eWOM across channels: Comparing the impact of self-enhancement, positivity bias and vengeance on Facebook and Twitter.

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Abstract

Previous word-of-mouth (WOM) research has shown that consumers exhibit a positivity bias when talking about themselves. When sharing personal details, versus talking about others, consumers tend to talk about the positive experiences they have with brands in order to self-enhance amongst friends. At the same time, consumers have been known to vent and take vengeance on brands in public venues. Turning to electronic worth-of-mouth (eWOM) and different social network sites (SNSs) little is known as to the extent to which either is dominant. Moreover, existing eWOM is channel agnostic and has yet to examine eWOM across various new technology-driven settings. To address these gaps, we consider two different SNSs for the same set of users. Facebook and Twitter messages are analyzed for a static group of 783 active U.S. consumers. Computational methods are used to extract historical eWOM messages (n = 47,907). Self-enhancement is found on Facebook and Twitter. Consumers generate eWOM that is more positive when they mention personal experiences (vs. non). While previous research has shown that consumers are more likely to believe and be persuaded by eWOM that contains personal experiences, our research shows that this eWOM also tends to be more positive. By comparison, vengeance and venting was rare, occurring in only 10.3% of eWOM across both SNSs. Moreover, eWOM appears to mirror consumer's broader, non-eWOM sentiment valence across SNSs. We also suggest that SNS affordances alter eWOM creation. Facebook, has substantial privacy expectations and limits direct brand interactions. Twitter is a more public platform with less privacy expectations and a larger customer service component. As a result, for the static group of consumers studied here eWOM is more prevalent on Twitter, but contrary to our expectations is also more positive. Here we add to the eWOM literature by showing that channel affordances do alter the amount and valence of eWOM generation.

Introduction

When consumers talk about services and products and describe characteristics to friends, they generate word of mouth (WOM; Westbrook, 1987). Consumers also digitally share opinions and product reviews on social networking sites (SNSs; Berger, 2016). Beyond email as a channel for electronic word of mouth (eWOM; Phelps, Lewis, Mobilio, Perry, & Raman, 2004), SNSs allow managers to create digital strategies that foster positive conversations online. This type of communication is of particular interest for marketing researchers because eWOM is effective at driving desirable behaviors such as sales and persuasion (Bughin, Doogan, & Vetvik, 2010; Ismagilova, Dwivedi, Slade, & Williams, 2017). As such, many marketers now employ tactics to increase the amount of positive brand-centric WOM their brands receive (Berger, 2016).

Given the numerous positive business outcomes that WOM and eWOM can generate, it is beneficial to understand the *why* behind WOM. Successful campaigns hinge on an understanding what drives consumers to create eWOM. Recent WOM literature has explicated the conditions in which consumers are motivated to share brand-related experiences with friends (Berger, 2016). Five key factors have been found: impression management, emotion regulation, information acquisition, social bonding, and persuasion. Less is known about the extent to which these factors actually motivate individuals to generate eWOM.

Moreover, when crafting campaigns, managers have several popular SNSs to choose from. Each channel offers unique affordances and gratifications. What is even more problematic is extent to which the WOM/eWOM literature is channel agnostic. Little is known about the degree to which consumers differ in the way they talk about brands across SNSs. Channel affordances may alter the way consumers talk about brands.

To begin to address these gaps, this study adopts perhaps the most studied WOM motivation, impression management, and its principal theory self-enhancement to assess the degree to which it exists in two different eWOM channels, Twitter and Facebook. *Do consumers self-enhance across SNSs and does that self enhancement lead to positive eWOM?* We also consider the fact that the SNSs have different affordances. Twitter is public platform known for customer service (Kwon & Sung, 2011; Liu, Kliman-Silver, & Mislove, 2014). *Does this lead increased amounts of eWOM?* Given that customer service often starts with customer complaints, *is vengeance and venting prevalent on Twitter?* (Berger, 2016). Facebook users, however, generally prefer their content to be private. (Liu, Gummadi, Krishnamurthy, & Mislove, 2011). *Does this inhibit eWOM creation on the platform?* Through a novel method that measures actual, historical eWOM, we analyze data for a large group of individuals identified through a popular panel service (n = 783). Tracking real-world behavior across platforms, eWOM amount (n = 48,162), valence, and generation (personal vs. non-personal) is assessed for 186 top consumer brands.

Social identity and impression management

Berger (2016) explicates WOM as an individual-level process that is goal-driven. A consumer is motivated to generate WOM to satisfy certain needs and wants (Gangadharbatla & Smith, 2007). Perhaps the most well-established need/want in the literature is impression management. The products or material possessions that an individual owns reflects and contributes to how they identify themselves (Belk, 1988). Individuals make decisions to own products, in part, to signal aspects of their identity (Berger & Heath, 2007). Consider the case of ‘hipsters’ and coffee, for instance. The type of coffee a hipster purchases is a choice. Because the product category is a topic of interest amongst hipsters, and coffee is something that hipsters tend to identify with, that choice is noticed by friends (e.g., fellow hipsters); as such, hipsters are likely to make deliberate choices about what brand of coffee they buy (Gavin, 2013). In these cases, impression management asserts that hipsters tend to make purchase decisions that will be evaluated positively amongst friends. People consume products to enact their desired social identities (Kleine, Kleine, & Kernan, 1993).

In these situations, consumers don't solely use products and hope others will notice. While owning a Rolex watch may turn some heads, if an individual wants to attain status amongst friends, they are much more likely to talk about the Rolexes they own as well (Yang & Mattila, 2017). Beyond direct experiences, stories often need to be shared. 'If we tell someone about a secret bar hidden inside a hot dog restaurant, it makes us seem cool' (Berger, 2016, p. 39). Beyond bars and luxury items, consumers talk about the everyday products they use with friends (Ismagilova et al., 2017). Word of mouth is one way in which we present to others who we are and who we want to be (Berger, 2016).

The tendency for individuals to disclose personal information stems from its central role in the development and maintenance of relationships. Prior research has shown that consumers generate eWOM on platforms, such as consumer opinion websites, to satisfy their desire for social interaction (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). In general, people who disclose personal information are liked more by peers (Collins & Miller, 1994). Moreover, self-disclosure is enjoyable and intrinsically rewarding to individuals. Tamir and Mitchell (2012) showed that individuals enjoy talking about themselves so much that they are willing to forgo small amounts of money to talk about themselves, as opposed to talking about others.

Self-enhancement

Much like the social identity and impression management research, self-enhancement also suggests that individuals have the tendency to associate themselves with brands. The nuance of self-enhancement lies in the 'positivity bias' component of the theory which explicitly links sharing to the desire to create and maintain a positive self-concept (a.k.a., self-image; Wojnicki & Godes, 2008). Not only do people tend to associate themselves with brands that tend to match their identities, they also tend to share positive experiences more than negative ones. Everyone knows the work colleague who had *the best dinner.* Wojnicki and Godes (2008) assert that those with positive self-images also tend to share the positive, satisfying outcomes they have with brands, products, and services. Even in online reviews, which are designed in part to allow criticism, reviewers express positive emotions including trust, joy, and anticipation (Felbermayr & Nanopoulos, 2016). In individualized (a.k.a., westernized) cultures, consumers are even willing to exaggerate their experiences with products in order to create positive impressions and gain social status amongst friends (Chung & Darke, 2006). As we have all suspected, it is possible that your work colleague's dinner was not truly that remarkable.

In a study of WOM and self-enhancement, Angelis, Bonezzi, Peluso, Rucker, & Costabile (2012) added a dimension they coin as generation. The researchers considered the specific situation in which consumers share information about *their own personal experiences* with products and services. In these situations, the researchers argue consumers are 'generating' WOM rather than retransmitting previously created content or other's experiences. The researchers compared times when consumers generated WOM (e.g., shared information about their own experiences) versus when consumers talked about the experiences that others had. Unsurprisingly, the results showed that consumers shared more content about themselves than they did about others. Those experiences tended to be overwhelmingly positive, thus illustrating the congruent relationship generational WOM had on positive self-concepts. Without the motivation of self-enhancement, consumers tended to share more negative WOM. When individuals talked about the experiences *others* had with a product, they tended to do so with more negativity. The researchers concluded individuals brag about themselves and gossip about others.

The majority of user generated content (UGC) on SNSs is personal in nature (Naaman, Boase, & Lai, 2010). As much as 80% of all UGC on popular SNS Twitter contained updates about one's self (Java, Xiaodan, Finin, & Tseng, 2007). In this way the literature is clear, consumers enjoy talking about themselves, both online and offline. Turning to audience reception, Kim et al. (2018) have found that when consumers share components of their social identity with Facebook friends in the eWOM the generate, audiences of these messages (e.g., their Facebook friends) have increased perceptions. Audiences find the eWOM to be more useful and tend to adopt the attitudes and opinions expressed more frequently. This is similar to extant research that also finds that when eWOM includes personal, subjective experiences and opinions about products, that eWOM generates favorable consumer responses (Kim and Song, 2018).

What has yet to be tested is the degree to which generation (e.g., personal vs. non-personal) matters for eWOM. Moreover, when individuals have a positive self-concept on SNSs, does that positivity bias transfer to their eWOM messages? Do those who express negatively valenced sentiment also express negative eWOM? Based on the discussion above, the following first set of hypotheses are posited:

> H1: Individuals will exert a positivity bias on Facebook and Twitter when talking about themselves and brands as opposed to talking about *other people.*

H2: Individuals will be mostly positive on Facebook and Twitter when talking about their personal eWOM experiences with brands.

H3: Individuals' personal eWOM experiences of brands is positively related to their general personal (non-eWOM) experiences expressed on SNS.

While consumers talk positively about themselves, they often gossip about others. To date, no research has addressed the degree to which eWOM that mentions others is negative. As such, the question begs empirical investigation.

H4: eWOM that mentions others will be more negative in nature when compared to personal eWOM content.

Considering channel differences

In his review of WOM motivators, Berger (2016) notes that WOM research makes two assumptions that are largely problematic: (1) it generalizes who individuals communicate with (e.g., typically defined as friends) and (2) it arrives at conclusions that are channel agnostic (e.g., usually online vs. offline). When considering specific eWOM contexts, each SNS comes with special technological affordances and differences that invariably alter the types of messages that are sent. Each site also has different audiences. In their recent review of eWOM research, Chu and Kim put forward charges for future research, among them the need for scholars to investigate eWOM in "new technology-driven settings" (2018, pp. 7). In a review of the literature, the scholars find that when compared to WOM research, relatively little work has been done on social media. Moreover, the majority of that research has been done on one platform, Twitter. The authors call for a broader assessment of more platforms and more comparisons of those platforms.

The privacy of Facebook

Facebook and Twitter are vastly different in terms of audience privacy. Twitter is largely an open platform with less than 2% of Twitter profiles being private (Liu et al., 2014). That means the majority of information created by users is open for all to see by simply searching for it (Vieweg, 2010). Brands use Twitter to listen to millions of users on the platform by following keywords and hashtags. Individuals use Facebook with an expectation of privacy and protection from external parties, such as brands (Liu et al., 2011). Conversely, when a public tweet is published, it can be viewed across the world, and users typically don't express the same privacy expectations (Vieweg, 2010). In this way, Twitter is a more public SNS.

On Facebook, brands, celebrities, and journalists alike are relegated to separate pages for fans to "like" (e.g., https://facebook.com/Kleenex/). While Facebook pages do act in some ways like personal Facebook accounts, they differ in key ways. Because of the aforementioned private nature of Facebook pages, page owners cannot access profile-related messages of its fans. Unlike Twitter, brands on Facebook cannot see what its followers or others are saying outside of its page. Kept in the dark about casual mentions that might be happening on individuals' profiles, brands are unable to communicate with people directly unless prompted to via their page. On Twitter however, consumers are known to identify with and communicate with brands (Phua, Jin, & Kim, 2017). Taking the openness and direct brand engagement opportunities of Twitter together, we expect more eWOM content on Twitter than Facebook.

H5: An individual's Twitter will feature a higher proportion of eWOM than an individual's Facebook.

Customer service

However, because it is easier for brands to directly interact with consumer comments on Twitter, is widely known as the leading SNS for customer service (Kwon & Sung, 2011). Research has shown that this two-way dialogue on Twitter results in enhanced brand attitudes and purchase intentions, where one-way communication on the platform does not (Colliander, Dahlén, & Modig, 2015). Whether it's a delayed flight or a cable company not showing up for a repair, people are known to use Twitter to complain about brands. Twitter is aware of and covets this SNS positioning; it has tailored its product to include features that make customer service easier for both businesses and consumers alike (Lull, 2016). Twitter also differs in the way that customer complaints are handled. To make a complaint known on Twitter, consumers simply '@' mention the brand in a tweet (Einwiller & Steilen, 2015). The tweet, and therein grievance, is filed with the brand and the world-at-large. With this action, 72% of Twitter users expect to receive a response from a brand within one hour (Krasne, 2017).

Users of Facebook also have the ability to complain about and to brands. They cannot however 'mention' brands in their messages in a public way like Twitter users do. A user may complain about a brand on Facebook to their friends, but again, Facebook users protect their content from brands (e.g. dfLiu et al., 2011). This means that Facebook users do not expect, and likely do not want, brands to see these messages. As aforementioned, the only way to interact with a brand is through a brand's dedicated page. These types of interactions are different from more common messages on Facebook such as wall posts and status updates. Organic (e.g., unsponsored and unpaid) messages that originate from brand pages are almost never seen outside of their respective pages (i.e., such as on friend of friends' news feeds; Manson, 2014). All things considered, if an individual complains to a brand on Facebook, it is likely that the complaint will not be seen by most of that person's friends.

By airing a complaint in public on Twitter, consumers are enacting what others have described as vengeance through negative eWOM (Wetzer, Zeelenberg, & Pieters, 2007). In a motivational analysis of WOM, Sundaram, Mitra, and Webster (1998) found that 31% of respondents generated WOM to seek vengeance on brands. Others have used a broader term, venting, to describe posting negative eWOM to in some way harm a brand or company (Jeong & Jang, 2011). Hennig-Thurau et al. (2004) found that venting was a major factor in generating eWOM. Given that vengeance has been linked as a motivating factor to sharing WOM (Berger, 2016), we expect that when talking about personal experiences, brand eWOM on Twitter will be more likely to contain vengeance, and as a result be more negative overall when compared to the relatively private platform of Facebook.

H6: Personal eWOM messages on Twitter will be more negative than personal eWOM messages on Facebook.

Method

This study gathered *historical* eWOM data from actual Twitter and Facebook accounts. By collecting the actual social media posts of a user, it is possible to retrieve eWOM data from users that is exhaustive and accurate. This is a key advantage over only survey or interview-based approaches, which can be problematic due to the difficulty respondents have in accurately recalling the frequency in which they do tasks that are too repetitive to individually enumerate, here the amount and valence of eWOM postings (Tourangeau, 2000). As a semi-public platform, Facebook presents numerous difficulties as they pertain to researchers' abilities to examine on-site behaviors (Zhang & Leung, 2015). Most notably, and in contrast to Twitter, the Facebook Graph API no longer allows for public scraping of user accounts (Wilson, Gosling, & Graham, 2012). While researchers still have success accessing what users do in public areas of Facebook (e.g., on a public Facebook page or group), their wall posts and stories are typically not accessible.

To address this limitation, we created a web service that allowed us to collect the actual posts they made on their Facebook and Twitter accounts. We asked Qualtrics for a sample of people who were broadly representative of active social media users in the U.S. To accomplish this, Qualtrics leveled a subpanel of users that have self-identified as active social media users. While they could not reveal specifics, Qualtrics asserted to us that the subpanel was diverse in terms of age, education, and race. Qualtrics suggested that we institute a 50/50 gender split control for the subpanel, due to the over representation of women on the panel. As it pertains to the active user criteria, we required that all users have a current account on both SNSs with at least 50 pieces of posted content on both SNSs. This safeguard was put in place to avoid scenarios where a user may create an account simply to qualify for the study. Of those that engaged with the study materials, 13.5% provided valid data. Among the 783 participants who successfully completed the survey and provided valid social media data, 59% were female and the average age was 39.

Upon contact by Qualtrics, potential respondents were provided with an overview of the study procedures. Given sensitivities surrounding the use of Facebook data, we explained that participation in the study would entail collection of information posted by the user to her or his Facebook page. We further contextualized this disclosure by explaining that any collected data would be anonymized and used only for the purposes of academic research. Participants were compensated for their data. We did not track users, instead we took a one time download of their existing Facebook and Twitter data. Our institutional review board (IRB) vetted all study procedures. Authors were not allowed to include information from a participant's news feed, or information about the participant's friends. The Qualtrics application created an anonymous identification code, which was piped to a custom web application that the researchers designed. This service asked users to link their Facebook and Twitter accounts by signing in. This login authenticated the researchers and allowed them to retrieve the actual posts of users in the study.[1] In layman terms, we downloaded all of the posts a user made on Facebook and Twitter, from the time they first posted, to the date of download. User post data was downloaded on June 3, 2017.

Detecting personal posts

To identify posts that mentioned an individual's self (e.g., the generational component), the authors built a supervised machine-learning algorithm inside of the DataRobot platform (Pearson, 2017). First, valid and accurate data needed to be created as evidence for the machine learning algorithm. Two coders coded messages as personal, about others only, and other (e.g., not mentioning any individual). See Appendix A for the example codebook used by researchers. The two coders agreed on all but two decisions ($\alpha = .961$). One researcher then coded an additional 6,900 messages. These messages were then used in an AVG Blender. A neural network ensemble model had the highest performance scores and was ultimately chosen. The model considered ngrams (a.k.a., unigram, bigram and trigram word combinations), parts of speech, and hashtags of a user's posts as predictive features. For mentions of an individual's self (i.e., personal mentions), the final model had an AUC = 0.92, an accuracy of 88.8%, and a false

[1] Status updates and shared stories were included. For more detail, the Facebook Graph API documentation lists the following content types: mobile_status_update, created_note, added_photos, added_video, shared_story, created_group, created_event, wall_post, app_created_story, published_story, tagged_in_photo, approved_friend. Facebook API documentation is found here: https://developers.facebook.com/docs/graph-api/reference/post For Twitter, all tweets for the user were downloaded. API documentation for Twitter is found here: https://developer.twitter.com/en/docs

positive score of 5.9%, suggesting that the model had above acceptable performance (Fawcett, 2004).[2] For mentions of others, the final model had an AUC = 0.84, an accuracy of 91.81%, and a false positive score of 4.62%, again suggesting it was above acceptable. All remaining posts were coded as other in the dataset.

Detecting brand mentions

Next, the researchers needed to identify brand mentions inside of Facebook and Twitter posts.[3] The aim of the study was not to identify all possible brands in the data, but to discover as many different brands as possible, while preserving high accuracy. To begin the retrieval process a large list of brands was needed. Ad$pender's database was chosen by the researchers because it maintains an extremely large collection of all consumer U.S. brands.[4] The top 2,000 unique brand names were chosen by the amount of national advertising spend from 2012-2016.[5] To discover matches, Tweets and Facebook posts were tokenized using Python's natural language toolkit (Bird, Klein, & Loper, 2009). If a token matched a brand name, it was flagged. All brands that had at least 10 or more mentions in the data (n = 279) were considered in this study. This initial matching technique included 78,289 messages in all. However, in manually reviewing a

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[2] All performance metrics went through 10-fold cross validation, each time training on a randomly selected 64% (n = 5,600) of the data.

[3] Only original textual content from the Twitter and Facebook users were considered (e.g., no retweets from Twitter and no photo albums from Facebook). Sponsored posts that users shared on Facebook were considered, but only their original text contribution was considered personal.

[4] Virtually all popular consumer brands that spend money on some form of advertising are included in Ad$pender's database. More information on Ad$pender here: http://www.kantarmedia.com/us/our-solutions/advertising-monitoring-and-evaluation/expenditure-and-occurrence

[5] 2,000 was chosen after manually inspecting multiple cut-off points (e.g., 500, 1000, 5,000 and 10,000) and checking each brand name against an English dictionary. 2,000 brands gave the researchers a robust list to match against, while protecting against vague names that would result in false positives. 10,000, for instance, introduced many brand names that were too ambiguous for matching.

sample of 500 matches, the researchers noticed that many brand names were also common English words (e.g., Tide, Abyss, etc.). To avoid spurious brand name matching, first each word was inspected against Python's natural language toolkit's dictionary of English words (Bird et al., 2009). Brand matches were pulled in two waves. First, if a word was not in the English dictionary, the researchers were more confident that the brand itself would yield few spurious matches (e.g., false positives). For this category, 10 random matches from each brand were reviewed by two researchers.[6] For brand names that were also English words, the researchers wanted to more strongly protect against spurious matching. Here 20 random mentions of these brand names were inspected.[7] A total of 3,655 messages were inspected. Brands that were 90% accurate or greater were chosen and used in the analysis. A total of 186 brands were accurate enough to be included. This gave researchers a large number of brand messages to assess, but minimized the erroneous matching that ambiguous brand names would incur.

In all, we identified messages that were personal (n = 433,026), about others (n = 83,422) or mentioned a brand (n = 47,907). Sex-based differences were assessed using a series of Mann-Whitney U tests (i.e., non-parametric t-tests). Across a number of behaviors, the results generally suggested that men were more likely to post positive content on Facebook while women were more likely to post positive content on Twitter. Overall, men were more likely to post negative brand content and women were more likely to post positive brand content. For an overview of message counts and percentages across categories, see Figure 1. For an overview of only eWOM messages, see Figure 2.

[6] If less than 50 matches existed, all were inspected.
[7] The following brand names were too common of words and had thousands of spurious matches in the data: Align, Alive, Boost, Gain, Glad, Guess, Off, People, Princess, Simple, Square and Wonderful. Because they could not easily be manually or machine-coded, they were removed from the analyses. If less than 20 matches existed, all were inspected.

Valence (sentiment) detection

Out of the box sentiment analysis tools are problematic for use in research, because they are not externally validated and true accuracies are unknown. To address these issues, a hybrid approach was adopted, where automatic annotations are validated with a manual content analysis (a.k.a., external validity check). First, all posts in this study were annotated by Google's Natural Language Sentiment Analysis tool via its Application Programming Interface (API). The tool leverages cutting-edge deep learning machine learning algorithms and also incorporates advanced natural language processing, which helps the algorithms understand complex aspects of language such as negation and sarcasm. Moreover, the tool was built to deliver customer insights, and to annotate 'customer conversations in email, chat or social media' (Google Cloud Platform, n.d.). The API accepts documents and returns an average sentiment score ranging from -1 (negative) to 1 (positive), with 0 being neutral. The entire corpus was processed through the API. Then, a random sample of 250 annotations were coded by two researchers. The researchers read a social media post and made a decision as to the valence of the sentiment (negative, neutral or positive). The two researchers agreed with each other (k = .91). Disagreements were due to the mixed valence nature of some posts (e.g., a post that was positive *and* negative). All disagreements were resolved by counting the number of positive and negative sentences in the post, and treating each sentence as one unit, with mixed sentences treated as 0. This procedure was chosen because it mirrors Google's averaging approach. With this new method in place, agreement was reached on all units. This data was used to evaluate the external validity of the Google annotations. Google's annotations matched the researcher's annotations 90.4% of the time, with an acceptable Krippendorff's Alpha (k = .818). As such, Google's tool, although not perfect, is an externally valid tool for this big data application.

In all, three sentiment valence categories exist: positive, neutral or negative. Each piece of content posted by a user was processed by Google's tool, and each piece of content in the study was ultimately assigned one of the three sentiment valence categories. Average sentiment scores were created for users in several ways: overall, by medium, by type (personal vs. about others) and by whether it mentioned a brand or not.

Results

Hypothesis 1 was concerned with the degree to which social media users exhibit positive valence when talking about the personal experiences they have with brands. Prior research suggests that brand-related messages would be significantly more positive when the message was personal in nature when compared to talk that concerned others. In all, 11,948 personal brand messages (across both SNSs) were found. Of this corpus, 5,752 messages were coded as positive in nature (48.14%). As it pertained to brand-related messages about others, 823 total messages were identified, 308 of which were coded as positive (37.42%). The result of a chi-square test suggested that these proportions were significantly different from one another ($\chi^2[1] = 35.47$, $p < .01$), indicating that a significantly larger percentage of personal brand talk was positive.[8] This finding supports Hypothesis 1.

[8] This hypothesis could also be considered in an individualistic (participant), unit of analysis. To formally test the stated hypotheses in this way, we assessed the equality of these percentages using a bootstrapping routine where the percentage of positive brand talk involving others was subtracted from the percentage of positive brand talk about the self for each sampled respondent (M = 34.71%, SD = 45.43%). This value was synthetically re-estimated 5,000 times using random re-draws of the original sample data (with replacement). The bias-corrected confidence intervals at the 99th percentile (i.e., .01 level of significance) were 30.55% and 39.03%. Because the upper and lower bounds of the obtained confidence interval did not cross zero, it is safe to conclude that the observed average percentage of positive personal brand talk is higher than the observed average percentage of others-specific positive brand talk, thus giving further support to Hypothesis 1.

Hypothesis 2 explored the degree to which all personal brand-related messages were positively biased. To test this hypothesis, the number of personal brand-related messages posted by each user was identified (M = 15.26, SD = 52.96). Inside of that, the total number of negative (M = 1.22, SD = 2.94), neutral (M = 6.69, SD = 38.37), and positive (M = 7.35, SD = 20.82) messages were identified for each user. The counts were then taken as a percentage -- negative (M = 14.09%, SD = 24.16%), neutral (M = 20.05%, SD = 26.06%), and positive (M = 49.64%, SD = 36.91%). Using these parameters, user-level percentages of negative eWOM were subtracted from user-level percentages of positive brand-related eWOM, resulting in a percentage-based measure where positive numbers represented a *greater* proportion of personal brand-related messages. Negative numbers represented a greater proportion of negative eWOM. Numbers equal to or approximating 0 represent an individual's tendency to talk about brands in equally negative/positive terms. The sample-wide mean was 35.55% (SD = 50.04%), suggesting that, across the sample, personal brand-related messages tended to be comparatively positive. To statistically evaluate the robustness of this estimate, the vector of individual values was subjected to a bootstrapping process in which the sample-wide mean was synthetically reconstructed 5,000 times using random re-draws of the original sample data (with replacement). The bias-corrected confidence intervals at the 99th percentile (i.e., .01 level of significance) were 30.90% and 40.11%. Because the upper and lower bounds of the observed confidence interval did not cross zero, it is safe to conclude that the observed discursive patterns significantly emphasized positive eWOM over negative eWOM in a personal context. This finding supports Hypothesis 2.

Hypothesis 3 was about assessing the degree to which the valence of personal, brand-related messages is related to — and perhaps reflective of — the general valence patterns of all personal messages that a user posts to Facebook and Twitter. To assess this hypothesis, the count-based measure of personal instances was taken for negative (M = 1.22, SD = 2.94) and positive (M = 7.35, SD = 20.82) eWOM for each individual and correlated them with the respective overall negative (M = 70.51, SD = 99.35) and positive (M = 362.00, SD = 494.36) social media posts for each individual. Significance was assessed by using 5,000 random bootstrapped estimates (with replacement) of the point estimate of interest. If the observed values at the upper and lower bounds of the bias-corrected 99% confidence interval do not include zero, it can be concluded that the observed point estimate is statistically non-zero in nature. As expected, negative, personal instances of brand-related messages were significantly associated with overall SNS personal negativity, r = .35, 99% CI [.19, .59]. Similarly, the measure of positive, personal instances of brand-related messages was shown to be statistically related to the overall measure of positive personal discussion on social media, r = .18, 99% CI [.10, .27]. Taken as whole, these findings support Hypothesis 3.

Hypothesis 4 examined the degree to which brand content that mentioned others, relative to personal, brand-related content was negative in nature. Out of the 11,948 messages that were personal and brand-related we observed 958 instances of negative commentary (8.02%). Alternately, out of the 823 instances of content that mentioned others eWOM, we observed 280 instances of negative commentary (34.02%). A chi-square test of proportions indicated that these proportions were statistically unequal, (χ^2 [1] = 594.74, p < .01), thereby offering support for Hypothesis 4.

For Hypothesis 5 we addressed eWOM data on the individual level to better control against the influence any one user had on global averages. The average percentage of all talk that was eWOM in nature on Twitter was 18.52%. On Facebook, this number was 14.63%. Subtracting the Facebook percentage from the Twitter percentage results in an across the sample difference of 3.89% (SD = 17.16%), meaning that, on a percentage basis, people tend to allocate a greater percentage of talk towards brands on Twitter when compared to Facebook. A bootstrap analysis indicated that this differences in percentage was, across, the sample, statistically different from 0, 99%CI = 2.20%, 5.45%. Support is given to Hypothesis 5.

Finally, Hypothesis 6 posited that personal, brand-related messages would be more negative on Twitter than Facebook. Out of the 10,974 personal, brand-related messages on Twitter, 832 total posts were coded as negative (7.58%). On Facebook, 976 messages were identified, 126 of which were negative in nature (12.94%). Across the same set of users, there were 665.5% more negative messages on Twitter than Facebook. However, there also were also 1,124.38% more brand related messages on Twitter than Facebook. In one sense, consumers clearly posted more negative content to Twitter than Facebook. However, when considering the ratio negative to positive, a chi-square test of proportions confirmed that the percentage of negative, personally-relevant eWOM was higher on Facebook than Twitter, $\chi^2[1] = 34.78$, $p < .01$. At the individual level, the mean percentage of personal talk that was negative on Twitter was 13.42% (SD = 24.73%). On Facebook, this number was 5.60% (SD = 20.00%). The average difference in these percentages was 7.82% (SD = 30.82%). 99%CIs, obtained using bootstrapping, 5.05% — 10.77%, indicated that this difference was significant nature.

As such, at the individual and aggregate levels, consumers do tend to generate a greater amount of negative content to Twitter when compared to Facebook. However, the overall the ratio (positive to negative) is more negative on Facebook than Twitter. Mixed support is given for H6.

Discussion

Theoretical contributions

Researchers have identified a paramount need to better understand what motivates consumers to generate eWOM (King, Racherla, & Bush, 2014). Our data here suggest that individuals tend to talk positively on SNSs when mentioning themselves. This effect is observed whether or not they mention brands, on both Facebook and Twitter. These findings bridge self-enhancement literature and the concept of positivity bias to the eWOM literature. This the first known empirical evidence for self-enhancement theory on SNSs. eWOM messages are more positive when personal in nature (vs. non-personal). Our data here show that most negative eWOM is non-personal in nature. Consumers use eWOM to talk about the negative experiences that others have. As such, venting and vengeance do exist on the SNSs, but are relatively rare.

As Angelis et al. (2012) said of offline WOM, we too provide some evidence that on SNSs, consumers *brag about themselves* and *gossip about others*. We add a caveat — while content regarding others is more negative than personal content — all eWOM is more positive on SNSs than negative. As others have suggested, this positivity bias is likely due to the desire to maintain a positive self-image amongst friends (e.g., Berger, 2016). Consumers are motivated to share positive experiences with friends in hopes of being evaluated positively by friends. Here our data suggest they use SNSs for the same reason. Invariably, Facebook and Twitter have many uses and gratifications. Impression management should be added to the top of that list. Our data observe two key behaviors as it pertains to uses and gratifications: (1) consumers mostly use Facebook and Twitter to talk about themselves[9] and (2) they do so positively.

[9] While not a central part of this study, we can assert this claim to be true. Considering all messages, not just eWOM, there were 433,026 posts that were personal (*M* = 553.03, *SD* = 649.54), whereas there were far less that were about others, 81,746 (*M* = 104, *SD* = 179.95). Consumers posted 531% more messages about themselves than about others.

Consumers do voice the negative experiences they have with brands on SNSs. It is widely known that venting on Twitter is one way to engage in customer service with a company. In sheer number, there were more negative eWOM messages on Twitter when compared to Facebook. However, there was also far more eWOM on Twitter. So much in fact, the overall ratio (positive to negative), suggests that Twitter was the more positive space for eWOM. Across both SNSs negative eWOM isn't very prevalent. Only 8% of personal, brand-related content was negative.

This brings into question vengeance and venting as a *common* motivator of eWOM on SNSs. Across both SNSs, only 10.3% of all eWOM was negative. At the same time, 77.32% percent of our sample generated at least one piece of negative eWOM. This is more than twice the percentage that self-reported to seek vengeance offline (as in Sundaram et al., 1998). This in itself raises an important theoretical distinction. When studying eWOM, motivators need to be assessed in terms of both occurrence and *prevalence*. While in a self-report survey, many individuals will likely report that they post to SNSs to seek vengeance. Our data says they do so rarely. Previous studies have shown that individuals have a hard time recalling the frequency in which they do inconsequential tasks, such as use media (Scherer, Bickham, Shrier, & Rich, 2015). Current literature would suggest that vengeance and venting is prevalent; and it is, solely in terms of individuals that have done it at least once. Only 18% of people in our sample posted more than 10 negative pieces of eWOM in their entire lifespans of using both Twitter and Facebook. Thus, we conclude that it is not common in overall eWOM generation.

On Twitter, we expected to see a higher percentage of negative eWOM given its affordances to customer service (Colliander, Dahlén, & Modig, 2015). Given that Twitter is widely known for customer service, and consumers have ways to engage with brands in a public space, we expected to see more venting and vengeance. Again, only 10% of eWOM was negative. Consumers don't appear to use Twitter's customer service and venting affordances to post negative eWOM. Given that vengeance is rare, future research should better explicate the conditions in which consumers are motivated to generate negative eWOM on SNSs, and do so with frequency in mind.

It's beyond our data here to offer concrete reasons why Twitter has more, positive eWOM than negative. However, the literature we put forward here positions Twitter as a uniquely open, public SNS. We also know that brands are much more active on Twitter in specific ways. Brands on Twitter perform active social listening and often seek to engage with customers as much as possible (Tsimonis & Dimitriadis, 2014). They also are able to do so on a level playing field. Brands can interact with consumers on Twitter as would a celebrity or journalist. On Facebook, brands are relegated to pages, and can only interact with those that "like" their page. That interaction only happens inside of that page. Perhaps, as a result, the siloed nature of Facebook brand pages inhibits the abilities of brands to seed positive eWOM. This would explain why we saw larger sheer number of negative eWOM on Twitter, but a lower ratio of positive to negative eWOM when compared to Facebook.

Consumers were more active and more personal on Twitter than Facebook. Golfers, politicians, and academics alike, use Twitter to manage their public persona.[10] Because Twitter is open, it seems to be the go-to SNS for self-presentation and identity management. As a result, self-concept and self-enhancement may be particularly prevalent on the platform, as individuals attempt to manage and convey positive self-images. While it was beyond this study and its data

[10] There exists a number of studies on how individuals in different professions manage their public personas, including Hull (2014) and Colliander et al. (2017).

to establish a causal link, further studies that uncover why individuals use these platforms, could better link eWOM motivations to SNS uses and gratifications.

Managerial implications

When launching eWOM campaigns on SNSs, managers should create tactics that encourage consumers to mention the personal experiences they have with products. When eWOM messages fail to explicitly mention the self, consumers do express more negativity. Advertisers should be direct in asking and encouraging consumers to share personal details. What was *their experience* with the product? When did *they* use it? How did it make *them* feel? It may be tempting to encourage consumers to give a product centric review that accentuates attributes and features. Our data shows this invites more negativity. Advertisers should not prompt consumers to write straightforward product reviews and then share it with their friends on Facebook and Twitter. Instead, our data suggests that eWOM campaigns should encourage consumers to create content that documents personal encounters and interactions. Moreover, Kim et al. (2018) have found that when consumers share social identity with Facebook friends, audiences of these messages (e.g., their Facebook friends) have increased perceptions. That is, friends find personal eWOM to be more useful and tend to adopt the attitudes expressed more frequently. Similarly, Kim and Song (2018) found that when consumers share personal experiences and opinions, audiences generate favorable consumer responses. Taken together, it’s clear that you should encourage consumers to insert themselves into the review. This can not only engage the positivity bias that comes with self-enhancement, but also garner more positive responses from audiences that see these messages.

We hypothesized that customer service on Twitter would be used for brand complaints. Overall, we did see a larger sheer number of negative eWOM messages on Twitter when compared to Facebook. However, across both SNSs we find that negative eWOM isn't very prevalent. Only 8% of personal, brand-related content was negative. Consumers do complain about the personal experiences they have with brands and products, but consumers overwhelmingly use SNSs to self-enhance. Even without considering self-enhancement, we found that 54.3% of eWOM is positive across platforms (62% on Facebook; 53% on Twitter). Only 10% of eWOM is negative (13% on Facebook; 10% on Twitter). The rest is neutral. Given that there is 543% more positive eWOM globally (477% on Facebook; 530% on Twitter), consumers don't seem to be primarily motivated to post negatively.

Conditions remain ripe on both SNSs to seed and generate positive brand-related messages. However, here we provide some initial evidence that eWOM varies both in quantity and valence by channel. The technological affordances of Twitter's platform seem to encourage consumers to mention brands, products, and services more so than Facebook. This reaffirms what Java et al. (2007) observed a decade ago; consumers use Twitter to talk about the things they do — as they do them. This includes the interactions they have with brands, products, and services. Google's Eric Schmidt put it aptly by asserting 'we are what we tweet' (Schmidt & Cohen, 2013, p. 22). Here we affirm – Twitter had higher amounts of personal talk, and more personal eWOM on the service.

All things together, marketers looking to seed eWOM may have an easier time doing so on Twitter than Facebook for three key reasons. First, people tend to generate more eWOM on Twitter. Second, consumers share more personal experiences on Twitter. Given what we know about self-enhancement, we can predict that consumers will be more positive when they are personal. This should result in more positive eWOM. Finally, our data suggests that consumers were all-around, inside of eWOM and out, more positive on Twitter. For these reasons we strongly suggest formulating eWOM campaigns that encourage users to post to Twitter as opposed to Facebook.

This paper also suggests that the valence consumers use when generating personal eWOM generally reflects the valence consumers use to talk about themselves overall. Those that tend to share more positive experiences about themselves on SNSs also tend to share more positive eWOM. Those that share more negative experiences about themselves share more negative eWOM. While self-enhancement is observed globally in our data, the degree to which individuals do so varies. Not all consumers feel the desire to share positive personal, positive experiences. This should encourage practitioners to seek out individuals that enjoy talking about themselves in a positive light on SNSs. These people, if seeded to generate personal eWOM, will likely do so in a positive way. Existing survey batteries that gauge consumer's desires to share positive experiences with friends (a.k.a. batteries that measure the desire to self-enhance or maintain a positive self-image), may be useful in screening consumers in the eWOM seeding process.

Limitations and future research

This study is the first analysis in eWOM area to take a set panel of users, recruited through a survey recruitment service, and collect their actual eWOM data. Methodologically, it opens a new chapter in eWOM research. It is now possible to analyze the actual observed behavior of consumers and the eWOM they generate on SNSs from an individualized point of view. In this way, methods that ask users to recall the messages they shared or state their intentions to share messages can be avoided. Instead, actual real-world behavior can be observed. While a sample size of 783 is not necessarily small, it is limited. Further investigation should attempt to replicate these results as well as investigate new platforms. Instead of comparing

Facebook and Twitter, it may be more revealing if the future scholars compare channels that are less personal (e.g., a product review channel). Such channels may be more negative.

The analysis here does not assess the degree to which self-enhancement fosters the creation of eWOM. Does the desire to talk about oneself not only result in positive eWOM, but also motivate consumers to generate eWOM content in general? Moreover, valence, while one important domain in eWOM, is one of many different message-related factors. Further work should apply the methodology put forward here to study eWOM beyond quantity and valence. For instance, consumption versus non-consumption and other types of quality indicators for eWOM may work for specific types of brands, products, and services.

Finally, contextual factors, such as demographics and geographics, may contribute to eWOM quantity and valence. Future studies may recruit representative samples of diverse populations and repeat this methodology to discover differences across populations.

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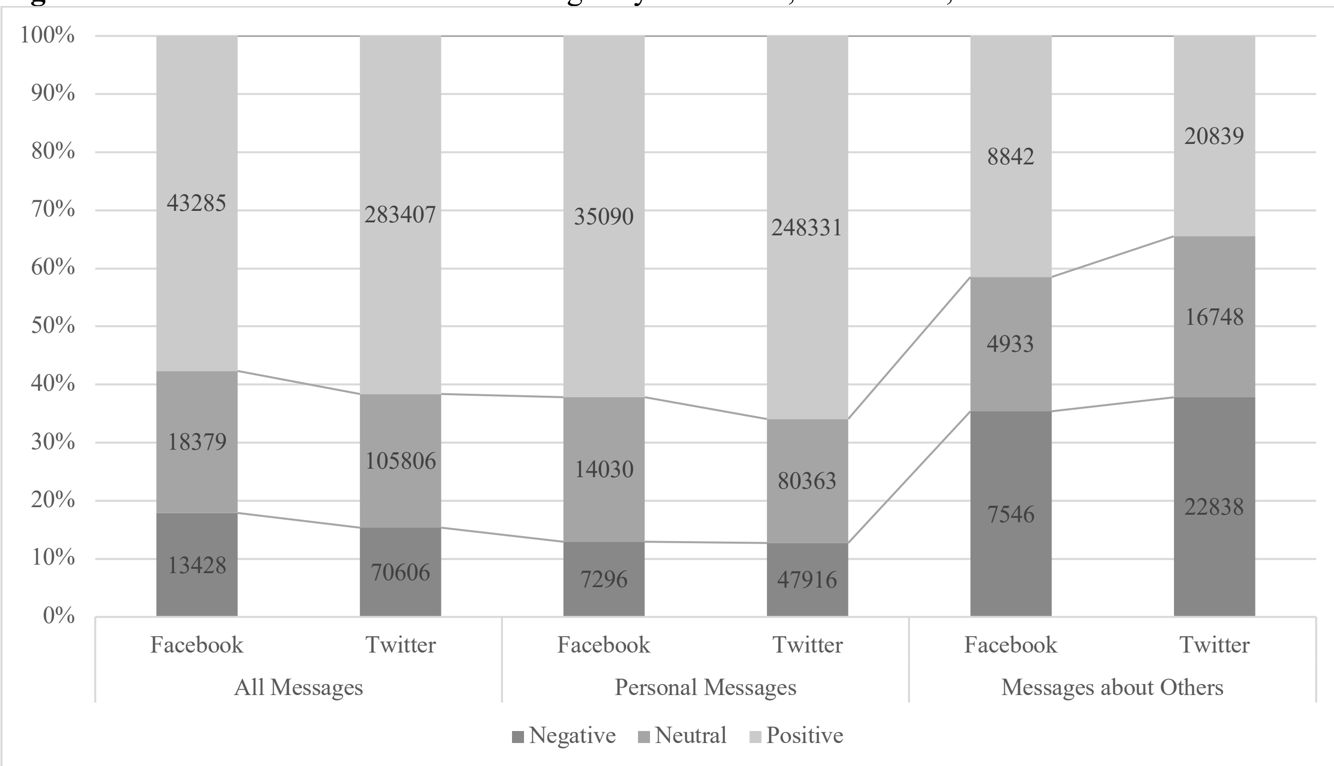
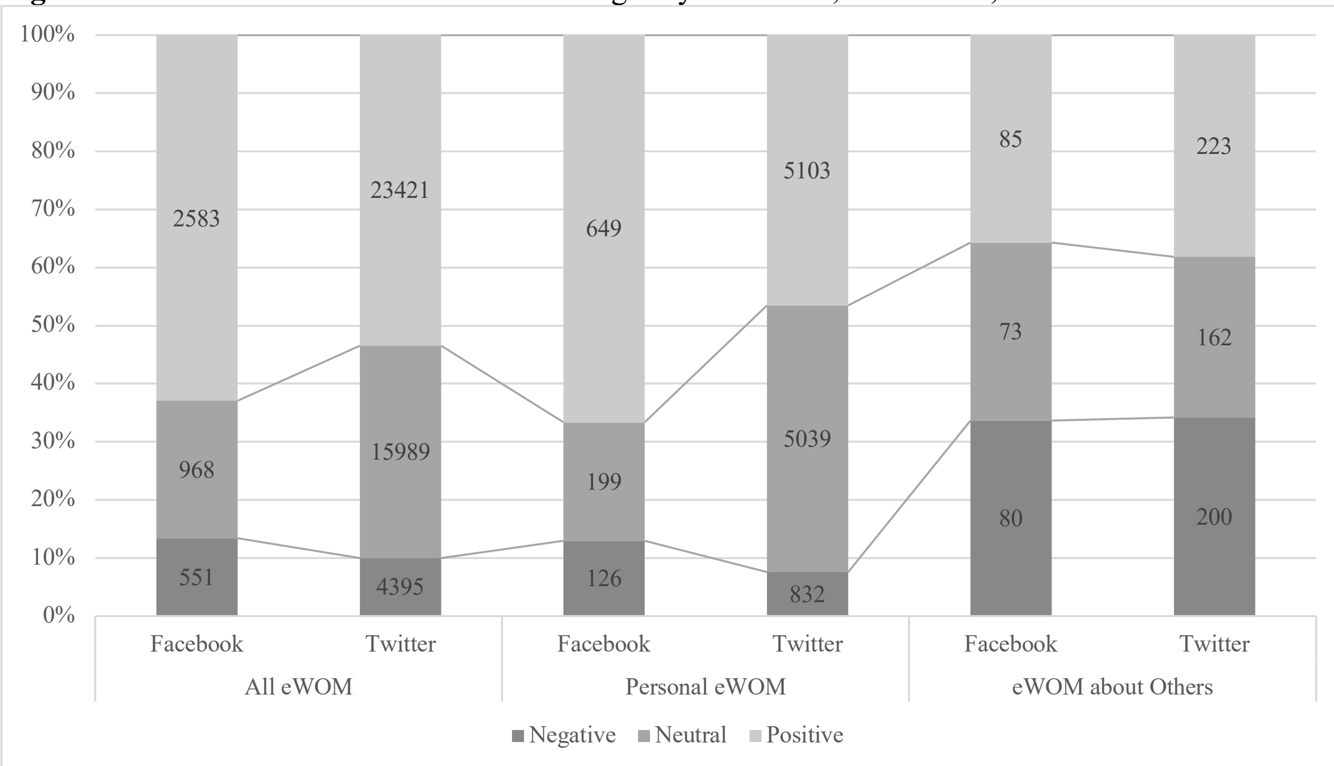
Figure 1 - Ratios and Counts of All Messages by Sentiment, Generation, and SNS



Notes: All messages from users (e.g., not just eWOM). Stacked bar chart by percentage. Raw message count for each sentiment SNS/sentiment/generation type denoted in appropriate shaded bar region.

Figure 2 – Ratios and Counts of eWOM Messages by Sentiment, Generation, and SNS



Notes: Only eWOM messages from users. Stacked bar chart by percentage. Raw message count for each sentiment SNS/sentiment/generation type denoted in appropriate shaded bar region.

Appendix A – Generational (a.k.a. Personal) Codebook

1. Is this post sharing a personal experience? *See examples below**

- I went to my local Starbucks and I love it! So nice.
- My new apartment is so pretty, I am very happy.
- I cannot believe what happened to me the other day, I walked down the street and saw three golden doodles.
- My wife and I are expecting a baby girl.
- Peter and I are so cute together.
- [Automated posts sharing personal experiences (e.g., reaching a new level of a game on Facebook)]

2. Is this post sharing an experience someone else (and not the individual) had? *See examples below**

- Local man gets a worm in his Starbucks Frappuccino
- I once had a friend get food poisoning from drinking 2 beers
- My sister is going to France!
- Donald Trump golfs 24 rounds of golf a day

3. If not 1 or 2, please code as three. *See examples below**

- Kraft singles give people cancer
- Next year the IRS will penalize those that don't e-file
- Next year is a leap year!
- [Automated tweets/posts that don't mention personal accomplishments]

*Examples are fictional and were created before data annotation based off of definition provided by Berger (2016) and Wojnicki and Godes (2008).