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The Effects of Content Characteristics on Consumer Engagement with Branded Social Media Content on Facebook

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Report Summary

Social media content marketing—designing brand content that is disseminated to consumers through social media—requires complex decision making, yet marketers lack a systematic understanding of how to design and disseminate content to maximize engagement and related marketing outcomes.

Andrew Stephen, Michael Sciandra, and J. Jeffrey Inman address this problem in the context of branded content on Facebook. They consider two aspects of marketers' decision making: design (i.e., what should each post say and look like?) and dissemination (i.e., to whom should each post be targeted?).

They use a dataset of 4,284 branded Facebook posts made over an 18-month period by nine brands across four industries to understand how marketers' social media content design decisions influence measurable consumer engagement outcomes (e.g., how many "likes" or "shares" posts are received or how many website traffic referrals are made).

They develop a typology of 14 social media content characteristics and propose and test a conceptual framework linking them to engagement outcomes. They also consider the increasingly common practice of brands paying to boost post reach on Facebook, which results in posts being seen by a wider (but possibly less relevant) audience.

Findings and implications

The authors find that persuasion-oriented content characteristics (relevance, message clarity, and advertising tone) are consistently important drivers of all engagement actions. Overall, content characteristics matter more than audience mix (which is influenced by marketers' decision to pay to boost post reach).

Contrary to marketing content in traditional channels, however, consumers appear to dislike and react against overt persuasion attempts in branded social media content. While content that is relevant to the focal brand generates more desirable engagement actions, adopting an advertisement-like tone works *against* marketers' goals (i.e., generates more negatives).

In particular, the authors suggest that marketers avoid a "hard sell" with core consumers on Facebook since they are somewhat less forgiving and more sensitive to pushy messages.

Further, for branding content, being informative in a general sense is insufficient; different types of information trigger different outcomes. For example, providing specific product-related information helps increase how many times a post is liked and its reach, but not other outcomes. Conveying general brand-related information in post is mostly ineffective, except for reducing negative reactions and increasing WOM.

Finally, the authors find, many current social media "best practices" (e.g., mentioning holidays, using rich media elements, or using calls to action) consistently have little impact on consumer engagement.

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Content marketing is an approach to marketing communication in which brands create and disseminate content to consumers with the intention that the content generates interest, engages consumers, and influences behavior. This has become increasingly popular in recent years (DeMers 2014), with 90% of marketers stating that they use content marketing in some form and 60% intending to increase content marketing in the near future (Pulizzi and Handley 2014). A particularly common form of content marketing takes place on brands' social media accounts or pages (e.g., in 2014, 80% of *Fortune 500* companies used Facebook for marketing purposes; Barnes and Lescault 2014). *Social media content marketing* involves marketers creating branded content that is disseminated to consumers through brand-owned social media channels, such as brand pages on Facebook. Marketers hope that consumers will see and "engage" with content (e.g., liking, sharing), which is believed to help drive marketing outcomes such as increased brand exposure, website traffic, or word of mouth (WOM).[1] However, despite some initial evidence suggesting that social media content marketing can be more effective than traditional advertising (Neff 2014), marketers remain unsure about their social media content strategies (Pulizzi and Handley 2014).

These concerns likely arise due to marketers lacking a systematic understanding of how to design and disseminate branded social media content in order to maximize engagement and related marketing outcomes such as website traffic referrals, WOM, or even sales. This research addresses this problem in the context of branded content on Facebook.[2] Marketers' social media content marketing decisions can be divided into two types: content design (i.e., what should each post say and look like?) and content dissemination (i.e., to whom should each post be targeted?). In this research we consider both by examining how they affect consumers' engagement with branded social media content.

The extent to which marketers control content design and dissemination varies considerably. With respect to content design, marketers have complete control over their posts, which means that they make decisions about the focus of each post, the post's appearance/layout,

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[1] In general terms, we consider engagement with branded social media *content* (i.e., a post) to refer to the set of consumer-determined actions such as "liking" or "sharing" the content that may signal consumers' attitudes toward and/or behavioral intentions with respect to the content and brand. Prior research has established that consumer engagement in general can be an antecedent of favorable brand perceptions, brand attitudes, and customer loyalty (Sprott, Czellar, and Spangenberg 2009).

[2] Facebook is one of many social media platforms used by brands. We focus on Facebook because it is a highly active platform that is used by a broad cross-section of global consumers on a regular basis. It is also the most popular platform for social media content marketing (Pulizzi and Handley 2014).

the types of information conveyed, and how messages are communicated. Despite this high degree of control, given the large array of options, designing branded social media content involves a relatively complex set of decisions. Unlike content design, marketers have very little direct control over content dissemination and, thus, who ultimately sees their posts.[3] Typically on major social media platforms such as Facebook it is not possible to target particular posts at specific consumers and available targeting options (e.g., based on demographics and location) are unlikely to be as accurate as more precise forms of targeting such as direct mail. On Facebook, a brand's posts are seen by various consumer types, ranging from people who are existing members of a brand's fanbase—core consumers who frequently engage with the brand and are likely targets—to people who are non-core consumers who rarely (if ever) engage with the brand. Facebook's content-assignment algorithm ("EdgeRank") automatically determines in real time the posts each user sees in their newsfeed. Even though marketers cannot precisely target specific individuals, on Facebook they can influence a post's audience mix, which is the extent to which a post's audience is narrower (mostly core consumers see a post) versus wider (the audience expands to include non-core consumers). On Facebook, audience mix is influenced by marketers deciding to pay to increase reach, a practice called "boosting."[4] When a post is *not boosted* it will have a smaller reach that tends to be biased toward core consumers (i.e., narrower audience mix).[5] On the other hand, when a post is *boosted* it will have a larger reach that invariably includes more non-core consumers (i.e., wider audience mix).

In this research, we consider how marketer-determined decisions about content characteristics (design) and audience mix through paying to boost post reach (dissemination) influence several common post-level social media engagement metrics with an empirical study of thousands of branded Facebook posts from several different brands. We use post-level engagement metrics as measures of consumers' *attitudinal responses* to content (e.g., positive responses indicated by "likes") and meaningful *marketing outcomes* triggered by content (e.g.,

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[3] We note that this might change over time as platforms such as Facebook introduce more targeting options. For example, beginning in September 2014, Facebook offered marketers the ability to target boosted posts at users based upon demographics and interests (Vertical Response 2014). However, the options are still very rudimentary.

[4] Although this practice was pioneered by Facebook, other platforms such as LinkedIn and Twitter have implemented their own "content filtering" systems in attempts to enhance user experience by using algorithms to allocate to users only those posts that are expected to be relevant based on users' previous actions.

[5] This is because one criterion used by Facebook's algorithm when assigning a brand's post to users is based on users' engagement with previous posts from that brand. Facebook's goal is to show users content that they will be interested in and deem relevant, and past engagement behavior is assumed to be a predictor of future engagement.

website traffic referrals indicated by "clicks" and WOM indicated by "shares"). Although we test how both content characteristics (design) and audience mix (dissemination) affect these metrics, our main focus is on content design since marketers have complete control over this aspect of social media content marketing decision-making.

We address two central research questions: (1) how do various types of content characteristics affect consumers' engagement actions related to their attitudinal responses to content and marketing outcomes, and (2) does audience mix (reaching a narrower audience of mostly core consumers vs. reaching a wider audience of core and non-core consumers) moderate these effects? The first question represents our primary focus on how branded social media content should be designed, and the second question explores the possibility that different types of consumer audiences react to content in different ways. We use a unique dataset of 4,284 branded Facebook posts made by nine brands over 18 months in 2012 and 2013. While confidentiality agreements preclude us from revealing the brands, they represent four industries (consumer-packaged laundry goods, retail, quick-service restaurants, and sports), and their total Facebook fanbase sizes ranged from around 130,000 to 30 million at the time of data collection.

Background

Understanding marketers' attempts to communicate with consumers through various forms of content is a well-researched topic in the marketing literature. The content of a marketing communication, which refers to what is said and shown in a marketing message, is important and has been linked to persuasion-related outcomes (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) developed a procedure for assessing the informational content of television ads, and Olney, Holbrook, and Batra (1991) and Sing and Cole (1993) studied how the informational and emotional content of television advertisements impact advertising effectiveness. Similar work has been done for print advertisements (e.g., Turley and Kelley 1997), and more recent studies have attempted to link traditional advertisement content characteristics to purchasing behavior (Bertrand et al. 2010; Liaukonyte et al. 2014). Relatedly, researchers have examined how content- and product-related factors affect advertising performance for digital advertising

with respect to online display (e.g., Goldfarb and Tucker 2011; Lohtia, Donthu, and Hershberger 2003) and mobile advertisements (e.g., Bart, Stephen, and Sarvary 2014; Danaher, Smith, Ranasinghe, and Danaher 2015; Drossos et al. 2007).

In contrast to the rich literature examining marketing communication content for conventional advertising in both traditional and digital channels, work that considers content in newer forms of marketing communication such as branded social media posts is scant, albeit with a few noteworthy exceptions. First, although not directly related to social media content marketing because of its focus on news articles instead of branded social media content, Berger and Milkman's (2012) study of *New York Times* articles shows that one type of social media engagement outcome—sharing content with friends, in their case via email—is affected by content characteristics, particularly how arousing a news article is perceived to be. Second, Kumar, Bhaskaran, Mirchandani, and Shah (2013) discuss the importance of content (or messaging) as part of social media campaigns for brands, however they focus primarily on WOM- and social influence-related factors as part of their framework for measuring the value of social media marketing and thus do not closely examine the role of content in driving social media engagement metrics. Third, closer to the current research, 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. Finally, Lee, Hosanagar, and Nair (2014) test how branded Facebook posts' numbers of likes and comments are influenced by two linguistic characteristics of post text (informativeness and persuasiveness) using natural language processing, finding that both are important.

Collectively, these studies suggest that social media content characteristics affect the extent to which consumers—as the audiences of brands' posts—engage with content. However, prior research has unfortunately focused on a limited set of outcomes that are not reflective of a more comprehensive (and managerially relevant) set of consumers' attitudinal and behavioral responses to branded social media content. Further, these studies look at narrower sets of content characteristics and, in the case of Lee et al. (2014), do not consider non-text aspects of posts such as rich media (e.g., images).[6] Prior studies also do not consider audience factors such as a post's audience mix or a post's reach. Our research therefore goes beyond these studies by (1)

[6] Lee et al. (2014) controls for the presence of non-text content, such as images, but does not go further by coding non-text aspects on potentially relevant dimensions and using these as covariates of interest in their model.

examining a more comprehensive and managerially relevant set of engagement actions as dependent variables, (2) considering a more comprehensive and specific array of content characteristics, and (3) assessing whether audience mix, which marketers influence through paid reach-boosting decisions, is important.

Conceptual Framework

The conceptual framework shown in Figure 1 provides a general description of how we expect branded social media content characteristics and post-level audience mix (narrower vs. wider) to be related to a number of 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.

(Figures and tables follow References.)

Attitudinal responses and marketing outcomes

An oft-stated objective for social media content marketing is the generation of "engagement" (Dubois 2014; Hemley 2013; Leung 2014). Engagement with content on social media platforms such as Facebook usually refers to consumers seeing posts and interacting with them in one of a number of ways, such as clicking "Like" or typing a comment under a post. 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).

Contrary to current marketing practice, we consider the measurable engagement actions taken by consumers in response to branded social media content (e.g., likes, comments, shares) to be indicators of underlying constructs. We treat these metrics as measures of consumers' attitudinal responses to content and of actual marketing outcomes. As shown in Figure 1, these are posited to be consequences of marketers' content design and dissemination 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).[7] On other social media platforms, equivalent 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.

A number of other measurable engagement actions represent actual outcomes of interest to marketers. We consider four outcomes in our framework. 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.

Content characteristics

Because of the flexibility afforded to marketers when designing branded social media content for platforms such as Facebook, many types of content characteristics can be considered. Prior research considers only a small set of content characteristics relevant to the current research. For example, De Vries et al. (2012) consider factors such as valence, Berger (2011) and Berger and Milkman (2012) consider arousal and emotionality, and Lee et al. (2014) consider the use of words associated with informativeness and persuasiveness.

[7] Although not as well known or as common as actions such as liking posts, Facebook users can mark a post as negative, which Facebook uses in its post-allocation algorithm. Some users treat this as a way to "dislike" posts. Interestingly, Facebook may be considering introducing a "dislike" button or something similar (Bell 2014).

We build on prior work by proposing a more comprehensive typology of content-related decisions available to marketers that captures the six categories of content characteristics referred to in Figure 1. These six categories of content characteristics and their specific elements were determined based on prior literature on social media-related content as well as older literature on advertising content mentioned earlier (e.g., factors such as arousal, persuasion, and information), an examination of branded social media content (particularly on Facebook) that led us to observe some common content characteristics used by brands (e.g., references to non-brand entities such as charities), and, finally, apparent "best practices" for social media content as reported in practitioner reports, white papers, and trade press (e.g., use of rich media elements). We now describe each content characteristic category and its components (see Table 1 for a summary).

Arousal-oriented. The first category is *arousal-oriented*. This refers to the extent to which branded content is designed with characteristics expected by managers to trigger—or arouse—affective responses in consumers. This includes generating positive emotional reactions (Berger and Milkman 2012), having positive valence (De Vries et al. 2012), or being humorous. Following prior literature, we consider two arousal dimensions: (1) positivity (how positive the post's tone is), and (2) humor (how funny or humorous the post is).[8]

Persuasion-oriented. The second category is *persuasion-oriented*. This refers to the extent to which branded content is designed with characteristics intended by managers to persuade or influence consumers' attitudes, opinions, or behaviors. Persuasion is a critical dimension in the traditional advertising literature, and has been considered in recent work in the context of social media (Lee et al. 2014). Often persuasion is considered in very general terms, such as the extent to which persuasive words or phrases are used in copy (e.g., Lee et al. 2014). We consider three specific elements that represent how persuasion-oriented a branded post is: (1) relevance (how appropriate the content is to, and fits with, the brand's image), (2) message clarity (how clear and fluent is the post's message), and (3) advertising tone (how much the post feels like or comes across as an advertisement).

These elements were chosen because they are context-specific indicators of three general factors known in prior literature to influence message persuasiveness or attitude change,

[8] Negativity could also be considered for social media posts more generally (i.e., including non-branded content), but in the case of brand-created content we do not expect managers to intentionally develop content that elicits negative responses and thus negativity is excluded from our typology

respectively: processing motivation (Petty and Cacioppo 1979), processing ability (Petty, Wells, and Brock 1976), and psychological reactance (Brehm 1966). First, message-brand relevance is important because content that seems to be incongruent with the focal brand could interfere with information processing and make a message less influential. 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. Second, message clarity is also important because more fluent messages (i.e., those that are more easily processed and understood) 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 and require fewer cognitive resources to do so. On the other hand, less fluent messages (lower message clarity) could also motivate active processing if consumers want to understand or have a comprehension-related goal. Finally, the extent to which a post has an advertising tone matters because if a message comes across to consumers as overtly persuasive in the sense that it feels like an advertisement, then consumers' persuasion knowledge could be activated (Friestad and Wright 1994). This, in turn, could lead consumers to be skeptical of the message as well as possibly psychologically react against it by going against the behaviors the message is either directly or indirectly advocating (e.g., purchasing a particular product, visiting a website, sharing information with a friend, going to a store).

Information. The third category is *information*. We consider the presence of specific types of information (e.g., price information, details about a promotional campaign, or mentioning particular product attributes), similar to research in the advertising literature (e.g., Resnik and Stern 1977). Prior research that considers information in social media posts (Lee et al. 2014) considers this in less detail than we do. Three types of information are considered: (1) product-related (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 (whether the post mentions value- or price-related information such as discounts or coupons), and (3) brand-related (whether the post mentions brand-related promotional information such as general news about the brand or brand-related events). These three types of information were selected because they correspond to components of a brand's marketing mix (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 take engagement actions such as "liking" a post, answering a question or leaving a comment, or following a link to an external website. 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 (Lee at al. 2014; 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 as a separate action because it is sufficiently common in practice to treat it separately 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).

Analysis

Data

We collaborated with nine brands to compile a unique dataset of branded social media content in the form of 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 1, however confidentiality agreements limit the information we can provide.

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. We assume each engagement or reach measure for the posts in our dataset is the "terminal" or final value of that time series; that is, each one is the maximum cumulative level reached for that post. Facebook does not provide time series data for post-level engagement and reach so our approach to data collection was to ask brands to download post-level engagement and reach data for our observation window a number of months after the end date of that window. Because of this, 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 rapidly decreases with the time since posting.

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). 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 consumers who are organically reached (due to EdgeRank).[9] 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

[9] Viral reach is also possible in the absence of 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.

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 wrote 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.[10] 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 collapsed them into single binary items that took

[10] Some extra measures were captured but not used because those characteristics turned out to be very uncommon.

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.[11]

The second stage had human judges 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.

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.

[11] An alternative specification for these variables was to average the multiple binary items. We did this and the results were robust to this different variable specification.

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.[12]

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. Although Facebook does not reveal the details of how EdgeRank works, it is generally known among social media marketers that the engagement and reach a brand receives for previous posts can affect the reach and engagement of subsequent posts. We allow for this through state-dependent effects; that is, in each equation we include one-post lags of all dependent variables as control variables.

Fourth, a brand's social media marketing prowess or, put differently, 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 decision variables. Brand fixed effects are used to help control for this possible relationship.[13]

Finally, the decision variables could be endogenous. Brand fixed effects help address this to the extent that endogeneity could come from 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 managers' decisions should be modeled as a formal learning process (cf. Erdem and Keane 1996) because not enough is known about how managers make social media content design and dissemination

[12] Specifically, for dependent variable y, the transformation is $\log(1 + y)$ where 1 is added to avoid taking logs of 0.
[13] 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 covariates in the model.

decisions.[14] Rather, we simply assume that there is some carryover from post to post, and therefore decision variables could be correlated with lagged decision variables. To address this we use 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).[15] Details of this are described next.

Empirical model specification

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 variable (i.e., each content characteristic and audience mix). 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 decision variable is regressed on its lag, the lags of all other decision variables, and, consistent with prior implementations of this approach and convention, the other covariates that appeared in the response functions (see below).[16] Thus, for decision variable $x_{k,ij}$, where k indexes the decision 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:

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

Where j -1 refers to the previous post made by brand i, $z_{m,ij}$ is the mth (out of M) exogenous covariate 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 decision variable into endogenous and exogenous parts (Danaher et al. 2015). Both $x_{k,ij}$ and $\delta_{k,ij}$ are then entered as covariates in the response

[14] Anecdotal evidence from conversations with some brands' social media managers suggests that a formal learning model would be inappropriate because managers instead try many approaches and test out new ideas without much structure, and sometimes repeat previously used approaches due to beliefs in their effectiveness.
[15] As Danaher et al. (2015) note, this is related to the residual approach in Stephen and Toubia (2010).
[16] Lagged decision variables can be thought of as similar to instruments. They are conceptually valid because prior and current decisions are related, but it is implausible for prior decisions to be (direct) drivers of current-post dependent variables. This is reasonable because on Facebook most users view branded posts in their newsfeeds, which means that branded posts are seen alongside unrelated posts and not close to previous branded posts.

functions that represent the conceptual model to be tested (see next section).[17] The inclusion of the residuals in the response functions decomposes each decision variable's effect on the dependent variables into exogenous and endogenous components (Danaher et al. 2015). Excluding control residuals combines these components into single, but biased, parameter estimates. Note that an alternative would be to replace decision variables with predicted values from Equation 1 (e.g., similar to 2SLS). However, Terza, Basu, and Rathouz (2008) show that the use of control residuals is superior, particularly when the residuals are probit residuals because $x_{k,ij}$ is binary (as is the case for most of our decision variables).

Response functions. The main part of our model involves estimating the effects of the decision variables on the six dependent variables, including interactions between audience mix and content characteristics, as well as the effects of the two attitudinal response dependent variables on the four marketing outcomes. Each dependent variable is 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 control functions, on each response for brand i's j^{th} post as follows:

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

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

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$_{ij}$]'. $\mathbf{1}$ 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). $\mathbf{B}_4$

[17] For the binary-scaled endogenous decision 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).

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.[18]

Results

Our results are reported across several tables and figures. In Table 3 we report fit statistics for the response function model in Equations 2 and 3. Four nested models are listed: (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. As shown in Table 3, both the mediation (3) and full (4) models fit well. Since the full model appears to fit slightly better than the mediation model, we base our results on it. We note that the mediation model, which corresponds to Figure 1, still has very good fit but it appears that allowing for direct effects of content characteristics on marketing outcomes (i.e., the full model) is empirically more appropriate. Thus, some of the effects of content characteristics on marketing outcomes are partially, not fully, mediated by attitudinal responses. In Table 4 we report error covariances, which due to their significance supports using a multivariate model.

Effects on attitudinal responses

We begin our reporting of results by considering how Likes and Negatives are affected by the fourteen content characteristics in our model and the extent to which audience mix moderates these effects. Attitudinal responses are important because, as we argue in our conceptual framework, we expect the managerial decision variables to influence the four engagement-related marketing outcomes through Likes and Negatives. Table 5 reports the unstandardized parameters for effects on Likes and Negatives, and Figure 2 plots standardized effects estimated at narrow (*AudienceMix* = 0) and wide (*AudienceMix* = 1) audiences (error bars are 95% confidence intervals). A number of content characteristics significantly affect Likes and

[18] Given the number of decision variables, we were concerned about possible multicollinearity. The mean correlation among content characteristics is .04 (SD = .14; see Appendix 3 for the correlation matrix), and all VIFs are small (M = 1.29, SD = .32, max. = 2.14). Thus, multicollinearity does not seem to be a problem.

Negatives, and audience mix moderates some of these effects. Thus, in general, marketers' content design and dissemination decisions appear to matter in terms of driving consumers' favorable and unfavorable attitudinal responses to branded Facebook posts.

In terms of affecting consumers' favorable attitudes (Likes), the most important content characteristics are persuasion oriented: relevance, message clarity, and advertising tone. As expected, the more a post is relevant to the brand and the less it feels like an advertisement, the more consumers like it (irrespective of audience mix). Interestingly, we also find a *negative* effect of message clarity on Likes; that is, the *less* fluent or clear a post's marketing message, the more consumers like it (and this is moderated by audience mix such that the effect is more negative for narrower audience mixes). This could be because clearer, more fluent messages are perceived as more persuasive (Lee and Aaker 2004), and consumers negatively react to posts that feel persuasive. Clearly, persuasion-oriented content characteristics are important, but to be influential in this context posts should not be overtly persuasive, which differs from traditional advertising wisdom.

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, could also be effective because a message that is not extremely easy to follow might draw consumers in and generate interest, which is detected 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 (indicated by the stronger effect of engagement calls to action on Negatives at lower audience mix). Finally, probably because they identify more closely with the brand, core consumers are also more receptive to general brand information (indicated by the stronger positive effect of brand-related information on Likes at lower audience mix).

Effects on marketing outcomes

We now consider the effects of content characteristics and audience mix on the four engagement-related marketing outcomes: exposure (Reach), feedback (Comments), WOM (Shares), and website traffic referrals (Clicks). We allowed the decision variables to affect these outcomes indirectly through attitudinal responses (per our conceptual framework) and directly (since restricting direct effects resulted in inferior model fit). We therefore focus here on standardized total effects, where a variable's total effect is the sum of its direct and indirect effects.[19] The total effects are reported in Table 6 (and the direct effects on marketing outcomes reported in Appendix 4). To illuminate interactions between content characteristics and audience mix, we plot standardized total effects of each content characteristic on each marketing outcome in Figures 3 and 4 estimated at narrow (0) and wide (1) audience mixes (error bars in Figures 3 and 4 are 95% confidence intervals). Finally, we note that while some content characteristics directly affect some marketing outcomes, the characteristics that seem to be most important (based on largest absolute total effect sizes) are mediated by attitudinal responses.

[19] We computed the standard errors for the total effects using the delta method (see, for example, Greene 2003).

Exposure (Reach). Persuasion-oriented characteristics are strong drivers of Reach. As with Likes, relevance positively affects Reach, and message clarity and advertising tone negatively affect Reach. Information- and arousal-oriented content characteristics also are important for increasing a post's audience size. Including product-related information increases Reach, but providing other types of information (value- or brand-related) has no effect. Thus, focusing posts on providing specific, concrete product information seems to be important. For arousal, a positive tone slightly increases Reach, but humor hurts (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). Other characteristics also influence Reach: including links/URLs to external websites helps, as does including rich media elements but only as audience mix gets wider.

Feedback (Comments). The three persuasion-oriented characteristics are also strong drivers of Comments, following the same pattern found for Reach. Information-oriented characteristics also encourage consumers to submit comments. However, for this outcome it is value- and brand-, but not product-related, information that matters. Providing general brand-related information increases Comments, but value-related information about things such as pricing decreases Comments. Calls to action also matter, with engagement requests (such as asking for comments or asking a question that can be answered in the comments box) increasing Comments (likely due to asking a question being a typical engagement request that is answered by writing comments). Inviting consumers to enter a competition reduces Comments, however. Finally, referring to non-brand entities increases Comments, as does including links to websites.

Word of mouth (Shares). Using content characteristics to encourage engagement by sharing posts with "friends" is important because it means that WOM is transmitted over one's social network. Encouraging social transmissions, however, can be difficult. Nevertheless, some characteristics do appear to help increase Shares. The three persuasion-oriented characteristics once again have strong effects directionally consistent with their effects on Reach and Comments. Other important factors are the inclusion of links to external websites, referring to non-brand entities (e.g., charities, sponsored sporting teams), and providing general brand-related information. Interestingly, providing concrete product- or value-related information does not matter, but including general brand-related information does positively affect Shares. Thus, consumers seem to be more inclined to spread WOM if a post is about something more general

(i.e., the brand) instead of something more specific (e.g., a new product), perhaps because they feel that general (vs. specific) information will have a greater chance of appealing to their friends' heterogeneous tastes.

Website traffic referrals (Clicks). Using social media content to generate website traffic, as measured by Clicks, is another particularly important outcome in our set of dependent variables. Generally, however, content characteristics do not seem to be extremely impactful with respect to driving website traffic since few content characteristics affect Clicks. Including references to non-brand entities increases Clicks (which is unlikely to be helpful since these links are probably to websites providing information about the non-brand entities rather than about the brand and its products). Including information about or inviting consumers to participate in a competition reduces Clicks, as does providing value-related information. Since coupons are a common type of value-related information included in posts and they typically need to be clicked on to redeem (e.g., to get a printable coupon from a webpage or to redeem a code embedded in a URL), this suggests that offering discounts through coupon/codes in Facebook posts may not be an effective way to drive coupon-related transactions.

General Discussion

Our empirical study of nine brands' Facebook content design and content dissemination decisions and the associated measurable engagement-related consequences over an 18 month period allows us to address two questions that have not received sufficient attention in the emerging research on social media marketing: (1) how do various types of content characteristics affect consumers' engagement actions related to their attitudinal responses to content and marketing outcomes, and (2) does audience mix (reaching a narrower audience of mostly core consumers vs. reaching a wider audience of core and non-core consumers) moderate these effects? Overall, we find that various content characteristics matter, different outcomes are driven by different sets of content characteristics and the moderating role of audience mix is comparatively less strong but still important and relevant because it suggests ways marketers can optimize or customize content to suit core consumers. We now discuss a series of key findings and related implications for theory and practice (see also Table 7 for approaches managers can take to achieve the various outcomes covered in our framework, and Appendix 5 for a "scorecard" of the significant effects across all content characteristics and dependent variables).

Key findings and implications

Persuasion-oriented content may not be effective. We find persuasion-oriented content characteristics to be consistently important drivers of all engagement actions. In line with our expectations, content should be relevant to the focal brand in order for desirable engagement actions to be generated. Relating this to persuasion theory, this suggests that if content can engender some level of processing motivation by being "on brand" in the sense that the message fits with the brand, it will help drive outcomes. Interestingly, we find that the hallmarks of persuasive marketing messages in traditional settings—adopting an advertisement-like tone and using very clear and fluent messages—work *against* marketers' goals. In the case of having an advertising tone, it is likely that branded content that seems like an overt attempt to persuade or seems "pushy" will be unsuccessful. This is consistent with our earlier arguments about persuasion knowledge being activated by posts that feel too much like advertisements, and reactance-type responses being ways for consumers to deal with persuasion knowledge. Further, our finding that having a clear and fluent message is not desirable is consistent with this argument, since clearer messages may come across as more persuasive. Additionally, the negative effects of message clarity could also suggest that lowering processing ability by having a less-clear message can increase post-level engagement because consumers have to allocate more resources to processing the message in order to make sense of it.

Ironically, for branded social media content to be influential in persuading consumers to engage in desirable ways (e.g., clicking a link, spreading WOM), marketers must design content that is *not* highly persuasion oriented. Branded content on Facebook should not put the "hard sell" on consumers and probably should not even try to "soft sell," particularly not when the audience comprises mostly core consumers since they are somewhat less forgiving and more sensitive to pushy messages.

Different types of information can matter in different ways. Another key finding relates to the types of information marketers convey through their branded posts. Being informative in a general sense is insufficient because different types of information trigger different outcomes. Providing specific product-related information helps increase how many times a post is liked and its reach, but not other outcomes. On the other hand, conveying general brand-related

information in posts tends to be mostly ineffective, except for reducing negative reactions and increasing WOM (and generating more comments if the audience is narrow). How information is conveyed is also important. For instance, using humor either is ineffective or negatively impacts desired outcomes such as Reach (particularly for core consumers). Careful thought about the types of information that can be conveyed and how they are conveyed is therefore required and, generally speaking, it seems that marketers should try to provide concrete information about products. This might be because the fast-paced nature of social media and large amounts of content to which consumers are exposed when they view their newsfeeds means that for information to be effective in driving desirable engagement actions, it needs to focus on something specific (such as a product). Additionally, for core consumers, brand-related information can be useful, presumably because it caters to their need for brand affiliation.

Current "best practices" may be suboptimal. Another interesting set of findings is the content characteristics that consistently do *not* matter or that have effects that run counter to current social media marketing "best practices." One example is posts mentioning holidays. This is a common content characteristic used by marketers, however it does affect any of the outcomes in our data. 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, we found little evidence to suggest that rich media elements generate positive returns on key marketing outcomes. Consistent with this finding, it appears that some social media managers are now recognizing the limits of costly-to-produce rich media elements (Hutchinson 2015). A final example is the use of calls to action, particularly with respect to asking consumers to engage with posts. Calls to action either have null or undesirable effects, perhaps because such posts feel pushy and trigger a backlash.

Audience mix plays a subtle but important role. We argued earlier that both content characteristics and audience mix (influenced by marketers' decisions to pay to boost post reach) are important and can jointly influence attitudinal responses and marketing outcomes. Indeed, our findings indicate that both content design and dissemination can affect engagement. It is apparent, however, that content characteristics matter a lot more. Given that marketers fully control content design but not content dissemination, making the fully controllable aspects of social media content marketing one's primary concern seems prudent.

Of particular interest in our conceptualization and analysis was the extent to which audience mix moderates effects of content characteristics on engagement. Our theory was that different types of audiences (core vs. non-core) might respond to content in different ways. We found some evidence of this, but it was not substantial and none of the significant interactions indicated dramatic changes in content characteristic effects on engagement (i.e., sign reversals). Instead, the significant interactions indicated subtle—albeit interesting—differential effects of content on engagement due to changes in audience mix. These interactions, which can be seen in Figures 2, 3, and 4 and are mentioned above in the results section, shed light on the content preferences of a brand's core consumers.

Overall, however, despite some interesting and important moderating effects of audience mix, whether a post reaches only core consumers (narrow audience mix; no boosting) or a combination of core and non-core consumers (wider audience mix; boosting) does not appear to matter a great deal. Although this could be for many different reasons (and is an interesting avenue for future research), one simple possible explanation for the lack of audience mix strongly moderating how content characteristics affect engagement is that non-core consumers may not pay as much attention (if any) to branded posts as core consumers do. In any case, our findings cast doubt over the value of paying to boost post reach beyond a brand's core audience.

Limitations and conclusion

Our findings are subject to a number of limitations. 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 its popularity. It would be interesting for future research to look at content marketing on other types of social media platforms.

Second, the dependent variables are imperfect measures of 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 industry standard measures. These measures cannot 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). Thus, the marketing outcomes considered here are outcomes *on Facebook* that may not be positive indicators of unobservable outcomes outside of Facebook.

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 conclude, social media content marketing is an increasingly strategically important part of a brand's marketing activities. Despite its importance, however, it is not well understood. This research is intended to advance our understanding of how content characteristics drive various types of meaningful engagement actions in response to brands' Facebook posts. We hope this encourages future work in this important but under-researched area.

Appendix 1

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 2

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, α = .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.	0 = no, 1 =

	The post mentions a charitable fund, foundation, institution, or day.	yes
	The post mentions or highlights the sponsorship of another organization, brand, or event.	
Holiday	The post mentions a major holiday or mentions "holidays" in general (e.g., major holidays would include New Years Day, Memorial Day…).	0 = no, 1 = yes
	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")	
Media elements		
RichMedia	The post contains a picture (NOT including a thumbnail image for videos or links).	0 = no, 1 = yes
	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).	
URLs	The post contains a link to another webpage (i.e., NOT a video link).	0 = no, 1 = yes

Appendix 3

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 4

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.

Appendix 5

Significant Effects Across Attitudinal Responses and Marketing Outcomes

		Number of Significant (p < .05) Effects Across Six DVs
Arousal-oriented	Positivity	1
	Positivity x Mix	0
	Humorous	3
	Humorous x Mix	2
Persuasion-oriented	Relevance	4
	Relevance x Mix	1
	ClearMessage	5
	ClearMessage x Mix	0
	AdvertisingTone	4
	AdvertisingTone x Mix	0
Information	Product	2
	Product x Mix	0
	Value	2
	Value x Mix	0
	Brand	2
	Brand x Mix	1
Calls to Action	Engage	2
	Engage x Mix	2
	Competition	3
	Competition x Mix	0
References	NonbrandRefs	4
	NonbrandRefs x Mix	0
	Holiday	0
	Holiday x Mix	1
Media Elements	RichMedia	1
	RichMedia x Mix	4
	URLs	5
	URLs x Mix	5

Significant effects at p < .05 for direct effects on attitudinal responses (Table 5) and total effects on marketing outcomes (Table 6).

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Figure 1

Conceptual Framework

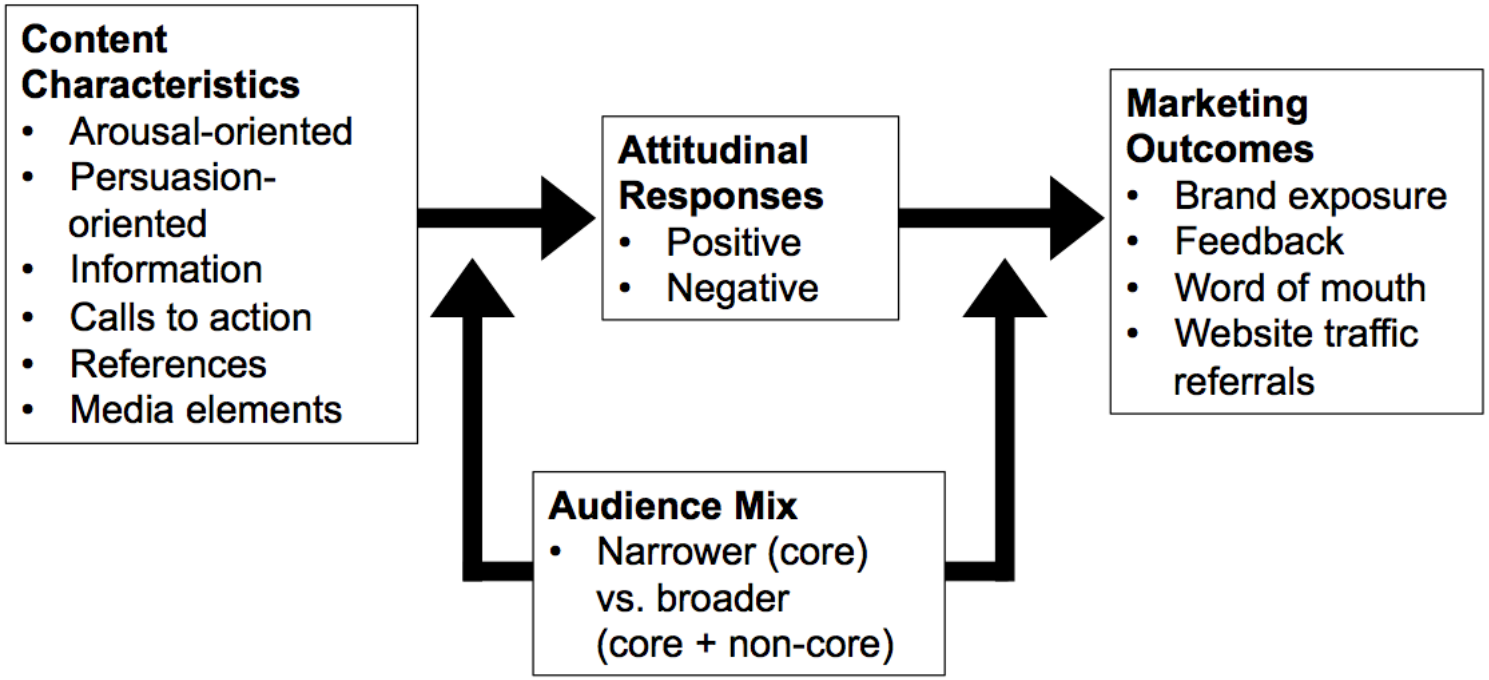
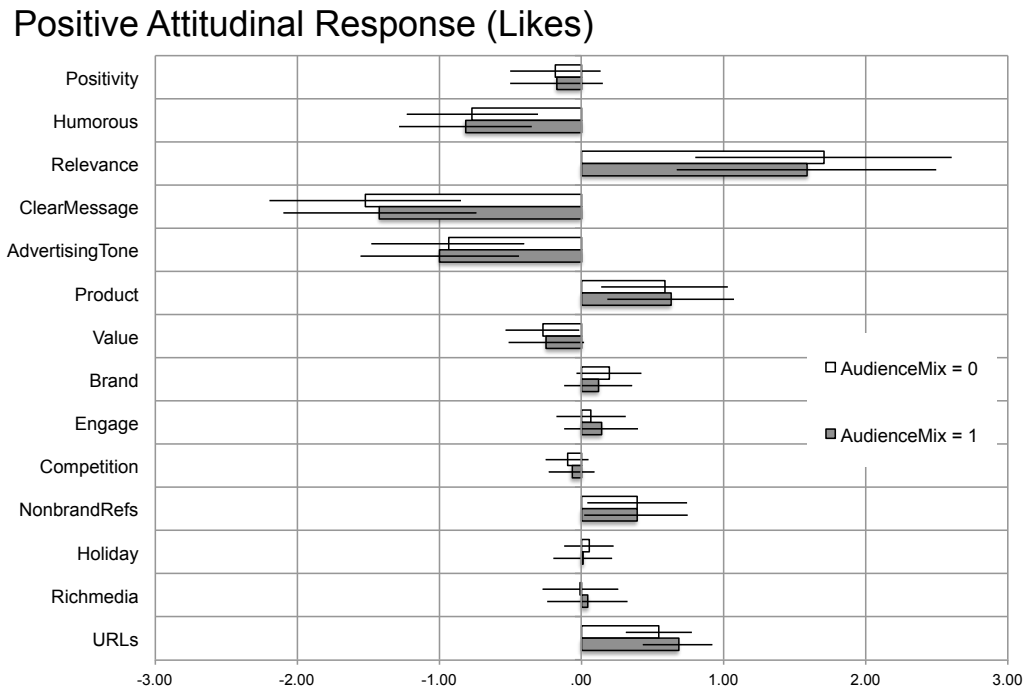


Figure 2

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



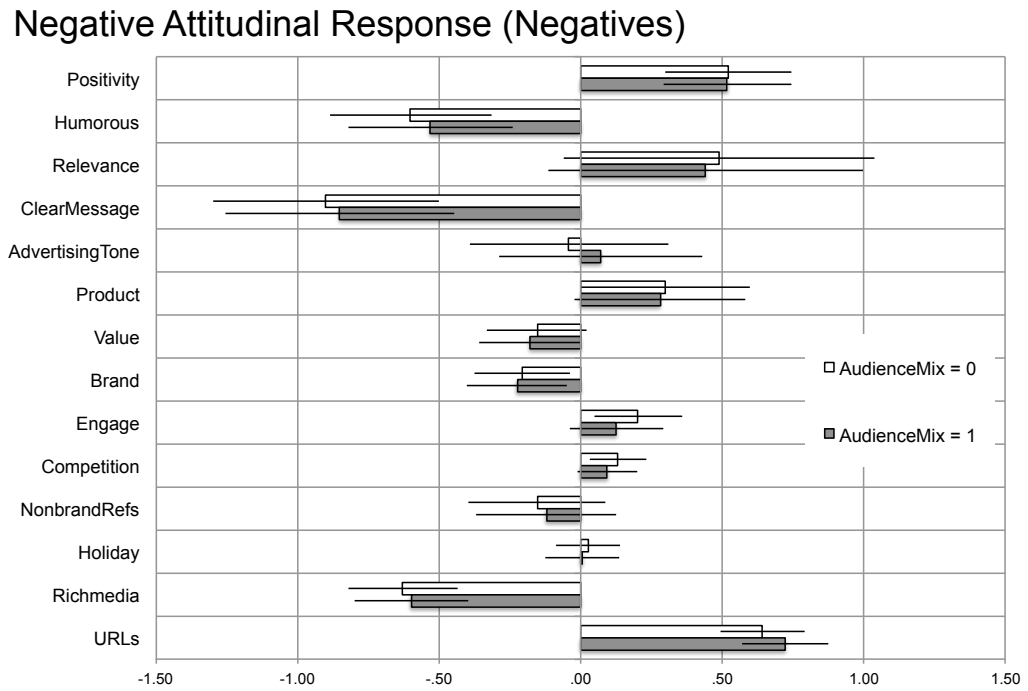
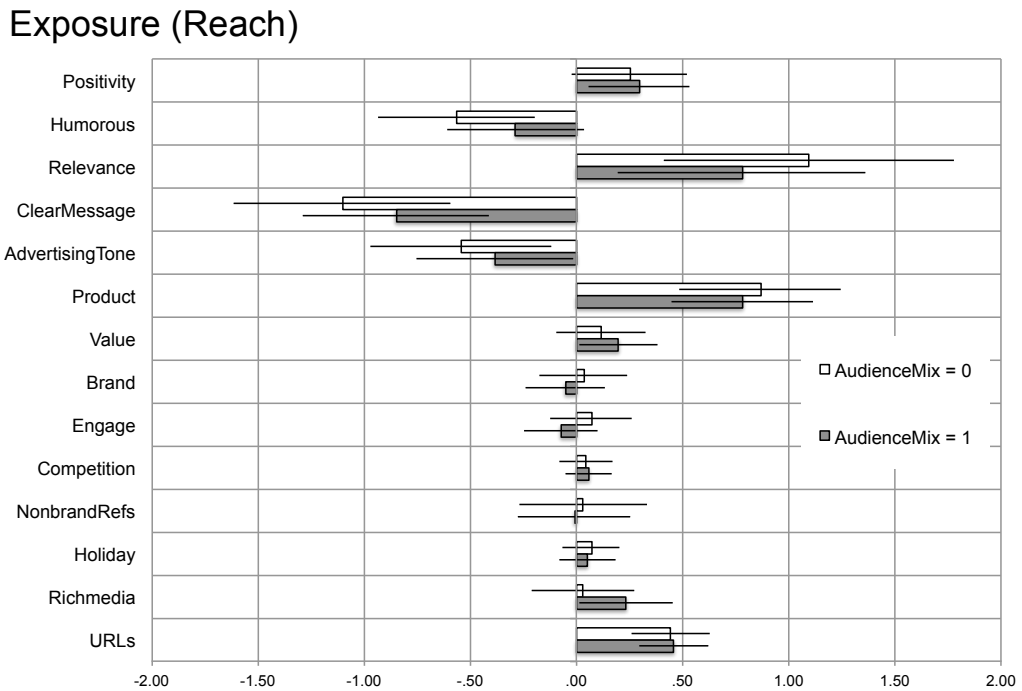


Figure 3

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



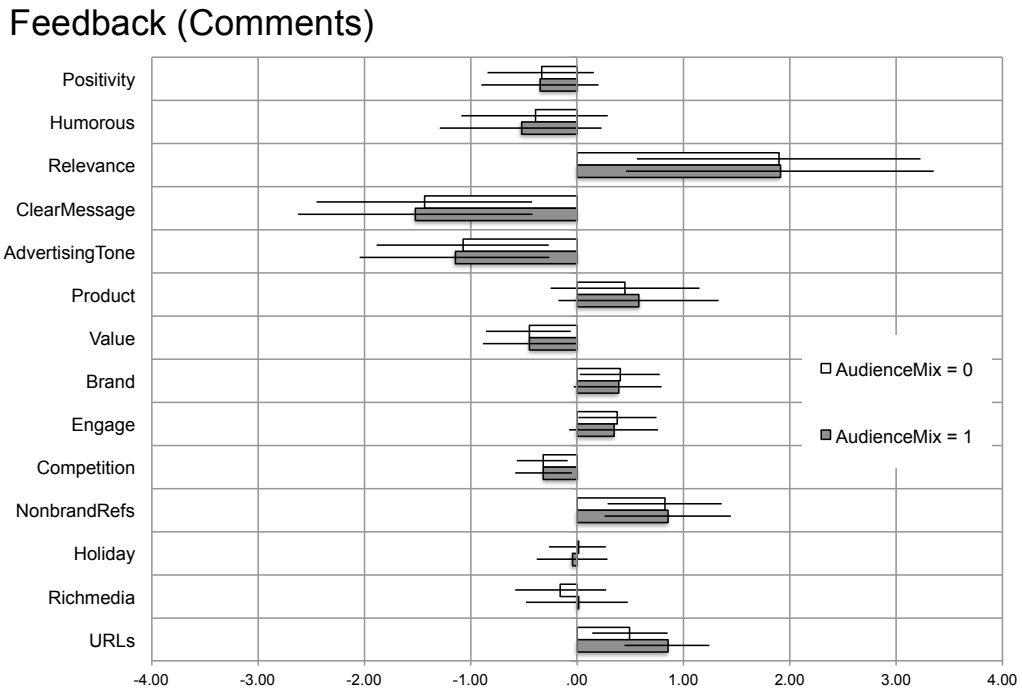
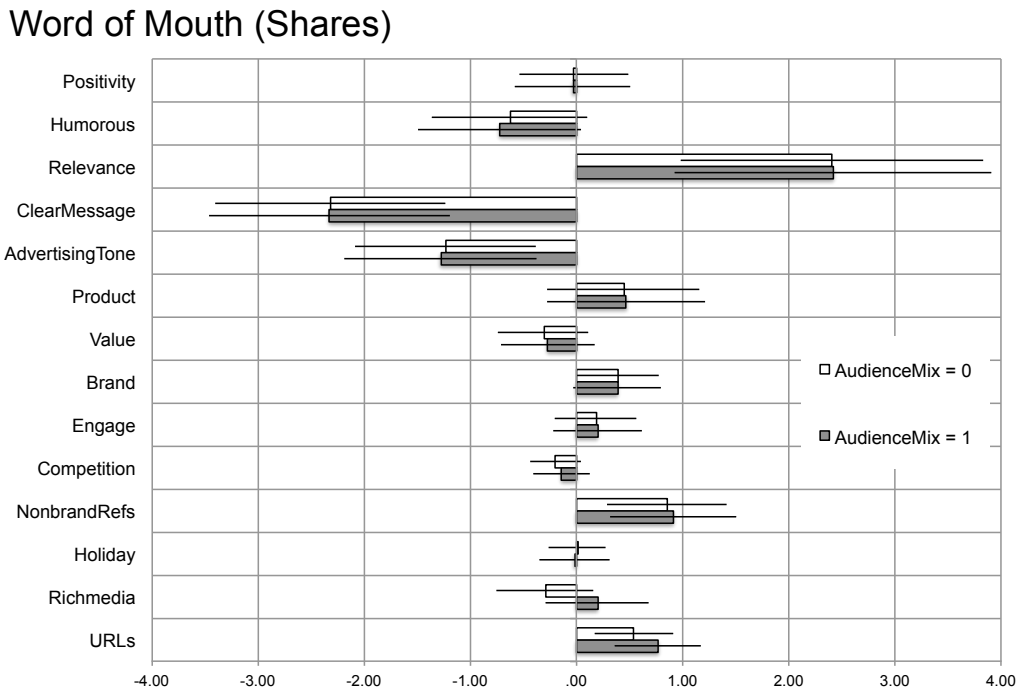


Figure 4

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



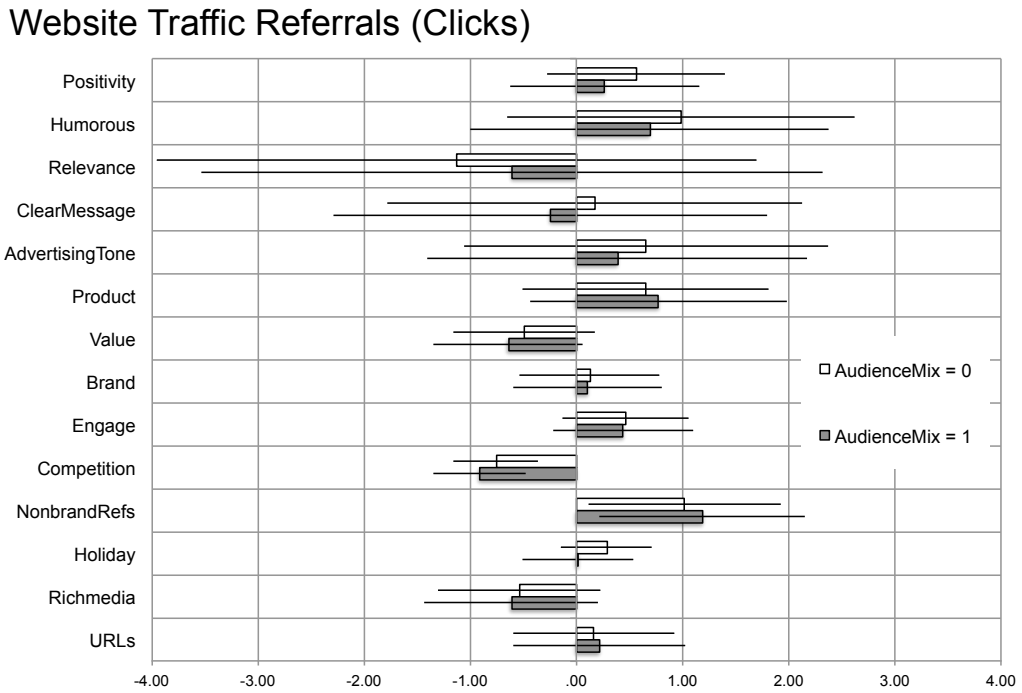


Table 1

Content Characteristics Used in Analysis

Variable	Description	Measurement	Mean (St. Dev.)
Arousal-oriented			
Positivity	Post is perceived as positive	6 items, 1-5, averaged, α = .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, α = .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)

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

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

Table 4

Error Variance-Covariance Matrix for Full Model

	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.

Table 5

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	***
	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	***

	Likes			Negatives		
	Est.	**SE**		**Est.**	**SE**	
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		

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

Table 6

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	**

		Reach			Comments			Shares			Clicks		
		Est.	**SE**		**Est.**	**SE**		**Est.**	**SE**		**Est.**	**SE**	
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.