect the dependent variables. This is because these outcomes are influenced by marketers' content design and dissemination decisions, which are likely to be functions of marketer (or overall brand) expertise, at least to some extent. We treat this as brand-level unobserved heterogeneity and assume that it is correlated with the content-related variables. Brand fixed effects are used to help control for this possible relationship. Note that the typical alternative to fixed effects when modeling panel data, random effects, would not help because brand random effects would be uncorrelated with content variables in the model.

Finally, the content variables could be endogenous. Brand fixed effects help address this to the extent that endogeneity could come from marketers' decisions being correlated with latent marketer expertise. However, brand fixed effects cannot handle endogeneity due to marketers' decisions being driven by other unobserved factors. In particular, we expect that marketers' decisions will be functions of what they have previously done (e.g., using a consistent style or switching styles frequently due, for instance, learning attempts). Note that we are not suggesting that the content-related decisions made by marketers should be modeled as a formal learning process (cf. Erdem and Keane 1996). That would be an overly strong claim about how marketers develop branded social media content. Although little is systematically known regarding these processes, anecdotal evidence from our conversations with some brands' social media managers suggests that a formal learning model would be inappropriate. Instead, managers try many approaches and test out new ideas without much structure, and they sometimes repeat previously used approaches due to beliefs—often unfounded—in their effectiveness. Because of this, we assume that there is some carryover from post to post, and therefore the content variables could be correlated with lagged content variables. To accommodate this we adopt a two-stage procedure based on Petrin and Train's (2010) control function method for handling endogeneity that has been recently used by Che, Chen, and Chen (2012) and Danaher et al. (2015). Additionally, as Danaher et al. (2015) note, this approach is related to the residual-based approach used by Stephen and Toubia (2010). Details of this are described next.

Model specification: First-stage control functions. The first part of our model involves estimating a set of control functions (i.e., first-stage regressions), one for each managerial decision, that is, the content variables. We closely followed Danaher et al.'s (2015) implementation of Petrin and Train's (2010) control function method. Each control function is a regression in which a content variable is regressed on its lag, the lags of all other content variables, and, consistent with prior implementations of this approach and convention, the other covariates that appeared in the response functions (see below). Lagged content variables are similar to instruments in an instrumental variables model. They are conceptually valid because prior and current content variables for the same brand are related, but it is implausible for prior content-related decisions to be (direct) drivers of current-post dependent variables because engaging with today's post cannot logically be due to something seen in yesterday's post. Thus, for content variable $x_{k,ij}$, where k indexes the content variables (from 1 to L), i indexes the brand (from 1 to N) and j indexes the post (from 1 to J_i), the control function is:

(1) $$x_{k,ij} = \gamma_{k,0} + \sum_{l=1}^{L} \gamma_{k,l} x_{l,ij-1} + \sum_{m=1}^{M} \lambda_{k,m} z_{m,ij} + \delta_{k,ij}$$

Where j -1 refers to the previous post made by brand i, $z_{m,ij}$ is the m^{th} (out of M) exogenous covariates (control variables) used in the response functions, and $\delta_{k,ij}$ is the residual. For content characteristics measured on 1-5 scales we used Tobit models with censoring below at 1 and above at 5 to estimate Equation 1. For all other decision variables we used binary probit models (for audience mix, which is continuous in [0,1], the model was binomial with a probit link).

The control functions partition each content variable into endogenous and exogenous parts (Danaher et al. 2015). Both $x_{k,ij}$ and $\delta_{k,ij}$ are then entered as explanatory variables in the response functions that represent the conceptual model to be tested and that are estimated in the second stage of this procedure (see next section). For the binary-scaled endogenous content variables, the predicted value used in the second-stage model is the predicted probability from a binary probit model, following Petrin and Train (2010) and Danaher et al. (2015). The inclusion of the residuals in the second-stage response functions means that each content variable's effect on the dependent variables is decomposed into exogenous and endogenous components (Danaher et al. 2015). Excluding the first-stage control-function residuals in the second-stage response function model means that these components are not decomposed, resulting in biased parameter estimates for the effects of the various content characteristics on the multiple engagement outcomes. Note that an alternative approach would be to replace content-related variables with predicted values from Equation 1 (e.g., similar to two-stage least squares). However, Terza, Basu, and Rathouz (2008) show that the use of control residuals is superior, particularly in our case where many of our endogenous content variables are binary.

Model specification: Second-stage response functions. The main part of our model involves estimating the effects of the content variables on the six dependent variables, including interactions between audience mix and content characteristics, as well as the mediating effects of the two attitudinal response dependent variables on the four marketing outcomes. In this part of the model we treat each dependent variable as a response variable, and we model the effects of content characteristics and audience mix, as well as other control variables and the residuals from the first-stage control functions, on each response for brand *i*'s *j*th post as follows:

$$\log(\mathbf{Y}^*_{ij}+\mathbf{1}) = \mathbf{A}_0 + \sum_{i=1}^{N-1}\mathbf{A}_{1,i} + \mathbf{A}_2\log(\mathbf{Y}^*_{ij}+\mathbf{1}) + \mathbf{A}_3\log(\mathbf{Y}^*_{ij-1}+\mathbf{1}) + \mathbf{B}_1\mathbf{X}_{ij} + \mathbf{B}_2\mathbf{W}_{ij} + \mathbf{B}_3\mathbf{Z}_{ij} + \mathbf{B}_4\Delta_{ij} + \mathbf{e}_{ij} \quad (2)$$

$$\log(\mathbf{Y}_{ij}+\mathbf{1}) = \begin{cases} \log(\mathbf{Y}^*_{ij}+\mathbf{1}) & \textit{if } \log(\mathbf{Y}^*_{ij}+\mathbf{1}) > 0 \\ 0 & \textit{if } \log(\mathbf{Y}^*_{ij}+\mathbf{1}) \le 0 \end{cases} \quad (3)$$

Equations 2 and 3 are a fixed effects dynamic multivariate Tobit model. $\mathbf{Y}_{ij}$ = [Likes_{ij}, Negatives_{ij}, Reach_{ij} Comments_{ij}, Shares_{ij}, Clicks_{ij}]'. **1** is a vector of ones. $\mathbf{A}_0$ are intercepts and $\mathbf{A}_{1,j}$ are brand fixed effects for N = 9 brands. $\mathbf{A}_2$ are effects of attitudinal responses on marketing outcomes (i.e., effects of Likes and Negatives on Reach, Comments, Shares, and Clicks). $\mathbf{A}_3$ are state-dependent effects of lagged dependent variables on themselves and each other. $\mathbf{B}_1$ are effects of the decision variables $\mathbf{X}_{ij}$ (content characteristics and audience mix) on the dependent variables. $\mathbf{B}_2$ are interaction effects between audience mix and each content characteristic (product terms $\mathbf{W}_{ij}$). $\mathbf{B}_3$ are effects of control variables $\mathbf{Z}_{ij}$ (logged inter-post time and month). $\mathbf{B}_4$ are effects of control function residuals (Δ_{ij}). Finally, $\mathbf{e}_{ij} \sim N(\mathbf{0},\Sigma)$ and Σ is a full error variance-covariance matrix. We were concerned about multicollinearity given the many content variables, but this was not a problem: the mean correlation among content variables is .04 (SD = .14; see Appendix C), and variance inflation factors are small (M = 1.29, SD = .32, max. = 2.14).

Results

Model fit and selection. First, we consider a set of four nested models: (1) a baseline with no effects of content characteristics or audience mix, (2) a version with only audience mix effects, (3) a mediation model corresponding to our conceptual framework (Figure 1) where managerial decisions affect attitudinal responses directly and marketing outcomes only indirectly through attitudinal responses, and (4) a full model that is the same as the mediation model but also allows for direct effects of managerial decisions on marketing outcomes. Fit statistics are reported in Table 3.

We find that models 3 and 4 (i.e., with mediation/process) both fit well. Model 4 (full model, allowing for direct and mediated content effects on marketing outcomes through attitudinal responses) has slightly better fit, and thus we report those results. The superior fit of model 4 over model 3 simply means that some of the effects of content characteristics on marketing outcomes are only partially mediated by attitudinal responses. Additionally, significant and relatively large error covariances (see Appendix D) support using a multivariate model instead of estimating a model for each dependent variable separately.

Table 3: Models and Fit

	Model	**Content**	**Audience Mix**	**-2 LL**	**AIC**	**BIC**	**Pseudo R^2**	**Mean Abs. Error**	**Root Mean Sq. Error**
1	Base model	No	No	74,590	74,836	75,618	.83	6.28	6.44
2	No content effects	No	Yes	71,552	71,822	72,680	.85	5.99	5.99
3	Mediation model	Yes	Yes	69,674	70,144	71,639	.86	5.62	3.67
4	Full model	Yes	Yes	68,652	69,398	71,771	.89	4.78	3.75

How do content characteristics affect attitudinal responses (Likes, Negatives)? We first consider the effects of content characteristics on Likes and Negatives. Table 4 reports the unstandardized parameters for effects on Likes and Negatives. Figure 2 shows spotlight analysis plots of the standardized effects at narrow (*AudienceMix* = 0) and wide (*AudienceMix* = 1) audiences (error bars are 95% confidence intervals). Several content characteristics significantly affected Likes and Negatives, and audience mix moderated some of these effects.

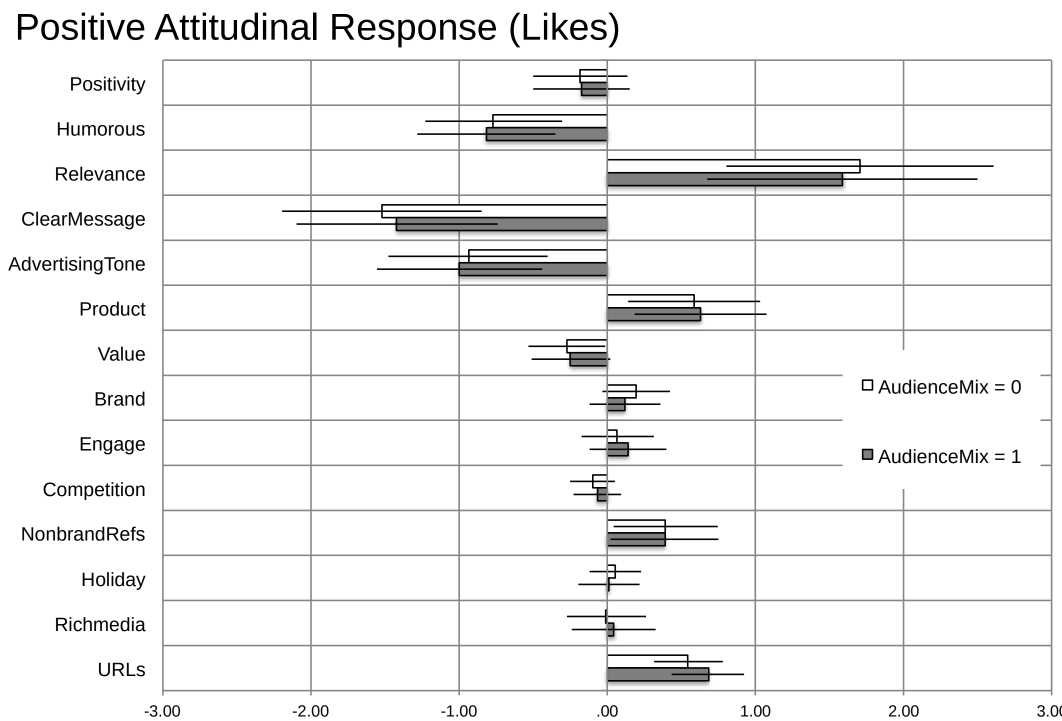
Table 4: Effects of Content Characteristics and Audience Mix on Attitudinal Responses

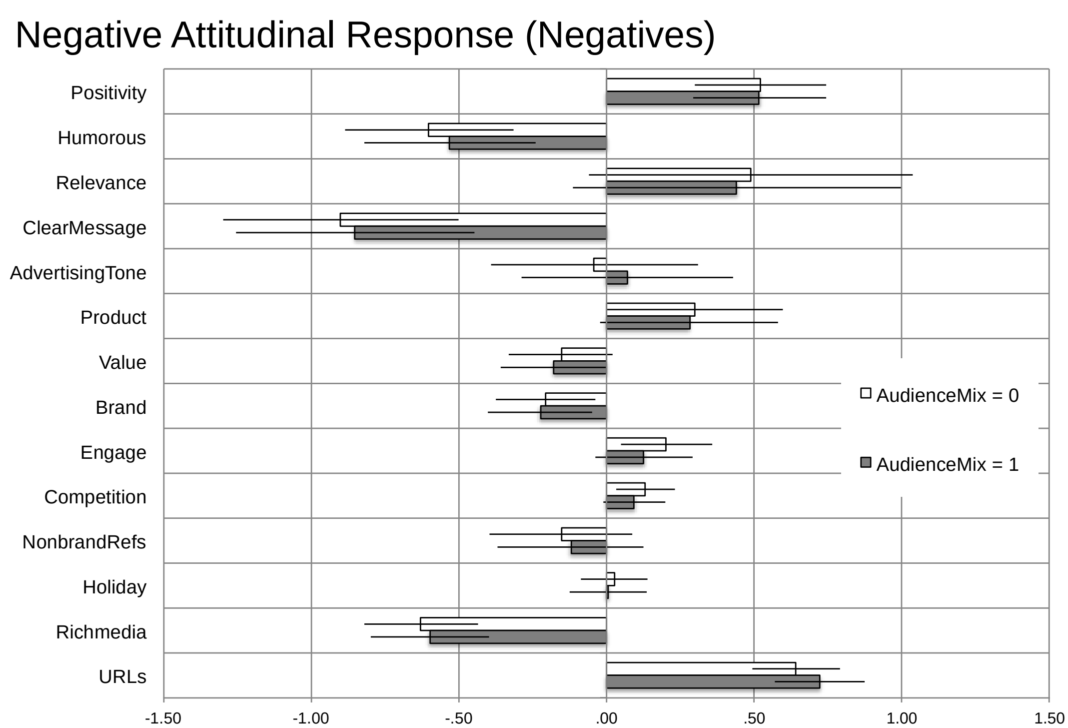
		Likes			Negatives		
		Est.	**SE**		**Est.**	**SE**	
Arousal-oriented	Positivity	-.88	.77		1.92	.53	***
	Positivity x Mix	.04	.22		-.02	.14	
	Humorous	-2.89	.87	***	-1.73	.54	***
	Humorous x Mix	-.19	.16		.20	.10	**
Persuasion-oriented	Relevance	7.05	1.87	***	1.54	1.14	
	Relevance x Mix	-.48	.30		-.15	.19	
	ClearMessage	-9.42	2.09	***	-4.25	1.24	***
	ClearMessage x Mix	.62	.34	*	.23	.22	
	AdvertisingTone	-2.68	.77	***	-.09	.50	
	AdvertisingTone x Mix	-.16	.20		.24	.13	*
Information	Product	4.01	1.52	***	1.55	1.02	
	Product x Mix	.28	.23		-.09	.14	
	Value	-2.54	1.21	**	-1.09	.81	
	Value x Mix	.26	.29		-.17	.18	
	Brand	1.01	.58	*	-.80	.43	*
	Brand x Mix	-.41	.22	*	-.08	.14	
Calls to Action	Engage	.35	.63		.79	.40	**
	Engage x Mix	.37	.23		-.30	.15	**
	Competition	-.90	.68		.89	.44	**
	Competition x Mix	.29	.27		-.25	.17	
References	NonbrandRefs	3.38	1.52	**	-1.01	1.04	
	NonbrandRefs x Mix	-.04	.39		.21	.25	
	Holiday	.40	.67		.16	.43	
	Holiday x Mix	-.31	.44		-.12	.28	
Media Elements	RichMedia	-.02	.70		-2.52	.51	***
	RichMedia x Mix	.26	.26		.12	.17	
	URLs	2.78	.60	***	2.50	.38	***
	URLs x Mix	.70	.20	***	.31	.12	**
Other Variables	Mix	.97	1.31		-1.50	.83	*
	Lag log(Likes + 1)	.32	.01	***	–	–	–
	Lag log(Negatives + 1)	–	–	–	.39	.02	***
	log(Interpost Time)	.18	.05	***	.13	.03	***
	Month	-.04	.02	**	-.04	.01	***

	Likes			Negatives		
	Est.	**SE**		**Est.**	**SE**	
Intercept	33.84	6.30	***	12.78	3.78	***
Brand 1	-1.84	.44	***	-.79	.27	***
Brand 2	-1.81	.42	***	-.36	.27	
Brand 3	-4.64	.81	***	-1.64	.51	***
Brand 4	1.29	.49	***	1.19	.32	***
Brand 5	.08	.71		.83	.45	*
Brand 6	-6.06	1.19	***	-1.82	.74	**
Brand 7	-1.75	.45	***	-.65	.28	**
Brand 8	-3.79	.47	***	-.86	.30	***
Control residuals	Yes			Yes		

* $p < .10$, ** $p < .05$, *** $p < .01$. Audience mix (“Mix”) ranges from 0 to 1. For brand fixed effects, Brand 9 is the reference brand.

Figure 2: Standardized Effects of Content Characteristics at Different Levels of Audience Mix on Likes and Negatives





With respect to positive attitudinal responses to content (Likes), based on effect sizes the most important content characteristics are the three persuasion-related dimensions: relevance, advertising tone, and message clarity. Relevance and message clarity were the strongest effects. The relevance and advertising tone effects were as expected (positive and negative, respectively). The more a post is perceived as relevant to the brand, the more Likes that post will receive because it likely encourages consumers to process the information (whereas irrelevant posts are probably just ignored). And, as we argued earlier, posts that have more of an "advertising feel" receive fewer Likes, probably because it triggers some psychological reactance.

Arguably the most interesting persuasion-related effect here is the negative effect of message clarity on Likes. Unlike branded messages in traditional advertising or conventional marketing communications where high message clarity is important, it appears that the opposite is true in this context. *Lower* message clarity—posts that are less clear, less fluent, less easily understood—trigger more positive attitudinal responses. Why is this the case? Earlier we mentioned that a negative effect of message clarity on any form of engagement is conceivable if brands' social media audiences prefer communications that are more consistent with the social/conversational nature of the medium. In other words, messages that are *not* very clear or *not* highly polished (i.e., lower message clarity) may be favored because they are more consistent with the social communication norms on Facebook. This should be particularly the case among those consumers who see a brand's post who know the brand well, or who are relatively highly involved with that brand in social media. These individuals—core fans—are more likely than others to have a stronger relationship with the brand they follow and regularly engage with, and thus their expectations may be higher with respect to a brand communicating with them in a less formal, more conversational manner. Thus, we should expect audience mix to moderate the effect of message clarity on Likes, such that the negative effect is stronger as the audience mix gets narrower (i.e., mostly core fans). This was the case (albeit the interaction was only marginally significant).

Other content characteristics also drive Likes. Regardless of audience mix, avoiding humor helps, as does providing product-related information but not value- or price-related information. Providing general brand-related information also helps, but only for narrow audience mixes. Thus, while being informative can help increase favorable attitudes toward content, it depends on the type of information and, to a lesser extent, the type of audience reached. Finally, references to non-brand entities and including links to external websites increase Likes (and the positive effect of URLs gets stronger with increasing audience mix).

For negative attitudinal responses, a number of the characteristics that increase Likes (positive attitudes) also *increase* Negatives (negative attitudes). In particular, having less message clarity also increases Negatives, as does including links to external websites. On the other hand, including rich media, having humor in posts, and reducing the positivity of posts (or using a more neutral tone) reduces Negatives. Consumers appear to be less likely to signal their negative attitudes toward content when the content is interesting and arousing, although the type of arousing tone used matters (i.e., less positive, more humorous), even though the difference may be subtle. Finally, the often-used device of explicitly calling for engagement-related action (e.g., “Please like this post”) increases Negatives, particularly when the audience is narrower. Asking consumers to enter a competition also has a similar undesirable effect.

In sum, to generate favorable attitudinal responses (increasing Likes and decreasing Negatives), content should be relevant to the brand but not come across as overt marketing attempts in the persuasive style of, for example, traditional advertisements. Having lower message clarity, in addition to making a post seem less overtly persuasive and instead more conversational (and thus in line with the norms on Facebook), could also be effective because a message that is not extremely easy to follow might draw consumers in and generate interest, which is indicated by increased Likes (however, this will also increase Negatives, probably because some consumers will be frustrated or annoyed). In terms of differences in content effects due to changes in audience mix, it seems that narrower audience mixes of mostly core consumers are slightly more sensitive to persuasive or "pushy" posts (e.g., indicated by the stronger effect of engagement calls to action on Negatives at lower audience mix). This is consistent with our argument that posts violating the social communication norms of Facebook are likely to lead to less engagement, which should be most pronounced for core fans who "know" the brand well.

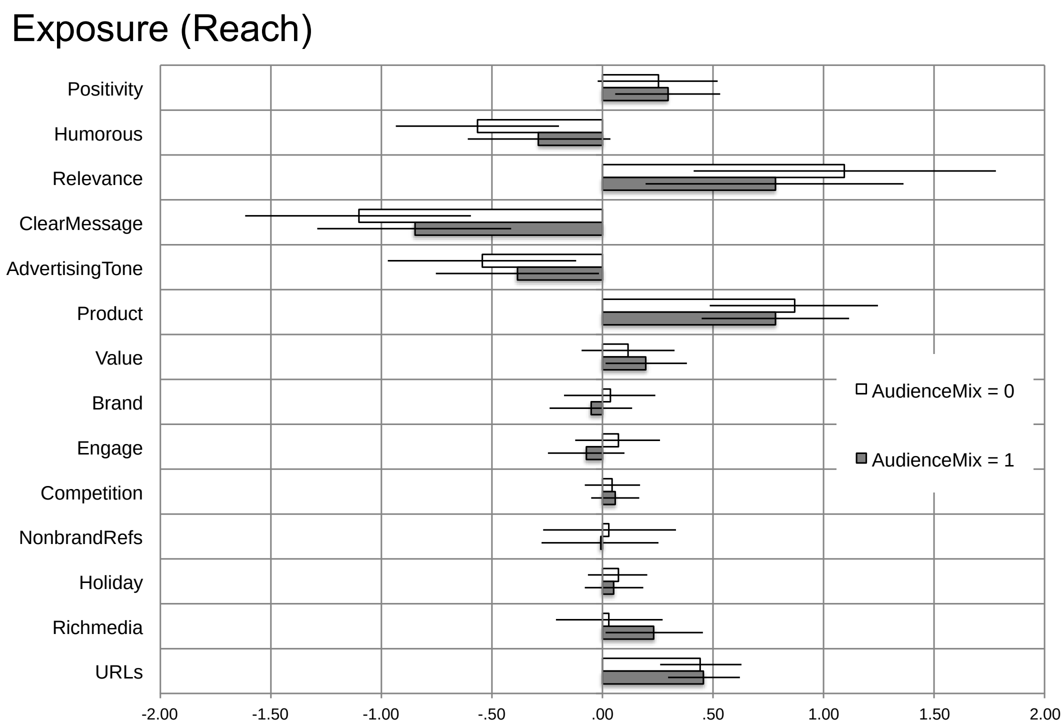
How do content characteristics affect marketing outcomes (Reach, Comments, Shares, Clicks)? We now consider the effects of content characteristics on the four engagement-related marketing outcomes: exposure (Reach), feedback (Comments), WOM (Shares), and website traffic referrals (Clicks). Content characteristics could affect these directly, as well as indirectly through attitudinal responses (Likes, Negatives). We report standardized total effects, where a variable's total effect is the sum of its direct and indirect effects (standard errors for the total effects were computed using the delta method; e.g., Greene 2003). Table 5 reports the total effects (see Appendix E for the direct effects on marketing outcomes). Figures 3 and 4 are spotlight analysis plots of the standardized effects at narrow (*AudienceMix* = 0) and wide (*AudienceMix* = 1) audiences (error bars are 95% confidence intervals). We found that a number of content characteristics affected these marketing outcomes, directly and indirectly through attitudinal responses. Also, the characteristics that have the strongest effects on these outcomes tend to have their effects mediated by attitudinal responses.

Table 5: Standardized Total Effects of Content Characteristics and Audience Mix on Marketing Outcomes

		Reach			Comments			Shares			Clicks		
		Est.	SE		Est.	SE		Est.	SE		Est.	SE	
Arousal-oriented	Positivity	.25	.13	*	-.34	.21		-.03	.24		.56	.37	
	Positivity x Mix	.08	.05		.02	.08		.04	.09		-.07	.13	
	Humorous	-.57	.18	***	-.40	.29		-.62	.34	*	.99	.72	
	Humorous x Mix	.09	.03	***	-.02	.04		-.05	.05		-.03	.07	
Persuasion-oriented	Relevance	1.09	.34	***	1.90	.56	***	2.40	.66	***	-1.12	1.24	
	Relevance x Mix	-.02	.09		-.30	.14	**	-.15	.16		-.26	.22	
	ClearMessage	-1.10	.25	***	-1.43	.43	***	-2.32	.50	***	.17	.86	
	ClearMessage x Mix	-.11	.10		.21	.16		.16	.19		.14	.26	
	AdvertisingTone	-.55	.21	**	-1.07	.34	***	-1.23	.39	***	.66	.75	
	AdvertisingTone x Mix	.00	.06		.05	.09		.04	.11		.29	.15	*
Information	Product	.86	.19	***	.45	.29		.44	.33		.65	.51	
	Product x Mix	.01	.01	*	.02	.01		.00	.02		-.04	.02	*
	Value	.12	.11		-.45	.17	**	-.31	.20		-.49	.29	*
	Value x Mix	.01	.01		.01	.01		.02	.01		-.03	.02	
	Brand	.03	.10		.41	.16	**	.39	.18	**	.12	.29	
	Brand x Mix	-.02	.01	**	-.01	.01		-.01	.02		-.04	.02	
Calls to Action	Engage	.07	.10		.38	.15	**	.19	.18		.46	.26	*
	Engage x Mix	-.03	.01	***	-.01	.01		.00	.02		-.01	.02	
	Competition	.05	.06		-.32	.10	***	-.20	.11	*	-.76	.17	***
	Competition x Mix	.00	.01		.01	.01		.02	.02		-.03	.02	
References	NonbrandRefs	.03	.15		.83	.23	***	.85	.26	***	1.02	.40	**
	NonbrandRefs x Mix	.00	.01		.00	.01		.00	.01		-.01	.02	
	Holiday	.07	.07		.01	.11		.01	.13		.29	.19	
	Holiday x Mix	.00	.01		-.01	.01		-.01	.01		-.05	.02	**
Media Elements	RichMedia	.03	.12		-.15	.18		-.30	.21		-.54	.33	
	RichMedia x Mix	.07	.02	***	.06	.03	**	.20	.03	***	-.12	.05	**
	URLs	.44	.09	***	.50	.15	***	.54	.17	***	.16	.33	
	URLs x Mix	.06	.01	***	.09	.02	***	.07	.02	***	-.03	.03	

* $p < .10$, ** $p < .05$, *** $p < .01$. Total effect = direct effect + indirect effects through attitudinal responses. Standard errors computed using the delta method.

Figure 3: Standardized Total Effects of Content Characteristics at Different Levels of Audience Mix on Reach and Comments



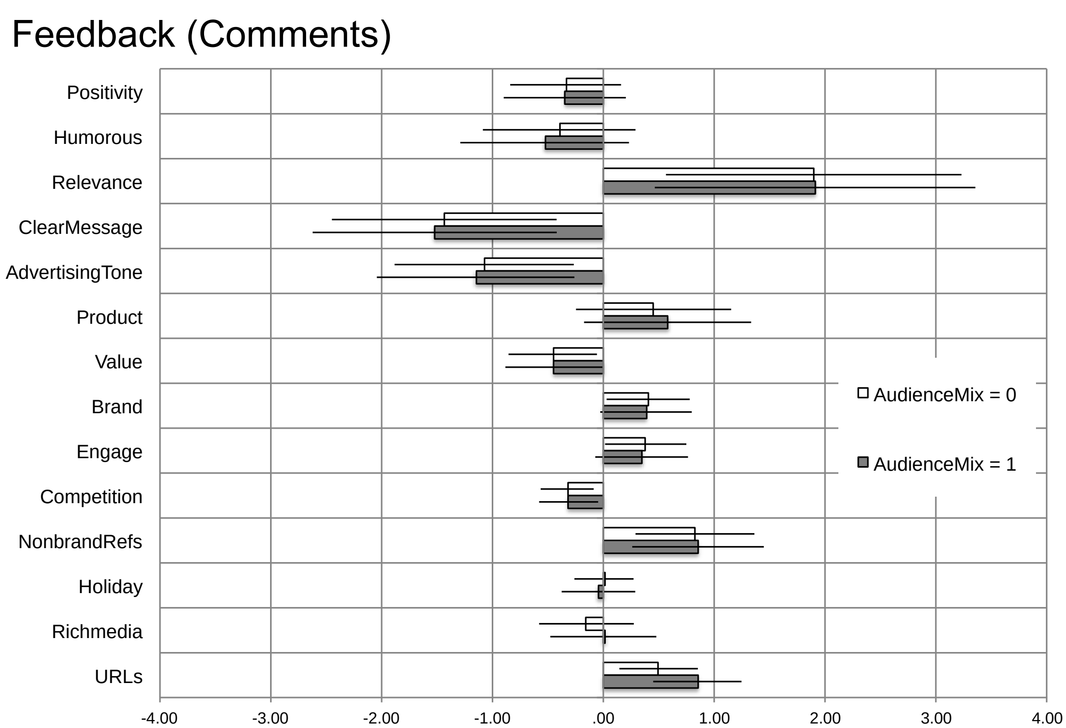
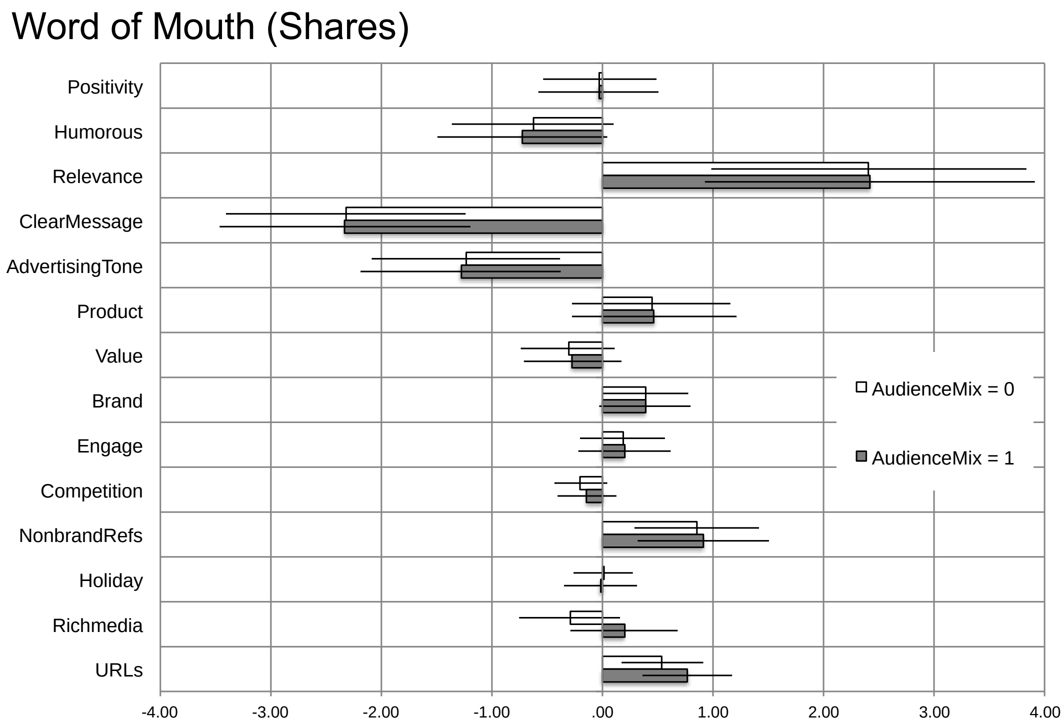
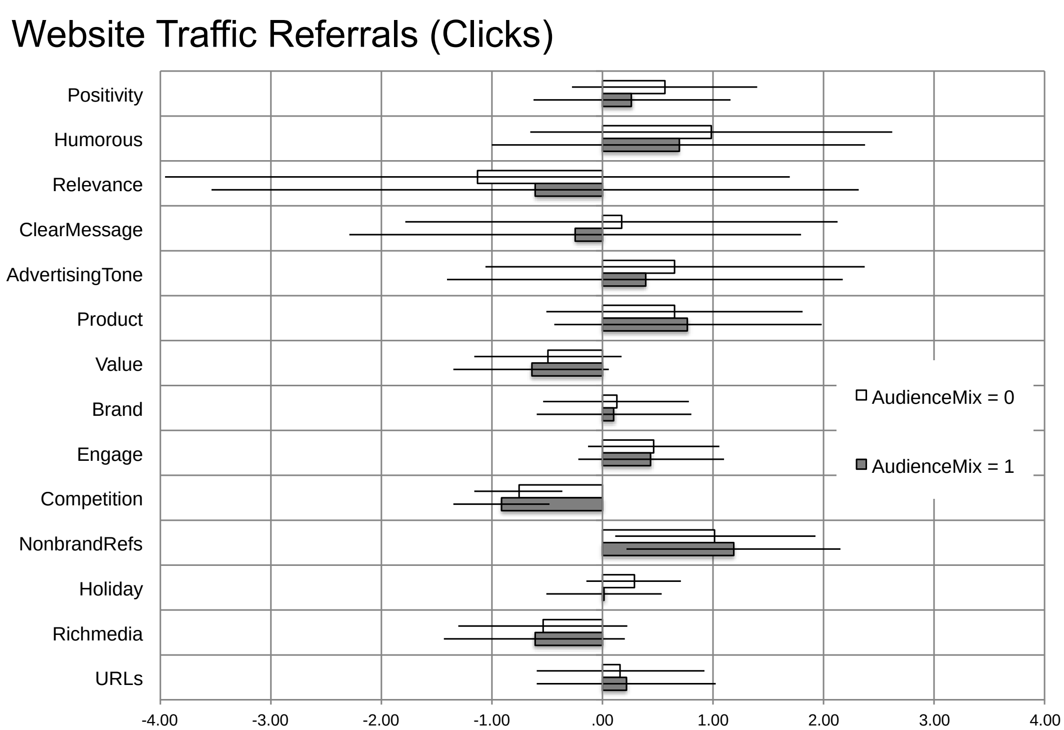


Figure 4: Standardized Total Effects of Content Characteristics at Different Levels of Audience Mix on Shares and Clicks





Similar to our findings for positive attitudinal responses, the three persuasion-oriented content characteristics have relatively strong effects on the majority of the marketing outcomes (except for Clicks, which were largely unaffected by the many content characteristics tested). As we saw for Likes, relevance of the message to the brand had a positive effect on Reach (exposure), Comments (feedback), and Shares (WOM). Similarly, advertising tone and message clarity both had negative effects on these three outcomes. Taken together with the findings reported above for attitudinal responses, it appears that branded content on Facebook that attempts to overly persuade consumers through the inclusion of certain hallmarks of traditional advertising will not be effective in generating a variety of important consumer engagement actions. As mentioned earlier, this could be because such content violates social communication norms and is inconsistent with consumers' expectations in that setting.

In addition to the effects of persuasion-oriented content characteristics, we find a number of other interesting influences on marketing outcomes that should be highlighted. First, information- and arousal-oriented content characteristics are important for increasing Reach. Including product-related information increases Reach, but providing other types of information (value- or brand-related) has no effect. Providing specific, concrete product information seems to be important for generating exposure. In terms of arousal and Reach, using a positive tone slightly increased Reach, and humor decreases Reach (although the negative effect is mitigated by increasing audience mix, suggesting that non-core consumers are more forgiving when it comes to brands' attempts to be funny).

Second, information-oriented characteristics also influences the amount of feedback posts received (Comments) and the tendency for consumers to spread WOM (Shares). However, unlike for Reach, where more concrete and specific product-related information have a positive effect, for Comments and Shares we find that the inclusion of more general brand-related information lifts these two engagement behaviors. This suggests that consumers seem to be more inclined to talk about—either through commenting on a post or spreading WOM to their friends—branded content that is more general. Content that is more specific (product-related information) seems to increase exposure but not these more involved forms of engagement. Also, we find a negative effect of the inclusion of value-related information (e.g., about pricing) on Comments. This is consistent with our earlier argument that violations of social communication norms on Facebook results in less engagement, since talking about money or pricing is not normally done in social contexts.

Finally, also consistent with this argument is the finding that calls to action affects the amount of feedback (Comments) received by posts. On the negative front, encouraging consumers to enter a competition has a negative effect on Comments. This is probably a reactance-type response and is consistent with the notion that asking (or telling) people to do something is not normal in social communications. On the positive front, however, it is normal to ask questions and for people to answer those questions. In line with this, we find a positive effect of asking for feedback (questions, comments) on Comments.

GENERAL DISCUSSION

Our research seeks to understand how characteristics of content posted by brands on social media, specifically Facebook, affects various types of consumer engagement. Despite the widespread use of social media marketing, and the growing body of literature on social media marketing and consumer behavior, surprisingly little is known about how branded content affects consumer behavior. From a substantive perspective, this is an important issue because social media is a fast-growing marketing communications channel and consumers are increasingly turning to social media platforms for not only social information (e.g., about friends' lives) but also news and brand information. Theoretically, we need a better understanding of consumer engagement with brands in social media because of the central role brands play in many consumers' lives and the fact that social media is now where many consumer-brand interactions occur. Specific to this research, it is theoretically interesting to identify the types of branded content that are more effective at engendering consumer engagement, and to see if it is what brands say (e.g., information characteristics) or how they say it (e.g., persuasion characteristics) that impacts engagement the most. We find that it is how brands communicate with consumers in social media that appears to be more influential in driving engagement behaviors.

More specifically, across engagement actions—attitudinal responses and marketing outcomes (except Clicks)—we consistently find that the persuasion-oriented content characteristics have relatively large effects. The findings about persuasion-oriented content characteristics shed light on how consumers expect brands to communicate with them in social media. Consumers appear to respond most favorably to content that is relevant to the brand (i.e., "on brand" or "on topic"), does not come across as an overt advertising-like persuasion attempt, and that is not overly polished or fluent in terms of the clarity of the message being conveyed. The positive relevance effect is not surprising, given that persuasion theory would suggest that content that is relevant (i.e., "on brand" or "on topic") should engender a higher level of processing motivation. Similarly, the negative effect of advertising tone is consistent with our arguments about persuasion knowledge and psychological reactance, and thus indicates that branded content that departs from norms of *social* communication on Facebook and is instead more like *marketing* communication tends to generate a variety of unfavorable engagement responses from consumers.

This is also the case for the negative effect of message clarity on almost all engagement actions considered here, which is a particularly interesting finding. A hallmark of conventional persuasive marketing communications or traditional advertising is fairly clear, fluent, and easily understood messages. Basically, advertising copy tries to convey information in a manner such that it can be quickly and easily understood. This is not the same for social communications, however. Instead, messages communicated between people often are not as polished or precise, particularly in social settings, including those online (e.g., Facebook). Thus, our finding that various types of consumer engagement with branded content *increases* when that content has *less* message clarity suggests that messages that are more like social communications and less like marketing communications are favored.

Combined with the negative effect of advertising tone, this suggests that the some of the hallmarks of conventional marketing communications—persuasive advertising copy, specific and clear messages—may not work well for brands in channels such as Facebook. Instead, brands may be better off acting more like a *social person* and communicating to consumers on social media in a less formal, less advertising-like style. Further evidence for this was found with respect to the effects of certain types of "calls to action" on Comments. If a call to action in a post was consistent with social communication norms, such as asking a question or asking for consumers' thoughts or ideas, the post received more Comments. On the other hand, if a call to action was inconsistent with such norms, such as telling consumers to enter a competition, there was a negative effect on Comments (i.e., a reactance-type response). More research is needed to better understand this, however the findings reported here suggest that a key reason for why branded content will or will not drive consumer engagement in social media lies in the extent to which the branded content is consistent with the social communication norms of the social media channel in which the content is disseminated.

Although not the primary focus of this research, we included a number of content characteristics that were not central to testing if what is said versus how it is said matters more for consumer engagement with branded content. These were included because they are fairly common in branded social media content that we observed and/or are considered by industry experts to be important drivers of engagement (i.e., “best practices”). Interestingly, we found many of these content characteristics consistently did *not* affect engagement. One example is posts that mention holidays. This is a common content characteristic used by marketers, however there is no evidence in our analysis that it affects engagement at all. Another example is the inclusion of rich media elements such as images or videos. Marketers consider this to be extremely important and devote costly resources to producing higher-quality images and videos. However, there was little evidence to suggest that this affected engagement. Consistent with this, some social media managers have recognized the limits of costly-to-produce rich media elements (Hutchinson 2015). In general, it seems that much of what social media marketers do is either ineffective or, worse, backfires on them.

In addition to testing the effects of content characteristics on engagement, recall that we also sought to see if the type of consumer audience moderated these effects. As discussed earlier, we used audience mix—narrow/core fans versus wide/core and non-core fans—as a proxy for the extent to which a post was seen by only those consumers who know the brand well and interact with it a lot on Facebook (core fans, narrow audience mix) or instead by a broader audience that extended to include non-core fans and thus a wider mix. Our initial thinking was that some types of content might work best for core fans and other types of content might work best for non-core fans. This did not appear to be the case, and the majority of the interaction effects with audience mix in our model were not significant. Those that were significant simply strengthened or attenuated an effect, instead of turning it on or off or reversing its sign. We did find, however, that some of the moderating effects of audience mix that strengthened or attenuated an effect were informative in the sense that they corroborated our arguments about content generating more engagement if it was consistent with social communication norms on Facebook. Nevertheless, audience mix (which is influenced by brands' decisions to pay Facebook to reach wider audiences) does not appear to play a major role here. This could be for many different reasons (and is an interesting avenue for future research), though a simple explanation is that regardless of a post's audience, the only consumers who really pay attention to it are the core fans. Hence, even if audience mix is wider and encompasses non-core fans in addition to core fans, content will only be attended to by the core fans. If this is true, this casts serious doubt over the value that brands get from paying Facebook to widen a post's audience.

To conclude, we consider a number of limitations of this study and suggest some directions for future work in this area. First, we considered only Facebook. Brands conduct social media content marketing across a range of platforms (e.g., Facebook, Twitter, Instagram, Pinterest) and use different content and styles on different platforms. We focused on Facebook because of data availability and, more critically, its popularity as the major social media platform used by both consumers and brands in the world. We have no reason to suspect that our findings would not hold in other social media platforms that allow brands to post content with text and/or visual elements (images, videos) and that allow consumers to engage with that content in similar ways as on Facebook. Nevertheless, an interesting extension of this research would be to look at branded content on other types of social media platforms.

Second, the dependent variables are imperfect measures of engagement and, specifically, consumers' attitudinal responses to content and the four marketing outcomes. We used these variables because they are measured by Facebook and provided to all brand page owners for free; that is, they are standard measures in this industry. They cannot, however, capture all marketing outcomes triggered by posts because they do not account for off-Facebook behaviors (e.g., WOM *on Facebook* is measured by Shares but WOM outside of Facebook due to branded content on Facebook is obviously not captured in the Shares measure). They also do not measure consumer-brand engagement more deeply. Nevertheless, we believe that these measures are good indicators of off-Facebook actions as well as more abstract constructs.

Finally, our results are limited to a set of nine brands in a finite time window. Although not a representative sample, the nine brands included in our data cover a broad set of industries and are different sizes (e.g., one brand is one of the world's best-known brands, whereas another is well known only within the geographic region it serves). Thus, we feel that there is sufficient variation between the brands to make this a reasonable sample. Nevertheless, we do not make claims about broad generalizability of our findings to other industries.

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Appendix A: Brand Information

Industry	Description	Number of Posts	Approximate Facebook Audience
CPG Laundry	Laundry detergent for sensitive skin	249	300,000
CPG Laundry	All purpose laundry detergent	246	300,000
Retail	Wholesale warehouse club	414	150,000
Quick-service restaurants	Fast-food dessert/ice-cream chain	551	7,000,000
Quick-service restaurants	Fast-food burger chain	542	30,000,000
Sports	Collegiate sports team	1,189	130,000
CPG Laundry	Fabric softener	598	700,000
CPG Laundry	All purpose laundry detergent	419	300,000
Retail	Gas and convenience store chain	76	200,000

Appendix B: Items Used For Content Coding

Variable	Items	Measurement
Arousal-oriented		
Positivity	The post makes me feel enthusiastic. The post is motivational/inspirational. The post makes me feel happiness. This post was engaging. I thought the post was entertaining. The post captured my attention.	1 = SD to 5 = SA, $\alpha = .91$
Humorous	The post is funny/humorous.	1 = SD to 5 = SA
Persuasion-oriented		
Relevance	The post is consistent with the brand. The post fits with the brand. The post makes sense for this brand. The post is relevant to the brand.	1 = SD to 5 = SA
ClearMessage	The post makes sense. The message being conveyed is clear and easy to grasp.	1 = SD to 5 = SA
AdvertisingTone	This post feels like an advertisement for the brand.	1 = SD to 5 = SA

Information		
Product	This post provides information on how to use the product/brand. This post provides information on a benefit or feature of the product/brand. This post provides information on occasions to use the product/brand. The post directly promotes a new product.	0 = no, 1 = yes
Value	The post provides information on pricing. The post includes or mentions a coupon.	0 = no, 1 = yes
Brand	The post provides news about the firm, product, or brand. The post directly promotes an event.	0 = no, 1 = yes
Calls to Action		
Engage	The post poses a question for users to respond. The post explicitly requests users to post a picture. The post explicitly requests users to “like” the post. The post explicitly requests users to “share” the post. The post explicitly requests users to click on a link.	0 = no, 1 = yes
Competition	The post mentions or includes a contest or sweepstakes. The post includes or mentions a product give-away.	0 = no, 1 = yes
References		
NonbrandRefs	The post directly promotes a charity or charitable cause. The post mentions a charitable fund, foundation, institution, or day. The post mentions or highlights the sponsorship of another organization, brand, or event.	0 = no, 1 = yes
Holiday	The post mentions a major holiday or mentions “holidays” in general (e.g., major holidays would include New Years Day, Memorial Day…). The post highlights or mentions a special occasion NOT considered a major holiday or special day (e.g., minor holidays such as “national bosses day” or “national cake day”)	0 = no, 1 = yes
Media elements		
RichMedia	The post contains a picture (NOT including a thumbnail image for videos or links). The post contains a link to a video (a video that would open in a new tab or window to play). The post contains an embedded video (a video that plays within the post and DOES NOT open in a new tab or window).	0 = no, 1 = yes
URLs	The post contains a link to another webpage (i.e., NOT a video link).	0 = no, 1 = yes

Appendix C: Correlations Between Content Characteristics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Positivity	1	1.00													
Humorous	2	.31	1.00												
Relevance	3	.16	-.06	1.00											
ClearMessage	4	.24	-.09	.48	1.00										
AdvertisingTone	5	.03	-.01	.61	.26	1.00									
Product	6	.00	-.02	.16	.09	.29	1.00								
Value	7	.00	-.06	.11	.09	.24	.12	1.00							
Brand	8	-.02	-.19	.20	.07	.12	.07	.02	1.00						
Engage	9	.00	.07	-.15	.02	-.08	-.02	-.06	-.28	1.00					
Competition	10	.03	-.05	.00	.00	.07	-.02	.03	.04	.03	1.00				
NonbrandRefs	11	.09	-.09	-.06	.01	-.04	-.03	-.03	.21	-.07	.08	1.00			
Holiday	12	.05	.06	-.17	.05	-.11	.02	-.02	-.11	.05	-.06	-.04	1.00		
Richmedia	13	.21	.09	.18	.06	.20	.07	.00	.09	-.15	-.02	-.01	-.02	1.00	
URLs	14	.01	-.13	.15	.06	.15	.03	.10	.27	-.14	.12	.17	-.10	.00	1.00

Appendix D: Error Variance-Covariance Matrix

	Likes	**Negatives**	**Reach**	**Comments**	**Shares**	**Clicks**
Likes	1.35					
Negatives	.55	.85				
Reach	.31	.40	.54			
Comments	.28	.27	.24	1.06		
Shares	.36	.49	.24	.35	1.08	
Clicks	-.06^{ns}	-.06^{ns}	-.07	-.04^{ns}	.14	2.18

All error variance and covariance parameters are significant (all $p < .05$) unless indicated by ns.

Appendix E: Direct Effects of Content Characteristics, Audience Mix, and Attitudinal Responses on Marketing Outcomes

		Reach			Comments			Shares			Clicks		
		Est.	SE		Est.	SE		Est.	SE		Est.	SE	
Attitudinal Responses	log(Likes + 1)	.10	.03	***	.54	.06	***	.75	.05	***	.24	.13	*
	log(Likes + 1) x Mix	-.13	.02	***	.11	.05	**	.06	.05		.45	.10	***
	log(Negatives + 1)	.35	.06	***	.07	.10		-.37	.10	***	.61	.19	***
	log(Negatives + 1) x Mix	-.08	.02	***	.00	.05		-.04	.05		-.35	.11	***
Arousal-oriented	Positivity	.32	.40		-1.11	.80		1.27	.80		1.37	1.68	
	Positivity x Mix	.20	.09	**	.04	.17		.06	.18		-.20	.36	
	Humorous	-.73	.38	*	.35	.75		-.39	.79		4.97	2.17	**
	Humorous x Mix	.24	.07	***	.00	.13		.05	.14		-.20	.28	
Persuasion-oriented	Relevance	2.22	.72	***	3.10	1.47	**	3.40	1.58	**	-6.65	3.92	*
	Relevance x Mix	.05	.12		-.43	.24	*	-.02	.25		-.40	.50	
	ClearMessage	-2.79	.83	***	-2.56	1.60		-6.23	1.86	***	5.77	3.94	
	ClearMessage x Mix	-.37	.14	***	.15	.28		-.03	.28		.03	.58	
	AdvertisingTone	-.89	.32	***	-1.28	.65	**	-.89	.66		2.31	1.70	
	AdvertisingTone x Mix	-.07	.08		.19	.17		.29	.17	*	.55	.35	
Information	Product	3.54	.71	***	.49	1.34		.02	1.36		1.94	2.87	
	Product x Mix	.23	.09	**	.17	.19		-.31	.19		-.72	.39	*
	Value	1.44	.52	***	-2.31	1.08	**	-.84	1.07		-2.63	2.22	
	Value x Mix	.23	.12	**	.20	.23		.13	.24		-.59	.48	
	Brand	.31	.32		1.36	.63	**	.57	.64		.79	1.34	
	Brand x Mix	-.26	.09	***	.07	.18		.18	.19		-.50	.38	
Calls to Action	Engage	-.04	.27		1.51	.53	***	.80	.53		1.48	1.12	
	Engage x Mix	-.36	.10	***	-.42	.20	**	-.37	.21	*	-.15	.43	
	Competition	.09	.32		-2.12	.65	***	-.42	.64		-6.12	1.40	***
	Competition x Mix	.11	.11		-.03	.23		.17	.23		-.60	.47	

		Reach			Comments			Shares			Clicks		
		Est.	**SE**		**Est.**	**SE**		**Est.**	**SE**		**Est.**	**SE**	
References	NonbrandRefs	.24	.74		4.62	1.39	***	3.10	1.39	**	7.40	2.99	**
	NonbrandRefs x Mix	.02	.16		-.17	.34		.26	.34		-.65	.69	
	Holiday	.31	.27		-.18	.58		-.18	.56		1.70	1.19	
	Holiday x Mix	-.02	.18		-.20	.37		.00	.38		-1.65	.78	**
Media Elements	RichMedia	1.01	.44	**	-.53	.84		-2.19	.86	**	-.91	1.78	
	RichMedia x Mix	.59	.11	***	.55	.23	**	1.84	.23	***	-1.41	.46	***
	URLs	.57	.28	**	.59	.60		1.10	.61	*	-1.48	1.41	
	URLs x Mix	.53	.08	***	.83	.17	***	.44	.17	**	-.69	.35	**
Other Variables	Mix	3.05	.54	***	-.90	1.11		-3.36	1.13	***	1.49	2.29	
	Lag log(Reach + 1)	.13	.01	***	–	–	–	–	–	–	–	–	–
	Lag log(Comments + 1)	–	–	–	.14	.02	***	–	–	–	–	–	–
	Lag log(Shares + 1)	–	–	–	–	–	–	.14	.02	***	–	–	–
	Lag log(Clicks + 1)	–	–	–	–	–	–	–	–	–	.17	.04	***
	log(Interpost Time)	.05	.02	***	.09	.04	**	.19	.05	***	-.15	.09	*
	Month	-.02	.01	***	-.01	.02		-.02	.02		.18	.03	***
	Intercept	11.59	2.44	***	5.43	4.71		13.03	5.45	**	-27.73	11.08	**
	Brand 1	.99	.18	***	-.92	.34	***	-.95	.37	**	2.83	.81	***
	Brand 2	1.16	.19	***	-1.52	.34	***	-1.18	.36	***	1.12	.74	
	Brand 3	-1.10	.31	***	-1.67	.63	***	-1.25	.70	*	3.51	1.51	**
	Brand 4	1.71	.24	***	-.69	.46		.18	.47		.47	1.05	
	Brand 5	2.25	.31	***	-.33	.61		-.57	.63		3.12	1.37	**
	Brand 6	.10	.47		-3.26	.95	***	-2.79	.99	***	6.31	2.54	**
	Brand 7	1.28	.21	***	-2.19	.35	***	-1.80	.37	***	.02	.78	
	Brand 8	1.47	.21	***	-2.11	.40	***	-1.80	.43	***	1.02	.81	
	Control residuals	Yes			Yes			Yes			Yes		

* $p < .10$, ** $p < .05$, *** $p < .01$. Mix ranges from 0 to 1. For brand fixed effects, Brand 9 is the reference brand