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Does who we are affect what we say and when? Investigating the impact of activity and connectivity on microbloggers' response to new products

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ABSTRACT

This paper examines whether microbloggers' past activity and connectivity influences the timing and valence of posted responses to new products. It shows that the timing of a post depends on the past microblogging activity of the poster and the number of posters he or she follows. Textual analysis also shows that the valence of a post is sensitive to the activity of posters, the number of posters followed, the timing of the posts, and the nature of the evaluations of the new product (cognitive vs. affective). These findings provide insights into the relationships among the nature of microbloggers' responses to new products, their previous posting activity, and their online network characteristics. Collectively, the findings of this research suggest that microbloggers' responses to new products should be interpreted after adjusting for posters' non-product-related characteristics.

1. Introduction

Consumers have embraced social media, generating massive amounts of online content about products that interest them (Brown, Broderick, & Lee, 2007). Marketers use this information, called electronic word-of-mouth (eWOM), to track their brands and gain insights into consumer behavior (You, Vadakkepatt, & Joshi, 2015). They are particularly interested in the evolution of sentiments contained in eWOM because its pattern tends to be correlated with brand awareness (Liu, 2006), sales (Srinivasan, Rutz, & Pauwels, 2015), and future online activity (Moe & Schweidel, 2012).

Because of its low cost and high volume, eWOM is useful for gauging early consumer response to new products (Hennig-Thurau, Wiertz, & Feldhaus, 2015). Furthermore, because its content is visible to and searchable by others, eWOM influences future online purchases. Therefore, despite having little control over eWOM (Godes et al., 2005), marketers prefer online conversations about their new products to be positive or neutral. However, eWOM related to new products contains a variety of sentiments (Srinivasan et al., 2015) because of variations in product evaluations and heterogeneity in posters' characteristics.

This paper focuses on the heterogeneity among posters and addresses the following research question: Does past online activity and the structure of online social networks influence the timing and valence of eWOM following the launch of a new product? Although eWOM takes many forms, this research focuses on microblogs, which are short, instantaneous, non-interactive, non-invasive, searchable posts. Almost one in five such posts mentions a brand (Jansen, Zhang, Sobel, & Chowdury, 2009), because of which microblogs are an influential form of eWOM that marketers are increasingly using to gain insights into consumers and stimulate new product adoption (Hennig-Thurau et al., 2015).

Building on the social psychology literature, which suggests that underlying attitudes precede overt behaviors (Ajzen & Fishbein, 1977), the assumption in the present research is that an individual generates a microblog when the intensity of his or her response to a new product exceeds a personal threshold (Daugherty, Eastin, & Bright, 2008). Because of underlying psychological factors, these thresholds, and therefore the propensity to post, vary across individuals. In addition, because individuals are connected with others on social media platforms, the roles they play within their communities are also likely to influence the microblogging responses (Zhao et al., 2015).

Four related studies were used to address the research question posed earlier. First, a pilot test (Study 1) examined whether the stated content and timing of eWOM depend on a poster's past activity and connectivity. Study 2 tested several key hypotheses using results from content analysis of tweets following the launch of Starbucks Via instant coffee. Study 3 was designed to replicate the key findings from Study 2 using data from a controlled study. Finally, Study 4 examined whether

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the readers of microblogs on new products are sensitive to changes made to adjust for posters' characteristics.[2]

The results of these four studies complement existing eWOM research that focuses on the relationships between individual orientation and the propensity to post (Cheung & Lee, 2012), mood and valence (De Choudhury & Counts, 2012), online connectivity and review objectivity (Goes, Lin, & Yeung, 2014), extroversion and online opinion leadership (Helm, Möller, Mauroner, & Conrad, 2013), frequency of posting and differentiation (Moe & Schweidel, 2012), and review timing and review value (Chen & Lurie, 2013). Both the timing and valence of microblogged responses to new products were found to depend on the heterogeneity across posters in terms of observable characteristics such as past posting behavior and the number of inbound and outbound connections within posters' online networks. Given these findings, we suggest that marketers should adjust for posters' characteristics while interpreting the aggregate microblogging sentiments regarding new products. Furthermore, potential receivers of aggregate sentiments may also be sensitive to changes made to adjust for poster characteristics. Therefore, sharing information about adjustments is also likely to influence receivers' future behavior.

2. Consumer roles and online word-of-mouth

2.1. Online word-of-mouth

eWOM is online product information generated by individuals not associated with a sponsoring firm (Godes et al., 2005). It encompasses virtual communities (Dholakia, Bagozzi, & Pearo, 2004), ratings (Moe & Schweidel, 2012), reviews (Cheng & Ho, 2015), blogs (Kozinets, De Valck, Wojnicki, & Wilner, 2010), and microblogs (Dass, Kumar, Kapur, & Topaloglu, 2011). Consumers find such information more reliable than messages from sellers (Wilson & Sherrell, 1993), and frequently use eWOM before making a purchase (Chen & Xie, 2008). Therefore, eWOM tends to improve customer acquisition (Trusov, Bodapati, & Bucklin, 2010), product awareness (Liu, 2006), subsequent eWOM (Moe & Schweidel, 2012), and online and offline sales (Liu, 2006; You et al., 2015).

Scholars have explored the underlying motivations for generating eWOM as well as the elements that make its content valuable for others. They have found that individuals generate product reviews to enhance their reputation, increase their sense of belonging to a community (Cheung & Lee, 2012), and help others (Verhagen, Nauta, & Feldberg, 2013). Those who are otherwise introverted are more likely to post online (Helm et al., 2013), especially about highly differentiated and exciting brands (Lovett, Peres, & Shachar, 2013), while those with high levels of brand commitment are more likely to retransmit content created by others (Kim, Sung, & Kang, 2014). Interestingly, as posters accumulate followers, they produce evaluations that are more objective (Goes et al., 2014), and derive greater value from image-related utility than from the intrinsic utility of posting (Toubia & Stephen, 2013). Individuals who post frequently tend to exhibit differentiation rather than a bandwagon effect (Moe & Schweidel, 2012) and express more polarized opinions (Schlosser, 2005).

eWOM can have normative and informative effects on its recipients (Filieri, 2015), reduce uncertainty about firms' offerings (Adjei, Noble, & Noble, 2010), and affect purchase intent (Lee & Shin, 2014). For example, a polarized post can have “a persuasion effect,” whereas a neutral post can have “an informative effect” (Liu, 2006). eWOM also moderates the effects of actual consumption experiences and can mitigate the effects of product failures (Sridhar & Srinivasan, 2012). The nature of the recipients' network, however, affects their responses, such that those in dense networks do not respond differently to posts with varying valence, while those in sparse networks value positive information (Sohn, 2009). Interestingly, strongly opinionated, negative information tends to be more viral (Godes et al., 2005), and negative evaluators have more credibility (Chevalier & Mayzlin, 2006) and are perceived to be more intelligent and competent (Hennig-Thurau et al., 2015).

2.2. Role expectations and eWOM

Social life for many consumers increasingly rests within the digital realm (Ho & McLeod, 2008), where they play various social roles (Gleave, Welser, Lento, & Smith, 2009). These roles, defined as “clusters of social cues that guide and direct behavior in a given setting” (Solomon, Surprenant, Czepiel, & Gutman, 1985), lead to social expectations that predict appropriate behaviors. These role expectations are dynamic (Lynch, 2007) and depend on contextual factors and individuals' positions within social structures. People maintain consistency in their role expectations and reduce incongruence to avoid feeling incompetent or immoral (Aronson, 1992).

Online social networks have created new roles, such as technical editors on Wikipedia (Gleave et al., 2009) or originators and propagators on Twitter (Zhao et al., 2015). These influential roles carry several labels such as lead users (Schreier, 2007), opinion leaders (King & Summers, 1970), or social hubs (Goldenberg, Han, Lehmann, & Hong, 2009). Influence from such members of a social network, especially those with a large number of followers and a high level of expertise, is particularly important for accelerating the adoption of new products (Cheng & Ho, 2015; Dass, Reddy, & Iacobucci, 2014; Goldenberg et al., 2009).

2.2.1. Effect of activity and connectivity on timing

Within the eWOM context, individuals create positive content because of altruism and self-enhancement and generate negative content for anxiety reduction or vengeance (Richins, 1983). Role expectations further affect these choices because members of a poster's online social network tend to make attributions about the content and timing of a post (Friestad & Wright, 1994). Therefore, influencers try not to be too late because temporal congruity affects the perceived reliability of a post about a new product (Chen & Lurie, 2013; Godes et al., 2005; Liu, 2006). Individuals with many social ties, however, adopt new products sooner because they are exposed to them earlier (Goldenberg et al., 2009). Similarly, those who follow many users in online social networks are also likely to gain exposure to the product sooner and post their responses earlier.

H1. Microbloggers who follow many other users are likely to post sooner in response to a new product than those who follow few other users.

The level of online activity increases the value of connections in a social network (Trusov et al., 2010) and provides intrinsic utility (Toubia & Stephen, 2013). Therefore, activity levels are likely to consolidate network position and increase an individual's influence. Social activity, however, also influences role expectations (Laverie, Kleine, & Kleine, 2002). Those who are perceived to be influential because of high levels of activity will therefore be careful about protecting their role-specific interests and will be slow and deliberate, rather than impulsive, in their online posting behavior (Zhao et al., 2015).

H2. Following the introduction of a new product, microbloggers who post frequently are likely to post later than those who post infrequently.

2.2.2. Effect of activity and connectivity on valence

Dual processing theories in social psychology suggest that two distinct processes in human cognition affect consumer information processing. One is fast, associative, and based on low-effort heuristics,

[2] All experimental studies followed the IRB protocol for exempt status. The participants were recruited on M-Turk and invited to participate in an online survey about social networking. Individuals were not identified in the data, which were kept confidential.

while the other is slow, rule based, and reliant on high-effort systematic reasoning (Cheng & Ho, 2015). Therefore, when the time lapse between a new product launch and the timing of the post is short, feelings and emotional arousal are likely to polarize role enactment in the direction of the poster's affective state (Clore & Storbeck, 2006). For those who deliberate longer, however, conscious processes may influence role behaviors (Lynch, 2007), so the focus may shift toward a cognitive evaluation of a product and away from a polarized, short-term response.

H3a/3b. A microblog following a new product introduction will contain more positively (negatively) valenced content if the time lapse between the product launch and the post is longer (shorter) than if the time lapse is shorter (longer).

As noted, social networks consist of heterogeneous members whose position and past activity are likely to influence the nature of their eWOM. For example, those who play the role of influencers make self-evaluations based on their social ties (Laverie et al., 2002) and tend to be more neutral than those who are mere lurkers (Schlosser, 2005). Similarly, loyal users generate neutral word of mouth, highly active posters are more opinionated (Moe & Schweidel, 2012), and category experts tend to be more positive (De Choudhury & Counts, 2012). Therefore, a high level of past activity should correspond to the role of an expert or influencer and should increase the positive content and reduce the negative content in a microblog following a new product launch.

H4a/H4b. A microblog following the introduction of a new product will contain more positively (less negatively) valenced content if the poster is more active than if the poster is less active.

Individuals form social networks because of two basic motivations: safety and efficacy (Greenberg, 1991). Furthermore, individuals often strive for competence and mastery to maintain their egos. When the drive for self-efficacy is strong, individuals create diverse relationships (Brown et al., 2007) and play specific roles such as that of the social hub. These roles influence the form of content exchanged over dyadic relationships within networks. As the number of followers in a network increases, the image-related utility from sharing content increases and often supersedes the intrinsic utility from generating a post (Toubia & Stephen, 2013). Those with a large following are likely to be more positive in their communication to facilitate a favorable self-image of an expert (De Choudhury & Counts, 2012).

H5a/5b. Positively (negatively) valenced content in a microblog following the introduction of a new product will increase (decrease) with an increase in the number of the poster's followers.

Prior research on role theory also suggests that people view subjectively expressed cognitive and affective messages as being more diagnostic of their real self than objectively observed behavior (Andersen & Ross, 1984). People believe that others learn more about their essential nature by accessing their thoughts and feelings rather than by watching them. Cognitive and affective cues intertwined within microblogs are mechanisms used to express role identity (Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2015). For example, altruism, self-enhancement, and reciprocity may initiate positive word-of-mouth, while anxiety reduction and vengeance may trigger negative word-of-mouth (Richins, 1983). More generally, affective and cognitive states often co-exist within the context of online activity (Richard & Chebat, 2016). When a poster is more affectively or cognitively charged, the valence of his or her post will deviate further from a neutral position in terms of the expressed attraction or aversion toward a new product.

H6a/6b. Positively (negatively) valenced content in a microblog following the introduction of a new product will increase (increase) with an increase in the affective content of a post.

H7a/7b. Positively (negatively) valenced content in a microblog following the introduction of a new product will increase (increase) with an increase in the cognitive content of a post.

3. Studies

3.1. Study 1

In this pilot study, individuals with microblogging accounts were queried regarding the structure of their online social network and online posting activity. Using M-Turk, 123 participants (mean age 33.4 years, 58.5% female) were recruited and paid 25 cents each for participating. Each participant reported the number of times per week he or she posted on Twitter (0 = never, 1 = 1 post/week, …, 5 = 5 posts/week) and the number of connections he or she had on the platform (1 = 0–100 connections, 2 = 101–200 connections, …, 5 = 400 + connections). Thereafter, participants responded to four questions on 7-point scales (1 = strongly disagree and 7 = strongly agree) regarding whether their posting activity and number of online connections influenced the time lapse and content of their posts.

3.1.1. Study 1: results

Four linear models were separately estimated to determine the effects of past posting activity and number of connections on the time lapse and content of online posts. Participants with higher levels of activity ($\beta = 0.388$, $p < 0.05$) and more connections ($\beta = 0.308$, $p < 0.05$) tended to agree more with the statements that the two factors affected when they posted. Similarly, participants with higher levels of activity ($\beta = 0.320$, $p < 0.05$) and more connections ($\beta = 0.301$, $p < 0.05$) were also more likely to agree that the two factors affected what they posted. These results provide some initial evidence that activity and connectivity may influence the timing and content of microbloggers' posts, and are consistent with hypotheses H_1 and H_2.

3.2. Study 2

3.2.1. Sample and data collection

The objective of Study 2 was to test hypotheses H_1 through $H_{7a/b}$ using actual microblogging data collected following the launch of a real new product. Microblogging data were collected from Twitter.com for the four-week period immediately following the launch of Starbucks Via instant coffee. Via was chosen because its launch was not pre-announced, which enabled calibration of the time lapse between posts and the launch date. It was also a prototypical consumer product and generated a large volume of tweets. After the four-week window for data collection, the number of tweets about the product was negligible. All posts including the keywords “Starbucks VIA,” “Starbucks and VIA,” “#VIA,” and “#Starbucks” were gathered, yielding a sample of 5038 microblogs. Three independent judges verified that each post pertained to Starbucks Via and coded each post for positive, negative, or neutral valence. Inter-coder reliability (Cohen's Kappa $k > 85\%$) was high. The judges discussed any differences until they reached a consensus.

Data on the number of tweets generated by each poster in the past, the number of his or her Twitter followers, and the number of others that he or she followed were also collected. No participant posted more than one tweet about Via. The 26 days following the product launch were coded consecutively from 1 to 26 to form the time lapse variable. Computer-aided text analysis using the Linguistic Inquiry and Word Count (LIWC, 2007 edition) software (Pennebaker, Francis, & Booth, 2001) was conducted to extract the cognitive and affective components from each post. The linguistic tool contains a dictionary that includes 910 words for “affect” and 622 words for “cognitive mechanisms.” The LIWC sub-dictionaries are based on words from multiple sources, including emotion rating scales such as PANAS (Watson, Clark, & Tellegen, 1988). The validity of LIWC to successfully measure positive and negative emotions and cognitive strategies has been established by Pennebaker and Francis (1996). LIWC has been used more recently to extract sentiments from microblogs (Bae & Lee, 2012), assess moods based on social media activity (De Choudhury & Counts, 2012), and generate scores for people's cognitive and affective states (Sridhar & Srinivasan, 2012).

3.2.2. Model

It was hypothesized that the time lapse between a new product's launch and a post is a function of the microblogger's past activity and the number of other posters that the microblogger follows on Twitter. The time lapse between the launch of the product and the posting of microblog i by an individual poster was therefore modeled as follows:

$$(Time\ Lapse)_i = \beta_0 + \beta_1\ (Activity)_i + \beta_2\ (Numbers\ Followed)_i + \varepsilon \quad (1)$$

It was also hypothesized that the positive and negative valence of posts is a function of the time lapse, the past activity of the poster, his or her number of followers, and the cognitive and affective content of the post. Accordingly, both positive and negative valence of the content in microblog i were modeled separately as follows:

$$(Positive\ Valence)_i = \beta_0 + \beta_1\ (Time\ Lapse)_i + \beta_2\ (Activity)_i + \beta_3\ (Number\ of\ Followers)_i + \beta_4\ (Affective)_i + \beta_5\ (Cognitive)_i + \varepsilon \quad (2)$$

$$(Negative\ Valence)_i = \beta_0 + \beta_1\ (Time\ Lapse)_i + \beta_2\ (Activity)_i + \beta_3\ (Number\ of\ Followers)_i + \beta_4\ (Affective)_i + \beta_5\ (Cognitive)_i + \varepsilon \quad (3)$$

Each valence was operationalized as a 0/1 dummy variable relative to neutral valence. The affective and cognitive content of each post was extracted using LIWC, and time lapse was operationalized as the number of days between a post and the launch date of Via. The variables for poster activity, number of followers and users followed, affective content, and cognitive content were log transformed. The data did not pose problems of multicollinearity, and the Pearson correlation coefficients among the variables were between 0.10 and 0.15. Regression Eq. (1) and logistic regression Eqs. (2) and (3) were estimated simultaneously using maximum likelihood estimation (MLE).

3.2.3. Study 2: results

The results of the simultaneous equation analysis provide support for the majority of the hypotheses (Table 1). The time lapse was longer when a poster's past activity was higher ($\beta = 0.25$, $p < 0.05$) but shorter for posters who followed a large number of users ($\beta = -0.101$, $p < 0.05$). These results are consistent with H_1 and H_2.

The likelihood that a post had a positive valence was higher when the time elapsed was longer ($\beta = 0.14$, $p < 0.05$), the past activity was higher ($\beta = 0.03$, $p < 0.05$), and the number of the poster's followers was smaller ($\beta = -0.025$, $p < 0.05$). The presence of both affective ($\beta = 0.14$, $p < 0.05$) and cognitive content ($\beta = 0.14$, $p < 0.05$) increased the likelihood of positive valence. These results are consistent with hypotheses H_{3a} through H_{7a}, except H_{5a}.

The likelihood of negative valence was higher when the time elapsed was shorter ($\beta = -0.003$, $p < 0.05$) and the past activity was higher ($\beta = -0.075$, $p < 0.05$). The number of followers had no effect ($\beta = 0.001$, *n.s.*). The presence of affective content had no effect on negative valence ($\beta = -0.001$, *n.s.*), but cognitive content had a positive effect ($\beta = 0.01$, $p < 0.05$). These results suggest that the factors that drive positive valence may differ somewhat from those that drive negative valence.

Table 1
Results from the model estimation of the Twitter data (Study 2).

Parameters	Time lapse (Eq. (1)) estimates (std. error)	Positive (Eq. (2)) estimates (std. error)	Negative (Eq. (3)) estimates (std. error)
Intercept	8.166 (0.518)**	0.207 (0.042)**	0.813 (0.034)**
Time lapse		0.014 (0.001)**	−0.003 (0.001)**
Activity	0.251 (0.069)**	0.030 (0.006)**	−0.075 (0.005)**
Numbers followed	−0.101 (0.052)**		
Number of followers		−0.025 (0.005)**	0.001 (0.004)
Affective content		0.029 (0.001)**	−0.001 (0.001)
Cognitive content		0.013 (0.001)**	0.010 (0.001)**

** $p < 0.05$.

3.2.4. Discussion

These results suggest that posters' observable characteristics such as their past activity and connectivity affect the timing and valence of their microblog entries following a new product launch. As expected, frequent posters waited longer and were perhaps circumspect rather than impetuous in their microblogging behavior. Posters who followed many others were more likely to post early, presumably because they were informed on new products earlier. The content of posts was related to posters' observable characteristics and past posting behavior. Specifically, those who posted later, those with fewer followers, and those with limited past activity were more likely to post positively-valenced content. In contrast, those who posted earlier and those who were active were more likely to post negatively-valenced content. Finally, both affective and cognitive content had an effect on positive posts, whereas only cognitive content had an effect on negative posts.

3.3. Study 3

Although Study 2 was based on actual data from Twitter, there was no information available regarding when and how each poster was first exposed to information about Via. Therefore, Study 3 was a controlled experiment where participants were simultaneously exposed to information about a new product and queried on the time lapse and valence of a potential post. Participants then constructed an actual post with a limit of 140 characters.

3.3.1. Study 3: method

3.3.1.1. Participants. Using M-Turk, 201 respondents were recruited and paid 25 cents each for participation (mean age 35.4 years, 55.2% female).

3.3.1.2. Stimuli. Participants were shown an announcement from Burger King about a new burrito called “Whopperito.” The announcement contained the product image. Participants self-reported whether they would share this announcement on social media. Those who stated that they would (192 respondents) reported when (varying from “Instantly” to “Never”) they might post and whether the valence of their post would be positive, negative, or neutral. Finally, these participants typed their 140-character posts.

3.3.2. Study 3: results

Once again, the information in the posts created by participants and other self-reported information about participants were used to estimate Eqs. (1)–(3) simultaneously. Given the study context, inward and outward connectivity were not measured separately. Instead, connectivity was defined as the number of online connections reported by each participant. Unlike in Study 2, the data in Study 3 referred to stated intent rather than actual behavior.

Much like in Study 2, activity had a positive effect on the stated time lapse of the post ($\beta = 0.368$, $p < 0.05$), whereas the number of connections had a negative effect ($\beta = -0.24$, $p < 0.05$) (Table 2). Consistent with H_1 and H_2, active posters were more likely to post later, and those with many followers were more likely to post earlier. Time

Table 2
Results from the model estimation of the replication study (Study 3).

Parameters	Time lapse (Eq. (1)) estimates (std. error)	Positive (Eq. (2)) estimates (std. error)	Negative (Eq. (3)) estimates (std. error)
Intercept	4.94 (0.422)**	0.289 (0.161)	0.083 (0.125)
Time lapse		0.063 (0.021)**	− 0.013 (0.015)
Activity	0.368 (0.096)**	− 0.068 (0.029)**	0.045 (0.021)**
Number of connections	− 0.240 (0.090)**	− 0.004 (0.026)	0.013 (0.020)
Affective content		0.019 (0.011)	0.004 (0.008)
Cognitive content		0.007 (0.012)	− 0.017 (0.009)

** $p < 0.05$.

lapse had a positive effect ($\beta = 0.063$, $p < 0.05$) for positive valence (H_{3a}) but no effect ($\beta = -0.013$, *n.s.*) for negative valence (H_{3b}). Positive comments were likely to be posted later, but there was no systematic pattern to the timing of negative posts.

The effects of activity on stated valence were different from what was hypothesized in $H_{3a/3b}$. In this controlled setting, posters who were more active were less likely to write positively-valenced microblog entries ($\beta = -0.068$, $p < 0.05$) and were more likely to write negatively-valenced posts ($\beta = 0.045$, $p < 0.05$). This difference between Studies 2 and 3 could be the result of participants' beliefs that critics or negative evaluators are seen as more intelligent and competent (Hennig-Thurau et al., 2015). No other effect was statistically significant. Overall, despite widely differing methods, the results of Studies 2 and 3 are highly consistent. The effects of time lapse and valence are similar across Studies 2 and 3. The effects of connectivity are directionally similar but weaker in Study 3, perhaps because of the smaller sample size and greater sample homogeneity.

3.4. Study 4

Study 4 examined whether receivers of eWOM would be sensitive to adjustments in the aggregate sentiment of the posted content that account for the characteristics of microbloggers.

3.4.1. Method

3.4.1.1. Design and participants. A between-subjects design was used, and participants were randomly assigned to one of four cells. In all conditions, the cumulative raw sentiment scores for a new product were presented as 3 stars out of 5. The cumulative adjusted sentiment scores were manipulated as 1 star, 2 stars, 4 stars, and 5 stars. The next stage was to examine whether participants' responses to the new product were sensitive to the adjusted scores that accounted for microbloggers' characteristics. Using M-Turk, 94 participants were recruited and paid 25 cents each for completing the study (mean age 33.4 years, 45.7% female).

3.4.1.2. Stimuli. Participants read a scenario involving a new online platform called "Trueratings" (a fictitious name), which evaluates sentiments expressed in tweets after a new product launch. They were told that the platform offers two forms of aggregated scores: a "base sentiment," which provides an average sentiment score across all product-related tweets, and an "adjusted sentiment," which accounts for posters' characteristics. A high score means that most tweets contain positive sentiments; a low score means the opposite. Participants were told that although the site does not disclose the specific characteristics used for adjustment, it is generally known that past activity levels and social media connections influence what individuals tweet.

Participants were then told that "Extra Crispy" fries launched the previous week by a popular, mid-priced sandwich chain evoked a big response on Twitter. While the chain's advertising promoted the product's increased crunchiness owing to a new coating, the posts on Twitter also commented on flavor and other factors. Participants were then instructed to imagine that they came across a news story that mentioned the previous week's Trueratings scores for tweets about the new product. They saw the same base score but different adjusted scores and reported their evaluation of the reported social media response to the new product on a 3-item scale (1 = negative/unfavorable/bad and 7 = positive/favorable/good) and the likelihood they will try the product (1 = very unlikely and 7 = very likely).

3.4.2. Study 4: results

A one-way ANOVA of the averaged 3-item evaluation rating showed that the effect of the adjusted sentiment score as the independent factor was statistically significant ($F(3, 90) = 25.37$, $p < 0.05$). The average response for the two downward-adjusted conditions ($M_{Adj1} = 3.34$; $M_{Adj2} = 3.54$) was lower than for the two upward-adjusted conditions ($M_{Adj4} = 5.12$; $M_{Adj5} = 5.34$; ($t = 8.712$, $p < 0.05$)). The differences between the two downward-adjusted conditions and between the two upward adjusted conditions were not statistically significant ($p > 0.10$ for both) (Table 3).

Similarly, a one-way ANOVA of the likelihood to try the new product showed a similar response pattern ($F(3, 90) = 14.63$, $p < 0.05$). The average response for the two downward-adjusted conditions ($M_{Adj1} = 3.00$; $M_{Adj2} = 3.09$) was lower than for the two upward-adjusted conditions ($M_{Adj4} = 5.04$; $M_{Adj5} = 5.09$; ($t = 6.692$, $p < 0.05$)). The differences between the two downward-adjusted conditions and between the two upward-adjusted conditions were not statistically significant ($p > 0.10$ for both). These results show that participants' social media evaluation and likelihood to try the product were both sensitive to the direction of adjustment from the base score, though not necessarily to the magnitude of the shift.

4. Discussion and conclusion

Consumers receive information about new products from multiple sources, such as the firm (Srinivasan et al., 2015), organized media (Chen & Xie, 2008), and social media (Trusov et al., 2010). Given consumers' trust in high volume, peer-based communication (Wilson & Sherrell, 1993), marketers are interested in diagnosing the content of microblogs about their products, especially newly launched products. Marketers are also interested in the timing of the responses because, unlike reviews, microblogs are typically read soon after their creation.

Table 3
Social media response and likelihood to purchase as a function of adjusted sentiment scores (Study 4).

Sentiment scores	Social media response[a]	Likely to purchase[b]
Base score = 3, adjusted score = 1	3.34	3.00
Base score = 3, adjusted score = 2	3.54	3.09
Base score = 3, adjusted score = 4	5.12	5.04
Base score = 3, adjusted score = 5	5.34	5.09
	$F(3, 90) = 25.37$, $p > 0.05$	$F(3, 90) = 14.63$, $p < 0.05$

[a] 1 = negative/unfavorable/bad; 7 = positive/favorable/good.
[b] 1 = very unlikely; 7 = very likely.

This research shows that the timing and content of microblogs following new product launches depends on certain characteristics of the microbloggers. Active posters are likely to post later (H_1), whereas posters who follow many other users are likely to post earlier (H_2). Those who post earlier are more likely to post valenced content than neutral content ($H_{3a/3b}$), which is likely to be more positive and less negative for active posters ($H_{4a/4b}$). Posters with more followers are likely to post less positive content ($H_{5a/5b}$). Finally, both the positive and negative valence of a post increases with greater cognitive and affective content ($H_{6a/6b}$ and $H_{7a/7b}$).

4.1. Theoretical implications

The rise of social media has led to a broad interest in understanding the psychological underpinnings of posting behavior (Hu, Wang, Dai, & Huang, 2012) and identifying sources of misinformation (Qazvinian, Rosengren, Radev, & Mei, 2011). The findings of this research add to this stream of literature and provide evidence that both the timing and valence of a microblogger's response to a new product launch depend on the microblogger's role within the network and past microblogging activity. Specifically, active influencers are more likely to be circumspect than impetuous and more likely to post later than post their impulsive gut reactions. In contrast, microbloggers who follow many other users rather than being influencers themselves tend to react early. This finding is consistent with previous research, which suggests that product reviewers are aware of their reputation when creating online content (Cheung & Lee, 2012).

The studies presented in this paper also extend the literature on the way posting frequency affects differentiation in online content (Moe & Schweidel, 2012) by demonstrating the relationship between past activity and the timing of posts. The results also show that active posters who have successfully played the role of influencers may not need to earn additional credibility by being negative in their evaluations. In contrast, impulsive microbloggers who post early are likely to be more negative. These findings enrich the product reviews literature, in which posters with more followers have been found to be more objective (Goes et al., 2014).

The findings presented in this paper provide additional insights into the asymmetric effects of posters' characteristics on the valence of microblogs. Although both cognitive and affective content contributed to positive valence in microblogs, only cognitive content contributed to negative valence. While some of these differences may depend on the product or brand being reviewed, the general pattern of results is consistent with the premise that negative reviewers are perceived to be more competent (Hennig-Thurau et al., 2015). It follows, therefore, that those who aspire to build a reputation through critical comments are more likely to take a rational approach than an emotional approach to posting.

Finally, while past research has evaluated the effect of dense versus sparse networks on the recipients' preference for positive versus negative content (Sohn, 2009), it has failed to evaluate recipients' sensitivity to adjustments made specifically to account for posters' characteristics. This paper, however, shows that recipients of microblogged content are interested in objective information and may respond favorably to aggregate sentiments that parse out the effects of heterogeneity across posters. These initial findings suggest that recipients may not necessarily be interested in the opinions of influential microbloggers who post frequently for a large follower base, but rather in the aggregate evaluations from multiple microbloggers after removing the effects of the size of their following and the frequency of past activity.

4.2. Managerial implications

There is evidence of increasing interest in using sentiments in microblogs to forecast unit sales (Jansen et al., 2009), revenues (Du, Xu, & Huang, 2014), and stock prices (Oh & Sheng, 2011). The findings of this research suggest that adjustments for posters' characteristics are likely to remove heterogeneity and improve the predictive power of the underlying models and algorithms used for this purpose. In fact, even the diagnostic power of sentiment analysis could be improved by using adjusted rather than raw microblog data. For example, the findings imply that the observed drift toward a neutral valence over time (e.g., Hennig-Thurau et al., 2015) may not necessarily be because the market becomes apathetic toward a new product. Instead, the reason for this drift might be that the type of individuals who post early may differ from those who post late. Therefore, adjustment for microblogger characteristics should precede any interpretation of trends in online activity valence.

Marketers often cultivate and encourage well-connected individuals to post an early, positive response to new products. The findings of this research, however, suggest that this approach may sometimes fail because influential posters tend to be more deliberate and perhaps more conscious of their own role among their followers. Apparently, well-connected microbloggers tend to be more conscious of their reputation as opinion leaders and are averse to taking polarizing positions regarding new products. Therefore, an alternative approach of seeking active rather than well-connected individuals to write early posts may work. Such individuals tend to post early and positively, even if they have fewer followers. Marketers may then leverage better-connected individuals at a later stage if the initial response is positive.

5. Limitations and future research

Although this research offers some insight into the way the characteristics of microbloggers affect their posted responses to new products, future studies should address some of the limitations of this research. For example, although timing and valence were addressed, future research should examine the effects on eWOM volume, especially for markets where eWOM is positively correlated with revenues (Liu, 2006). Second, the assumption in this research was that receivers find polarized posts more useful than neutral posts. Consumers in some markets, however, prefer informative, neutral eWOM (Kasabov, 2016), so it would be useful to assess whether influential posters adjust their behavior in light of such beliefs. Third, the research focus was on individual differences observable on social media platforms. Future research involving behavioral studies can provide additional insights into specific psychological characteristics that drive observable behaviors.

The hypotheses and data were limited to microblogging. It is expected that on other platforms such as forums, domain expertise and opinion leadership may be valued more. Future research should examine whether in such cases deviation from a neutral position is more valuable and whether this deviation affects the valence of posts. Finally, a recent argument in the social media literature advocates targeting revenue leaders rather than opinion leaders during a new product launch (Haenlein & Libai, 2013). Given the limited scope of this research, this issue was not addressed. It is hoped that future research can explore the way individual differences affect interpretations of post-launch eWOM from opinion leaders or revenue leaders.

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