Twitter Power: Tweets as Electronic Word of Mouth

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In this paper we report research results investigating microblogging as a form of electronic word-of-mouth for sharing consumer opinions concerning brands. We analyzed more than 150,000 microblog postings containing branding comments, sentiments, and opinions. We investigated the overall structure of these microblog postings, the types of expressions, and the movement in positive or negative sentiment. We compared automated methods of classifying sentiment in these microblogs with manual coding. Using a case study approach, we analyzed the range, frequency, timing, and content of tweets in a corporate account. Our research findings show that 19% of microblogs contain mention of a brand. Of the branding microblogs, nearly 20% contained some expression of brand sentiments. Of these, more than 50% were positive and 33% were critical of the company or product. Our comparison of automated and manual coding showed no significant differences between the two approaches. In analyzing microblogs for structure and composition, the linguistic structure of tweets approximate the linguistic patterns of natural language expressions. We find that microblogging is an online tool for customer word of mouth communications and discuss the implications for corporations using microblogging as part of their overall marketing strategy.

Introduction

Collaboration and community are important characteristics of Web 2.0 development and are key features of social communication services like social network (e.g., MySpace, Facebook, and LinkedIn), virtual reality (e.g., Second Life), and online community (e.g., Wikipedia, YouTube, and Flickr) sites. Combined with the ubiquitous online access, these services provide constant connectivity among people that is previously unparalleled. There are numerous open questions concerning the overall impact of these social communication platforms. In this study we investigate the effects of services in the commercial sector, namely, the impact on the relationship between company and customer. Given their distinct characteristics, these social communication services, we believe, have the potential to substantially impact word-of-mouth branding, which can impact key elements of the company–customer relationship including brand image and brand awareness.

Word of mouth (WOM) is the process of conveying information from person to person and plays a major role in customer buying decisions (Richins & Root-Shaffer, 1988). In commercial situations, WOM involves consumers sharing attitudes, opinions, or reactions about businesses, products, or services with other people. WOM marketing is influential, multifaceted, and typically hard to influence (Dellarocas, 2003; Ha, 2006; Helps, Lewis, Mobilio, Perry, & Raman, 2004). Positive WOM is considered a powerful marketing medium for companies to influence consumers. WOM communication functions based on social networking and trust: people rely on families, friends, and others in their social network. Research also indicates that people appear to trust seemingly disinterested opinions from people outside their immediate social network, such as online reviews (Duana, Gub, & Whinston, 2008). This form is known as online WOM (OWOM) or electronic WOM (eWOM).

This broad reach of eWOM provides consumers tremendous clout to influence brand image and perceptions (Reynolds, 2006; Urban, 2005). In terms of brand management, companies can attempt to start eWOM and viral marketing operations (Wells, Moriarty, & Burnett, 2000), but once the WOM campaigns begin or are unleashed, they

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become uncontrollable because little or no tools are available to manage the content flow (Ennew, Banerjee, & Li, 2000). However, brand management is transforming as communication technology changes. Although similar to earlier forms of word-of-mouth, eWOM offers a variety of means to exchange information, many times anonymously or confidentially, as well as to provide geographical and temporal freedom; moreover, eWOM has at least some degree of permanence (Gelb & Sundaram, 2002; Kiecker & Cowles, 2001). As such, eWOM is seen as increasingly important by businesses and organizations concerned with reputation management. Corporations and other organizations are wrestling with how eWOM branding will affect existing processes, such as trademarks (Goldman, 2008).

One potentially new form of eWOM marketing is microblogging using Web social communication services such as Twitter. One paradigm for studying the constant connectivity of modern social networking services in the commercial area is called the attention economy (Davenport & Beck, 2002), where brands constantly compete for the attention of potential customers. In this attention economy, microblogging is a new form of communication in which users can describe things of interest and express attitudes that they are willing to share with others in short posts (i.e., microblogs). These posts are then distributed by instant messages, mobile phones, email, or the Web. Given its distinct communication characteristics, microblogging deserves serious attention as a form of eWOM.

Microblogs are short comments usually delivered to a network of associates. Microblogging is also referred to as micro-sharing, micro-updating, or Twittering (from Twitter, by far the most popular microblogging application). *Tweets* (short posts) may enter our lexicon just as Xerox has for copying and Google has for searching. For this paper, we will refer to this phenomenon as microblogging. Microblogging directly impacts eWOM communication because it allows people to share these brand-affecting thoughts (i.e., sentiment) almost anywhere (i.e., while driving, getting coffee, or sitting at their computer) to almost anyone "connected" (e.g., Web, cell phone, IM, email) on a scale that has not been seen in the past. While the shortness of the microblog keeps people from writing long thoughts, it is precisely the micro part that makes microblogs unique from other eWOM mediums, including full blogs, WebPages, and online reviews. A standard microblog is approximately the length of a typical newspaper headline and subhead (Milstein, Chowdhury, Hochmuth, Lorica, & Magoulas, 2008), which makes it easy to both produce and consume. The message is also asynchronous noninvasive, since one can choose who to receive updates from. They are also archival in the sense that these microblogs permanently exist and are searchable via Web search engines and other services. Since they are online, they are also typically accessible by anyone with an Internet connection. In short, these micro-branding comments are immediate, ubiquitous, and scalable.

For eWOM, these microblogs offer immediate sentiment and provide insight in affective reactions toward products at critical junctions of the decision-making and purchasing process. In this study we examine the expressions of brand attitudes in microblog postings.

Review of the Literature

Prior research has shown that WOM has particularly significant influences on new consumer purchases of products or services (Engel, Blackwell, & Kegerreis, 1969; Katz & Lazarsfeld, 1955). eWOM is a form of this communication, defined as a: "statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau, Gwinner, Walsh, & Gremle, 2004, p. 39). eWOM may be less personal in that it is not face-to-face (or maybe just personal in a different way than in the past), but it is more powerful because it is immediate, has a significant reach, is credible by being in print, and is accessible by others (Hennig-Thurau et al., 2004, p. 42). In terms of immediacy of eWOM branding, microblogging can occur very near the purchase decision or even during the purchase process (Barton, 2006). Thus, microblogging has significant implications for the success of advertisers, businesses, and products as a new eWOM communications, and understanding the ramifications of microblogging is critical for these stakeholders.

One can conceptually view eWOM expressions as utterances. Grice (1969) theorized that one could deduce meaning in comments by examining the underlying intentions. The intentions might be to share information, seek information, offer opinions, etc. This relates to the work of Allen & Perrault (1986), who postulated that the "world" is a set of propositions involving actions, plans, and speech. Speech is composed of utterances. These utterances could inform, warn, assert, or promise. Sundar (2008) stated that many people experience the world through their own self-expression and the expressions of their peers, which blurs the traditional boundary between interpersonal and mass communication. As media becomes more interactive, multimodal, and navigable, the receiver tends to become the source of communication.

Although there are no studies at this time on microblogging as eWOM communication, prior work has examined other forms of eWOM exchanges. Montoya-Weiss, Voss, and Grewal (2003) examined what drove customers to use an online channel (i.e., a Website) in a multichannel environment that included offline channels (i.e., brick and mortar store). The researchers concluded that Website design characteristics affected customer evaluations of online channel service quality and risk, which, in turn, drove online channel use. Nardi, Schiano, Gumbrecht, & Swartz (2004) investigated what caused people to express themselves online. They reported five major motivations for blogging: documenting one's life, providing commentary and opinions, expressing deeply felt emotions, articulating ideas through writing, and forming and maintaining community forums.

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Goldsmith & Horowitz (2006) investigated the consumer motivations for online opinion seeking. The researchers reported distinct factors, including risk reduction, popularity, lowering costs, easy information, accident, perception, inspiration from offline inputs such as TV, and prepurchase information acquisition. Thorson & Rodgers (2006) tested the effects of an interactive blog on attitudes toward a particular Website. Focusing on interactivity, perceived interactivity, and social interaction, participants in the high interactivity condition reported significantly higher scores on perceived interactivity, demonstrating that perceptions of interactivity were influenced by the presence of a single interactive element on a Website. The researchers concluded that there were persuasive effects resulting from providing an opportunity for Website visitors to share their thoughts and opinions.

Davis and Khazanchi (2008) evaluated the impact of eWOM attributes and factors on e-commerce sales using real-world data from a multiproduct retail e-commerce firm. The researchers validated a conceptual model of eWOM and its impact on product sales. Their research showed that the interactions among eWOM postings, product category, volume of postings, and product were statistically significant in explaining changes in product sales. Cheung, Lee, & Rabjohn (2008) examined the extent to which people were willing to accept and adopt online consumer reviews and the factors that encouraged adoption. The research findings reported comprehensiveness and relevance to be the most effective components of online postings. Park & Lee (2009) reported that negative eWOM had a greater effect than positive eWOM.

Related to eWOM communication is sentiment analysis or opinion mining, Zhang, Yu, & Meng (2007) stated that opinion mining required the retrieval of relevant documents and then ranking those documents according to expressed opinions about a query topic. Certainly, though, one could be interested in aspects other than a ranked list. Liu, Hu, & Cheng (2005) developed an application for analyzing and comparing consumer opinions for a set of competing products. Wijaya & Bressan (2008) leveraged the PageRank algorithm to measure movies based on user reviews. Their results compared favorably with the actual box office rankings. Lee, Jeong, & S. Lee (2008) presented a survey of the various techniques for opinion mining. Focusing on blogs, Conrad, Leidner, & Schilder (2008) developed methods for detecting the authority of those making opinions. Archak, Ghose, & Ipeirotis (2007) examined online product reviews in order to identify specific product characteristics and then weight each in terms of importance to customers.

Although certainly related to prior eWOM research, there has been limited published work in the microblogging area. McFedries (2007) presents a short overview of microblogging, commenting that one goal may be to enhance ones' cyberspace presence. Java, Song, Finin, & Tseng (2007) studied the topological and geographical properties of Twitter's social network. The researchers found that people used microblogging to talk about their daily activities and to seek or share information. Milstein et al. (2008) reviewed general background on Twitter and microblogging. Ebner & Schiefner (2008) and Grosseck & Holotescu (2008) examined microblogging in an educational setting. There are numerous popular press articles on using microblogging applications, mainly Twitter, for branding and related purposes (cf., Brogan, 2008; Postman, 2008; Thompson, 2008). Focusing on the social networking aspects, Huberman, Romero, & Wu (2009) focused on a scarcity of attention and daily activities that channeled people into interacting with only a few people, which their study of Twitter bore out.

From a review of the literature, it is apparent that eWOM is an important aspect of a consumer expression of brand satisfaction and may have critical impact on a brand's image and awareness. eWOM shows all the signs of becoming even more important in the future as these social networking applications become more widespread. It is also apparent that much of the focus of prior eWOM research has been on blogs, customer review sites, and WebPages. These are certainly aspects of eWOM, but there has been little prior work in the microblogging area. Microblogging is becoming increasingly important due to its immediacy to the product event and the increasing use of microblogging by a wider group of potential customers. As such, microblogging will probably have increasing influence on eWOM branding efforts.

As such, there are several fundamental yet unanswered questions concerning microblogging as eWOM. How prevalent are branding microblogs? How do people structure these microblogs? What types of branding sentiment do these microblogs express? What are their effects on online reputation management? What are the implications for brand managers? These are the questions that motivate our research.

Why are companies concerned about these online forms of expression? It is because they can affect (perhaps both positively and negatively) the brand image of company. Figure 1 presents a classical model of branding.

In Figure 1a general model of branding Esch, Langner, Schmitt, & Geus (2006) is shown aligned with the reasonable effects of eWOM microblogs. Esch et al. (2006) evaluated a branding model in the online branding environment. They reported that current purchases were affected by *brand image* directly and by *brand awareness* indirectly. These two components of brand knowledge seem to be the primary areas where eWOM microblogging would have a direct influence. Esch et al. (2006) already found that brand knowledge affected future purchases via a brand relationship (which includes brand satisfaction, brand trust, and brand attachment). It would again appear that microblogging could have an important influence in this area, requiring brand managers to actively engage in the microblogging space, given that WOM communication has been associated with brand satisfaction (Brown, Barry, Dacin, & Gunst, 2005). Esch et al. (2006) conjectured that consumers engaged in relationships with brands in a manner similar to the personal relationship they formed with people. These brand relationships may be the result of participation in brand communities (Muniz & O'Guinn, 2001). Similar to social networks, it seems that microblogging applications can have positive and

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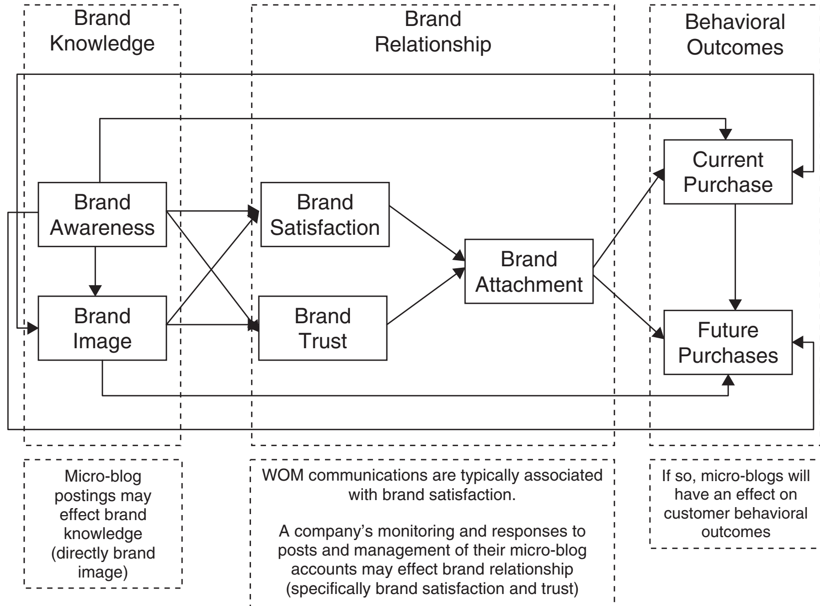

FIG. 1. General model of branding components and relationship to microblogging.

negative impacts as consumers engage in the brand communities. The possible effect of microblogging via eWOM on the brand knowledge and brand relationship is the theoretical underpinning for the importance of our research.

Research Questions

With this stimulus, our research questions are:

1. *What are the overall eWOM trends of brand microblogging?*
   To address this research question, we selected 50 brands and analyzed the microblogs that mentioned these brands over 13 consecutive weeks. We algorithmically analyzed the expressions or sentiments of these microblogs and categorized them to determine aggregate characteristics of brand microblogging expression. We also selected a sample of these microblogs and qualitatively coded the sentiment in order to determine an accuracy level for our automated methods. This series of analysis provided insight into the overall sentiment types and trends in brand microblogging.
2. *What are the characteristics of brand microblogging?*
   To address this research question, we quantitatively analyzed the microblogs from the 50 selected brands to determine their branding eWOM sentiment, characteristics, and structure in order to shed light on their underlying affective, cognitive, and contextual aspects. We examine tweets at the term and term-pair level, as well as the strength of term association using the mutual information statistic. Such an analysis will provide insight into the structure characteristics of microblogs.
3. *What are patterns of microblogging communications between companies and customers?*
   To address this research question, we selected and closely examined how one company uses its corporate Twitter accounts. Specifically, we analyzed the characteristics of how the company communicated with customers through Twitter and employed these accounts as brand management and eWOM tools. Working from an exploratory approach, we analyzed, both qualitatively and quantitatively, 1,907 microblogs posted by the company or tweets addressed to it as well as analyzed the social network of the resulting communications.

Research Design

To investigate our research questions, we used the Twitter social communication platform, one of the most popular microblogging services. However, all microblogging applications share a set of similar characteristics: (1) short text messages, (2) instantaneous message delivery, and (3) subscriptions to receive updates. So, although we used Twitter in this research, we expect our results to be applicable to other microblogging applications.

Twitter

Launched on July 13, 2006, Twitter is a microblogging service where users send updates (a.k.a., tweets) to a network of associates (a.k.a., followers) from a variety of devices. Tweets are text-based posts of up to 140 characters in length. The default setting for tweets is public, which permits people to follow others and read each other's tweets without giving mutual permission. Each user has a Twitter page where all their updates are aggregated into a single list (hence the name microblogging).

Tweets are not only displayed on a user's profile page, but they can be delivered directly to followers via instant messaging, Short Message Service (SMS), Really Simple Syndication (RSS), email, or other social networking platforms, such as Twitterrific or Facebook. The Twitter application program

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TABLE 1. Brands and products by industry sector.

Industry sector	Major brand	Product/service	Competitor	Known brand	Other
Apparel	H&M		Banana Republic	TopShop	
Automotive	Toyota	Prius	Honda	SMART ForTwo	Mini Clubman
Computer hardware	Dell		Lenovo	Averatec	MacBook Air, iPhone
Computer software	Microsoft	Windows Vista	Leopard		Windows 7
Consumer electronics	Sony	BRAVIA	Toshiba	Magnavox	Nintendo, Wii Fit
Energy	Exxon		Sunoco		
Fast food	Starbucks	Drive Through	McDonald's	Arby's	
Food	Kellogg's	Special K	Cheerios	Malt-O-Meal	
Internet service	Google	Gmail	Yahoo!	KartOO	Amazon, Facebook
Personal care	Oral-B	Oral-B Triumph	Crest	Aquafresh	
Sporting goods	Adidas	Adidas Originals	Reebok	Saucony	
Transportation	FedEx		DHL		Forever Stamp

interface (API) also allows the integration of Twitter with other Web services and applications. As the largest one of the microblogging service, Twitter's user base has grown, and it has attracted attention from corporations and others interested in customer behavior and service. Given its robustness, Twitter is increasingly used by news organizations to receive updates during emergencies and natural disasters. A number of businesses and organizations are using Twitter or similar microblogging services to disseminate information to stakeholders (see www.socialbrandindex.com for a partial list of brands employing Twitter). Twitter's growth rate is substantial, with several millions users as of 2008 (Bausch & McGiboney, 2008). Web applications such as Tweetrush (tweetrush.com) estimate traffic at approximately a million tweets a day. Putting those numbers in perspective, from August 2006 to August 2008, Twitter users created ≈100,000 books worth of content, 140 characters at a time (Milstein et al., 2008). As the largest, most well-known, and most popular of the microblogging sites, Twitter is an ideal candidate for our study of microblogging's impact in the eWOM area.

Identification of Brand

Given that we were interested in microblogging for branding purposes, we had to select key brands for investigation. We explored several lists of brands on the Web including American Customer Satisfaction Index,[1] *Business Week*'s Top Brand 100,[2] and BrandZ Top 100 Most Powerful Brands Ranking.[3]

To ensure a good cross-segment sample, we employed an industry classification method used by *Business Week* to make sure the brands spread out across major industries, but we also kept the categories closely related with items in daily life, under the assumption that these brands would be most likely mentioned in and affected by microblogging. We also counterbalanced this cross-industry approach by trying to select brands that provided similar products or services in order to make them more comparable.

For each industry sector, we included one major brand, one product from the major brand, one competitive brand, one comparably less competitive brand, and some other newsworthy brands. The major brand and the product from the major brand allowed us to explore the relationship between brand management and product management. The major brand and the competitive brand enabled us to compare competitive brands and identify potential means to use competitor's brand sentiment changes to develop or enhance the major brand management. The less comparative major brand could be tomorrow's major competitors and could also be a source of failure, from which we could learn to avoid. In the end, we settled on 50 brands. The brands with the industry sections and associated information are shown in Table 1.

Data Collection and Analysis

For our first research question (What are the overall eWOM trends of brand microblogging?), we were interested in tweets that mentioned a brand name and especially the expression of opinion or brand sentiment. We collected these tweets using the Summize tool. Summize4 was a popular service for searching tweets and keeping up with emerging trends in Twitter in real time. Like Twitter, Summize offers an API, so other products and services can filter the constant queue of updates in a variety of ways. The Summize[4] service analyzed tweet sentiment and gave the queried brand an overall sentiment rating for a given period using a five-point Likert scale and labeling each point from lowest to highest as wretched, bad, so-so, swell, and great.

We collected data for a 13-week period, from April 4, 2008 to July 3, 2008. This gave us 650 reporting episodes (13 reporting periods × 50 brands). To collect the date, for each brand in Table 1, we submitted queries to Summize in the format: [brand name] since:[start date] until:[end date] to retrieve the sentiment for that week period. Using Banana

[1]The American Customer Satisfaction Index http://tinyurl.com/24c8hj

[2]*Business Week*'s Top Brand 100 http://tinyurl.com/2e6ntj

[3]BrandZ Top 100 Most Powerful Brands Ranking http://tinyurl.com/6hsth3

[4]Summize was acquired by Twitter in August of 2008 and is no longer available as an independent service. See http://tinyurl.com/56j2zx

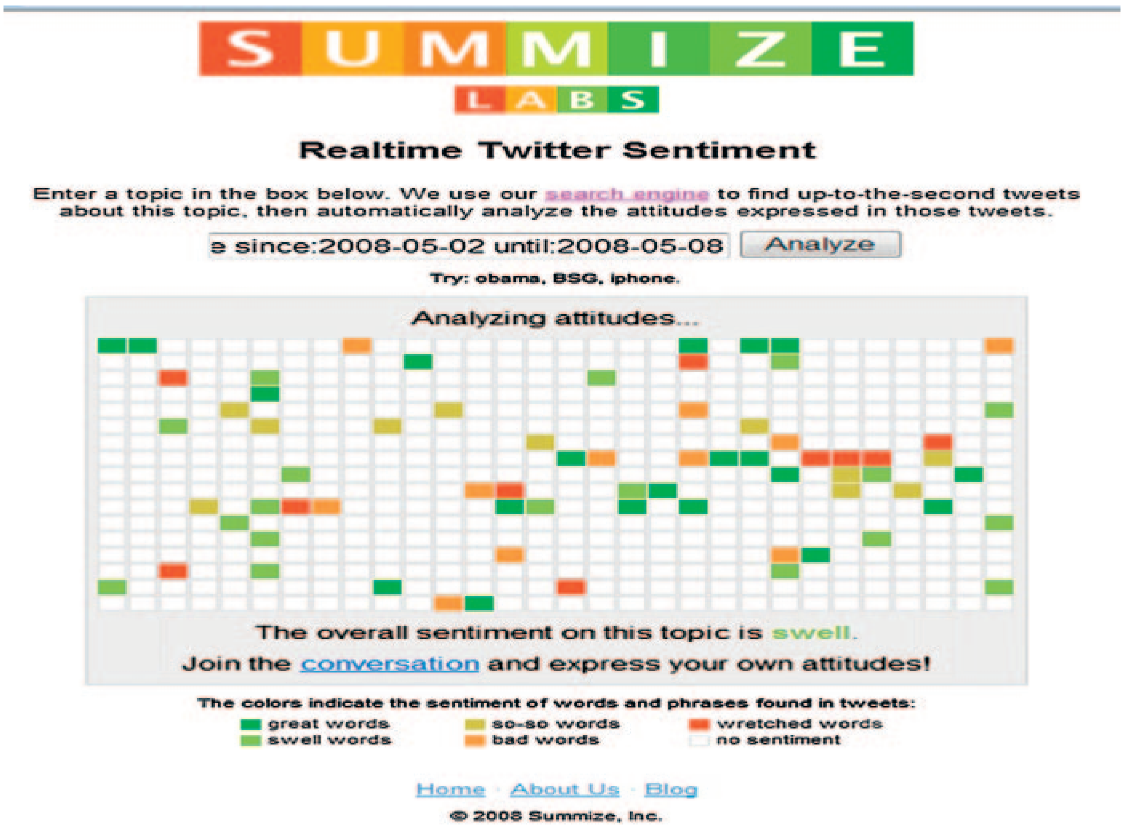

FIG. 2. Sample of Summize's graphical presentation of the brand sentiment.

Republic as an example, the query for the week from April 4, 2008 to April 10, 2008, is Banana Republic since:2008-04-04 until:2008-04-10. We repeated this process for the same brand the following week until we collected data for all brands[5] from all 13-week periods.

For each brand we then calculated the classification of each tweet. Summize uses a lexicon of ≈200,000 uni-grams and bi-grams of words and phrases that have a probability distribution to determine the sentiment of the brand for a given period. Summize trained its classifier with nearly 15 million views on topics ranging from movies to electronics, etc. The objective was to determine how people use adjectives in online utterances. Each feature (word) has some probability of being used either positively or negatively and is classified into one of the five Likert scale classes. The classifier is a multinominal Bayes model to determine the overall sentiment of each set of Twitter posts. The multinominal Bayes code picks the class with the greatest probability in a winner-take-all scenario. In response to a given query, the classifier processes the latest 125–150 tweets from the result set. Duplicate tweets are ignored and non-English tweets are filtered out. The classifier analyzes the whole tweet to determine its sentiment. Summize presents a graphical presentation of the brand sentiment as shown in Figure 2. Each color is the predominant sentiment for a given sentence we are parsing.

In order to verify the accuracy of the algorithmic classifier, we manually coded tweets from five brands (i.e., Banana Republic, SMART ForTwo, Wii Fit, Google, and Forever Stamp). To do this, we downloaded the most recent 250 tweets for these five brands. We compared the sentiment of the first set of 125 tweets to the second 125 tweets for each brand. We also compared the results of the manual classifications of the latest 125 to the automatic classifications. In order to conduct this analysis, we developed the manual coding scheme below by following Glaser & Strauss's (1967) coding development strategy:

- No Sentiment: Tweet has no emotion words or special punctuation, is matter-of-fact sounding, or contains just a brand mention (e.g., Wondering what time the Banana Republic store at the mall closes).
- Wretched: Tweet is purely negative overall feelings or only allowed a slightly positive word. For a product, "wouldn't buy it again," "wouldn't recommend it," or "had horrible time with it," (e.g., Screw you Google maps. It's a good thing I have this compass and sharp stick).
- Bad: Tweet contains mainly negative phrases and words, with a disappointed tone. There may be a few positive statements, but the negative feelings outweigh the positive ones (e.g., Sitting next to a "smart car" in traffic. These things just look weird. About as long as a rickshaw).
- So-so: The tweet is a mediocre or balanced sentiment. The positive and negative statements seem to balance each other,

[5]For each of these brands and data collection periods, we retrieved the actual tweets from the Twitter API using a similar approach due to the acquisition of Summize by Twitter during the data collection period.

or it is neither positive nor negative overall. Even if there are more negative phrases, the positive ones use a stronger language than the negative ones (e.g., Wii fit is fine, just leave enough room around you to wave your arms!).

- Swell: The tweet is mainly positive terms, such as good or nice. There may be some negative phrases; however, the positive ones are stronger and outweigh the negative ones (e.g., You might have those forever stamps that are all good no matter the price of a current stamp).
- Great: Purely positive in tone and wording in the tweet expressing strong affirmative feelings with no complaints. It may have the smallest negative word, but the tweet has mostly great-sounding phrases. For a product, the comments are: "would definitely recommend it," "use again it," (e.g., Heaven on earth, the Banana Republic outlet store 40% off sale).

As a baseline for comparison, we also collected 14,200 random tweets from Twitter and evaluated these tweets for mention of brand.

To address research question two (What are the characteristics of brand microblogging?), we performed a linguistic analysis of the tweets. We uploaded all tweets into a relational database and generated a term table and also a term co-occurrence table for each set of tweets. The term table contained fields for terms, the number of that term's occurrence in the complete dataset, and the probability of that term's occurrence. The co-occurrence table contains fields for term pairs, the number of times that pair occurs within the dataset irrespective of order, and the mutual information statistic (Church & Hanks, 1990).

To calculate the mutual information statistic, we followed the procedure outlined by Wang, Berry, & Yang (2003). The mutual information formula measures term association and does not assume mutual independence of the terms within the pair. We calculated the mutual information statistic for all term pairs within the dataset. Many times a relatively low-frequency term pair may be strongly associated (i.e., if the two terms always occur together). The mutual information statistic identifies the strength of this association. The mutual information formula used in this research is:

$$\mathrm{I}(w_1, w_2) = \ln \frac{\mathrm{P}(w_1, w_2)}{\mathrm{P}(w_1)\mathrm{P}(w_2)}$$

where $P(w_1)$, $P(w_2)$ are probabilities estimated by relative frequencies of the two words and $P(w_1, w_2)$ is the relative frequency of the word pair (order is not considered). Relative frequencies are observed frequencies (F) normalized by the number of the queries:

$$\mathrm{P}(w_1) = \frac{\mathrm{F}_1}{\mathrm{Q}'}; \mathrm{P}(w_2) = \frac{\mathrm{F}_2}{\mathrm{Q}'}; \mathrm{P}(w_1, w_2) = \frac{\mathrm{F}_{12}}{\mathrm{Q}'}$$

Both the frequency of term occurrence and the frequency of term pairs are the occurrence of the term or term pair within the set of queries. However, since a one-term query cannot have a term pair, the set of queries for the frequency base differs. The number of queries for the terms is the number of nonduplicate queries in the dataset. The number of queries for term pairs is defined as:

$$Q' = \sum_{n}^{m} (2n - 3) Q_{\mathrm{n}}$$

where Q_n is the number of queries with n words ($n > 1$), and m is the maximum query length. So, queries of length one have no pairs. Queries of length two have one pair. Queries of length three have three possible pairs. Queries of length four have five possible pairs. This continues up to the queries of maximum length in the dataset. The formula for queries of term pairs (Q') accounts for this term pairing.

For research question three (What are patterns of microblogging communications between companies and customers?), we conducted a case study on a specific company and thoroughly analyzed the tweets between the company Twitter accounts and the followers of these accounts. The company we selected from Table 1 was Starbucks, which has products and services closely related with everyday life (i.e., coffee and pastries) and has active twitter accounts. Starbucks is a world-famous coffeehouse chain (Wikipedia, 2009). English teacher Jerry Baldwin, history teacher Zev Siegel, and writer Gordon Bowker founded Starbucks in 1971, with its first store in Pike Place Market in Seattle, Washington (McGraw Hill Higher Education, n.d.) The company aims to be "the premier purveyor of the finest coffee in the world" (Starbucks, 2008). Its products include coffee, handcraft beverage, fresh food, coffee-related merchandise, and related items (Starbucks, 2008). Starbucks is active on the Web and is keen on building up its online community, as evidenced by accounts on Twitter, Facebook, and YouTube. It also built up its own online communities like My Starbucks Idea (mystarbucksidea.force.com) for collecting ideas to improve their products and service, and Starbucks V2V (www.v2v.net/starbucks) for getting people together to volunteer for community work. As such, Starbucks appears to be a company interested in the social networking communities.

Starbucks owns three twitter accounts: Starbucks (twitter.com/Starbucks), MyStarbucksIdea (twitter.com/MyStarbucksidea), and StarbucksV2V (twitter.com/StarbucksV2V). Since MyStarbucksIdea and StarbucksV2V had fewer tweets from people they followed than did Starbucks, we chose to study the company's chief Twitter account (i.e., Starbucks) only. The company first opened this Twitter account on 12 August 2008. Its first tweet was "Welcome to Starbucks Twitter land!" (twitter.com/Starbucks/statuses/885677980). We collected data from the day the company started using Twitter to 2 November 2008. By then, they had 7,751 followers and followed 7,779 Twitter users. Starbucks twittered 322 times and received 1,585 tweets. We used a mixed method approach and performed both quantitative and qualitative analysis of 1,907 tweets from Starbucks, its followers, and people it followed to determine the characteristics of how the company employed this account as an eWOM management tools.

We used action-object pair approach (Zhang & Jansen, 2008) to qualitatively analyze the microblogs, an approach

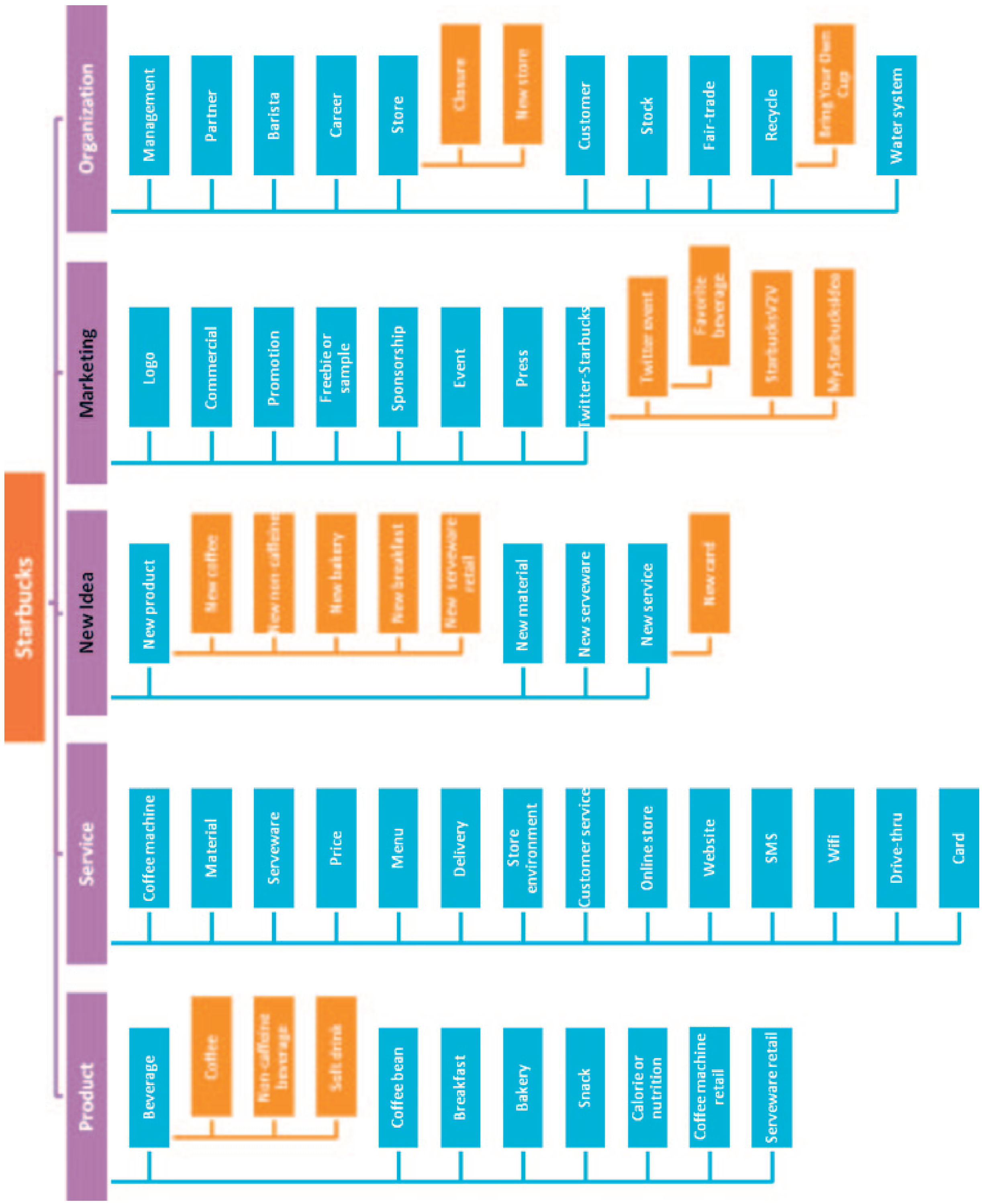

FIG. 3. Object codes.[6]

[6]Words in black are not codes and are used here solely for labeling purposes.

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TABLE 2. Action codes and definitions.

Action	Definition
Announcement	Declaring the upcoming objects
Answer	Handling question
Chitchat	Casual conversation
Comment	Expressing mixed or neutral feelings regarding objects
Confirmation	Giving assurance or validation regarding objects
Consuming	Drinking or eating objects
Expecting	Looking forward to objects from Starbucks
Forwarding	Pointing to potential useful objects
Maintenance	Managing objects
Missing	Feeling from the lack of objects and expecting to have them back
Negative comment	Critiquing, complaining
Notification	Letting one know on objects
Order via Twitter	Attempting to place order on Twitter
Patronizing	Physically being in objects or going to objects frequently
Positive comment	Complimenting, praising
Question	Expressing confusions or doubts toward objects
Recommendation	Providing positive advice regarding objects
Recommendation request	Seeking advice regarding objects
Request	Asking for objects
Research	Examining objects
Response	Giving unnecessary feedback on objects
Suggestion	Providing ideas to improve objects
Supplement	Adding on to objects

originally developed for transaction log analysis. An action is a specific expression to the object, and an object is a self-contained information object. These two components together form an action-object pair and represent one interaction between user and system. We extended the concept of this method and applied it to microblogging analysis. In our scenario, the object is material relevant to Starbucks, for example, its coffee, its service, and its promotion. The action is an expression as eWOM concerning the objects. For example, the action can be criticizing, asking a question, or providing a suggestion. Thus, the action and object together makes an action-object pair, and a thread of action-object pairs can tell a story regarding aspects of the Starbucks brand and customer satisfaction with that brand. For example, criticizing-coffee pair indicates the customer's dissatisfaction toward Starbucks' coffee. We used an open coding approach to develop coding schema for action and object. One tweet can be coded with multiple action-object pairs. The complete relationship of codes for objects is in Figure 3, and the complete list of codes for actions is in Table 2.

Results

Research Question #1: What Are the Overall eWOM Trends of Brand Microblogging?

From an analysis of 149,472 tweets collected over 13 1-week periods for 50 brands, we calculated the resulting sentiment analysis by week per brand, as shown in Table 3. From Table 3, more than 60% of the aggregate weekly sentiments for the brands were positive (Great or Swell). Just over 22% of the sentiment by brand were negative (Bad or Wretched). A small percentage (12%) was neutral (So-so), and an even smaller percentage of the brands (≈5%) had no tweets in a given week. So, although the positive tweets represented the largest quantity, there were a substantial percentage of negative tweets. Prior research in the impression formulation literature has shown that negative comments have a greater impact than positive ones (Skowronski & Carlston, 1989).

TABLE 3. Brand sentiment by week.

Sentiment by week	Occurrences	Percentage
Great	194	29.8%
Swell	200	30.8%
So-so	78	12.0%
Bad	102	15.7%
Wretched	42	6.5%
No Tweets	34	5.2%
Total	650	100.0%

The analysis in Table 3 is based on the Summize algorithmic analysis. However, we wanted to evaluate whether this algorithmic approach was effective because we could not locate any published works evaluating the automatic sentiment analysis of tweets. Plus, Summize uses only the most recent 125 tweets for the time period to determine the overall sentiment. However, this raises the question of whether this is an accurate sample to determine sentiment for a given week. We wanted to see if this approach affected our results. In order to investigate this, we downloaded the top 250 tweets of five brands over 4 random weeks for a total of 2,610 tweets in order to compare the automatic coding method of Summize to the same tweets manually coded method. We coded each tweet for sentiment using the coding schema outlined above and compared the sentiment results from the first 125 tweets to the second 125 tweets. Two coders independently coded each tweet using the coding scheme outlined above. Intercoder reliability was quite high (Cohen's $\kappa = 0.85$). Using the general linear model (Dobson, 2002), we identified no difference between the sentiment distribution of the first 125 and second 125 tweets by brand ($F = 0.58$, $p = 0.45$). Therefore, we are reasonably assured that the most recent 125 tweets are a representative sample of tweets for given weeks.

Using the sentiment of the first 125 tweets to represent the overall sentiment, we then created a block design and treated brand, sentiment category, and time (i.e., week) as blocking factors because they could potentially influence the sentiment percentage. We compared manual coding with system coding by using the general linear model. There was no difference between manual coding and system coding ($F = 0.00$, $p = 1.00$). Therefore, our findings from these two evaluations show that our algorithmic approach is accurate in classifying the tweets. The implication is that one can use standard text classification methods to analyzed tweets, and new methods are not required.

In addition to the overall sentiments, we performed a detailed analysis not at the week level but for the specific

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TABLE 4. Analysis of individual tweets for sentiment.

	Total (all)	Percentage (all)	Percentage (sentiment only)
Great	9,451	6.3%	33.0%
Swell	5,558	3.7%	19.4%
So-so	4,071	2.7%	14.2%
Bad	4,550	3.0%	15.9%
Wretched	5,032	3.4%	17.6%
No sentiment	120,810	80.8%	
Total	149,472	100.0%	28,662 (19.2%)

TABLE 5. Sentiment changes by week.

Change	Occurrence	Percentage
Change to negative	182	30.3%
Change to positive	184	30.7%
No change	195	32.5%
No tweets to negative tweets	8	1.3%
No tweets to positive tweets	13	2.2%
Tweets to no tweets	18	3.0%
Total	600	100.0%

tweets that make up this sentiment. Results are reported in Table 4.

As one can see from Table 4, more than 80% of the tweets that mentioned one of these brands expressed no sentiment. This indicates that people are using Twitter for general information, asking questions, other information-seeking and -sharing activities about brands or products, in addition to expressing opinions about brands or products. Of the 268,662 tweets expressing sentiment, more than 52% of the individual tweets were expressions of positive sentiment, while ≈33% of tweets were negative expressions of opinion. This is in line with prior work such as that of Anderson (1998), who showed that there was a U-shape relationship between customer satisfaction and the inclination to engage in WOM transfers. This suggests that extremely positive and satisfied and extremely negative customers are more likely to provide information relative to consumers with more moderate experiences.

However, there are dissimilar motivations behind positive WOM and negative WOM utterances (Anderson, 1998). The major incentive for people to spread positive WOM is to gain social or self-approval. Their positive WOM utterances demonstrate their splendid purchase decisions. Additionally, altruistic behavior of sharing expertise with others has also been shown to motivate positive WOM (Fehr & Falk, 2002; Richins, 1984). Hostility (Jung, 1959; Kimmel, 2004) and vengeance (Richins, 1983) motivates dissatisfied consumers to engage in negative WOM.

In further investigation of the microblogging trends, we examined how sentiment changed from week to week.

Table 5 shows the changes in sentiment from week to week for each of the 50 brands over the 13-week period. Beginning with the starting week for each brand, we then calculated the change. We see that ≈32% of the time there was no change from one week to the next. More than 64% of the time, there was a change in sentiment or a change to no tweets. Based on prior work, this propensity of microblogs to change categories has important implications for businesses. Benedicktus & Andrews (2006) reported that there was limited long-term effect if reputation did not decline to a lower category (e.g., from average to poor) and that many more periods of positive comments were required to rebuild trust than were required to damage it. However, most of the changes were to adjacent categories. So the changes could be the by-product of using the Likert scale. So if a brand was right of the edge of two categories, a few tweets either way in a given week could move a brand sentiment classification from one category to the adjacent category.

In order for a company to perform brand management, it is important to know people's opinions about brands and products. It is critical to recognize the company's position in the market, especially in its own industry sector, and to compare with its competitors. Therefore, we compared the sentiment of brands we studied in each of 12 industry sectors. We statistically compared the brands within each of the 13 industry sectors to determine if there were differences among the brands. Table 6 presents the results.

We found statistically significant differences between brands in seven industries including automotive, computer hardware, computer software, consumer electronics, food, personal care, and sporting goods. We also conducted post-hoc analysis by using a Tukey test at a 5% family-wise error rate to identify the exact differences between brands. In automotive, Mini Clubman has a different sentiment than Honda and Smart Car. In computer hardware, Averatec has a different sentiment than MacBook Air, iPhone, and Lenovo. In computer software, Windows Vista and Windows 7 have different sentiment classifications. In consumer electronics, Magnavox has a different sentiment than the rest of that group. Kellogg's and the rest of the brands in the food category have different sentiments. In personal care, Crest has a different brand sentiment than Aquafresh and Oral-B Triumph. In sporting goods, the sentiment of Adidas Originals is different than the rest of the brands. Overall results of this analysis are shown in Table 6.

This differentiation among brands within an industry section shows that microblogging as eWOM is a promising measure for companies to use for competitive intelligence. Companies can also use microblogging as a part of their marketing campaigns to attempt to differentiate themselves from their competitors.

Since this set of 149,472 microblog postings all contained branding comments identified by Summize, we wanted a dataset as a base of comparison. We downloaded 14,200 random tweets via the Twitter API. We downloaded 1,092 tweets from each week of the data sample period used above.

We analyzed each of these 14,200 tweets for occurrences of mentions of a brand or product. After importing our 14,200 tweets into a relational database, we queried the database with our 50 brands, identified, and labeled all tweets that

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TABLE 6. Brand sentiment comparison in industry sector.

						Post-hoc[a]		
Index	Industry Sector	Brand	F-value	DF	P-value	Brand	Level A	Level B
1	Apparel	Banana Republic, H&M, TopShop	1.17	2	0.328	No significant difference among brand sentiment across brands		
2	Automotive	Honda, Mini Clubman, Prius, Smart ForTwo, Toyota	4.16	4	0.006*	Honda, Smart ForTwo	A	
						Toyota, Prius	A	B
						Mini Clubman		B
3	Computer Hardware	Averatec, Dell, iPhone, Lenovo, MacBook Air	5.61	4	0.001*	MacBook Air, iPhone, Lenovo	A	
						Dell	A	B
						Averatec		B
4	Computer Software	Leopard, Microsoft, Windows 7, Windows Vista	5.19	3	0.004*	Windows 7	A	
						Microsoft, Leopard	A	B
						Windows Vista		B
5	Consumer Electronics	BRAVIA, Magnavox, Nintendo, Sony, Toshiba, Wii Fit	12.61	5	0.000*	Wii Fit, BRAVIA, Nintendo, Sony, Toshiba	A	
						Magnavox		B
6	Energy	Exxon, Sunoco	0.00	1	1.000	No significant difference among brand sentiment across brands		
7	Fast Food	Arby's, McDonald's, Starbucks, Starbucks Drive Through	1.78	3	0.168	No significant difference among brand sentiment across brands		
8	Food	Cheerios, Kellogg's, Malt-O-Meal, Special K	5.72	3	0.003*	Special K, Cheerios, Malt-O-Meal	A	
						Kellogg's		B
9	Internet Service	Amazon, Facebook, Gmail, Google, KartOO, Yahoo!	0.78	5	0.565	No significant difference among brand sentiment across brands		
10	Personal Care	Aquafresh, Crest, Oral-B, Oral-B Triumph	6.87	3	0.001*	Crest	A	
						Oral-B	A	B
						Aquafresh, Oral-B Triumph		B
11	Sporting Goods	Adidas, Adidas Originals, Reebok, Saucony	21.79	3	0.000*	Adidas, Reebok, Saucony	A	
						Adidas Originals		B
13	Transportation	DHL, FedEx, Forever Stamp	0.52	2	0.599	No significant difference among brand sentiment across brands		

*$p < 0.05$.
[a]Levels not connected by same letter (A, B) are significantly different.

mentioned these brands. We then used an open coding technique where we qualitatively reviewed individual tweets. When a product or brand mention occurred, we would query the entire dataset for all occurrence of this brand (i.e., a modified snowball technique [Patton, 1990]). Coders reviewed each of these tweets to verify that they contained a brand mention. We repeated this process until all tweets in the database had been examined and coded.

Of the 14,200 random tweets, 386 tweets (2.7%) contained mention of one of the brands or products from our list (Table 1). There were 2,700 tweets (19.0%) that mentioned some brand or product, inclusive of the brands that we used in this study. Therefore, microblogging appears to be a rich area for companies interested in brand and customer relationship management.

In addition to determining whether these tweets mentioned the brands, we classified 2,700 tweets into general categories, similar to the work outlined previously (Broder, 2002; Jansen, Booth, & Spink, 2008; Rose & Levinson, 2004) classifying Web queries. We classified these branding tweets into the following four categories, again following Glaser & Strauss's (1967) coding development strategy.

- Sentiment: the expression of opinion concerning a brand, including company, product, or service. The sentiment could be either positive or negative.
- Information Seeking: the expression of a desire to address some gap in data, information, or knowledge concerning some brand, including company, product, or service.
- Information Providing: providing data, information, or knowledge concerning some brand, including company, product, or service.
- Comment: the use of a brand, including company, product, or service, in a tweet where the brand was not the primary focus.

A tweet could be coded into more than one category. For example, a tweet that expresses sentiment could also provide information, or a tweet seeking information may also provide information.

Therefore, these categories were hierarchical. That is, we first determined whether a tweet expressed sentiment. If not, we then examined it to see whether it sought information.

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TABLE 7. Branding tweets by category.

Classification	Occurrences	Percent
Comments	1,310	48.5%
Sentiment	602	22.3%
Information providing	488	18.1%
Information seeking	300	11.1%
Total	2,700	100.0%

TABLE 8. Linguistic statistics for tweets.

	Tweet length (words)			Tweet length (characters)		
Tweet measures	14.2 K tweets	38.8 K tweets	2.6 K tweets	14.2 K tweets	38.8 K tweets	2.6 K tweets
Average	15.4	14.3	15.8	86.3	89.1	102.6
SD	6.8	6.4	6.6	36.5	35.3	36.4
Max	33	33	43	142	155	185
Min	1	1	3	1	1	16

If it did not seek information, we then determined whether it provided information. Comments were the catch-all category. The results of this coding analysis are shown in Table 7.

As can be seen from Table 7, most tweets that mention a brand do so as a secondary focus. These tweets account for just under half of the branding tweets in this sample. Users expressed brand sentiment in 22% of the tweets. Interestingly, 29% of the tweets were providing or seeking information concerning some brand. This shows that there is considerable use of microblogging as an information source. This would indicate several avenues for companies, including monitoring microblogging sites for brand management (i.e., sentiment), to address customer questions directly (i.e., information seeking), and monitoring information dissemination concerning company products (i.e., information providing).

Research Question #2: What Are the Characteristics of Brand Microblogging?

For this research question, we did a linguistic analysis of three sets of tweets. From the 149,472 microblog postings, we downloaded the first 100 tweets (fewer if there were fewer than 100 tweets) for each brand during each week of the data collection period. This gave us 38,772 tweets containing branding terms. We also separately examined the 2,610 tweets, performing qualitative analysis to ensure that this sample adequately represented the overall population. Finally, we analyzed the 14,200 randomly downloaded tweets.

We believe a comparison of the linguistically analyzed results from these three datasets will provide insight into the semantic structure of branding tweets.

From Table 8, one can see that the statistics for tweets are similar across all three sets. The average words-per-tweet is nearly 16. As a comparison, the average Web search queries is approximately three terms (Jansen & Spink, 2005; Wang et al., 2003). The length of the average English sentence is about 25. So at the aggregate term level, tweets have more in common with standard written sentences than with related short expressions, such as Web queries. One of the successes of the microblogging service is this shortness of the microblog. It may be that the tweet length is a familiar length for information processing.

We then examined tweets at the specific term level, as shown in Table 9.

From Table 9 we see that tweets contain many of the skip words (e.g., the, a, to, us, for, etc.) that are common in natural language usage. However, there are some high occurrences of nonskip words, which is uncommon in natural language expressions. Nevertheless, this may be due to the focus on branding and the demographics of the Twitter user population. The average frequency of occurrence ranged from 4.3 to 12.1 terms (standard deviation [SD] ranging from 40–166 terms), reflecting the various size of our data sample that causes the wide variations. When examining the average probability of occurrence, we see the average in a tight range from 0.0003–0.0005 (SD ranging from 0.0030–0.0060), reflecting the normalization of the dataset sizes. The clustering of the probability of occurrence indicates that our samples are representative of the same population. Our findings show a spread of terms that, in extremely large sample sizes, would probably follow a power law probability distribution common in many natural language and Web services. More important, these data help explain our earlier finding that automatic text classification techniques work with microblogging. It appears that these posts have much in common with natural language utterances. This natural language usage is even more pronounced when we examine term pairs with the highest mutual information statistics (MIS), as shown in Table 10.

Although there are some exceptions, many of the term pairs are natural language in structure and semantics. The average MIS ranged from −0.6 to 1.8 (SD ranging from 4.24–4.96); this finding suggests that there is, again, a large divergence of terms used in tweets. These linguistic findings indicate that tweets share some characteristics of natural language sentences, which is why natural language classifiers are successful in automatically categorizing them. However, there are also some differences, probably due to the technology employed in posting tweets.

Research Question #3: What Are the Patterns of Microblogging Communications Between Companies and Customers?

For communication patterns between a brand and potential customers (i.e., followers of the corporation Twitter account), we explored four aspects of the communication pattern: range, frequency, time, and content (i.e., How varied were the topics of communication between Starbucks and its customers?; How often did Starbucks and its customers twitter each other?, When did they twitter?; and What did they twitter about?).

TABLE 9. Terms in tweets.

Index	Dataset Term	2.6K Frequency	2.6K Probability	38.8K Frequency	38.8K Probability	14.2K Frequency	14.2K Probability
1	the	946	0.10	16468	0.36	7911	0.40
2	to	773	0.08	12808	0.28	6825	0.34
3	a	905	0.09	12050	0.26	5633	0.28
4	i	709	0.07	9648	0.21	5432	0.27
5	is	432	0.04	6266	0.14	3597	0.18
6	of	333	0.03	6018	0.13	3584	0.18
7	for	407	0.04	7111	0.16	3514	0.18
8	and	492	0.05	7334	0.16	2908	0.15
9	in	391	0.04	6587	0.14	2723	0.14
10	at	190	0.02	4032	0.09	2492	0.12
11	my	363	0.04	6301	0.14	2207	0.11
12	you	221	0.02	3096	0.07	2182	0.11
13	have			2334	0.05	2177	0.11
14	be			1920	0.04	2134	0.11
15	it	327	0.03	4253	0.09	2032	0.10
16	on	359	0.04	5623	0.12	1918	0.10
17	or					1767	0.09
18	that	217	0.02	3139	0.07	1705	0.09
19	can					1353	0.07
20	with	223	0.02	4014	0.09	1202	0.06
21	just	245	0.03	2987	0.07	1142	0.06
22	me	153	0.02	2208	0.05	1141	0.06
23	this			2024	0.04	1038	0.05
24	but					1003	0.05
25	i'm					950	0.05
	Average (of entire dataset)	4.3	0.0004	12.1	0.0003	10.9	0.0005
	SD (of entire dataset)	40.0	0.0030	166.2	0.0040	121.4	0.0060

TABLE 10. Term co-occurrence.

2.6K tweets Term pair	MIS	38.8K tweets Term pair	MIS	14.2K tweets Term pair	MIS
Chooses them	6.90	Ting tiding	8.51	Thank you	4.74
Guh a	6.90	Microcompact they	7.54	matrix_sbo null	4.65
Finalizing the	6.90	Approaching the	7.46	Room to	4.39
Fenced the	6.90	Newark to	6.44	Drandolph the	4.39
Paternity the	6.33	Tiding tiding	6.41	Played wii	4.39
Importing to	6.33	Mele the	6.38	Uploading the	7.54
Chem. i	6.33	refuse to	6.31	Mhitoshi google	7.54
Evidence exceptions	6.33	stock-index futures	6.16	Services google	4.35
Footprints in	6.33	Saddle ramsey	6.16	Haripakorss google	4.24
Riverwalk the	6.33	Decade a	6.07	Linksgoogle google	4.19
Average (of entire dataset)	1.8		−0.63		−0.11
SD (of entire dataset)	4.24		5.11		4.96

Concerning range, Table 11 shows that Starbucks received 1,585 tweets from 1,038 people that it followed. Starbucks followed 7,779 twitter users. People can only send tweets to Starbucks if it followed them. Therefore, Starbucks received tweets from 13.3% of its followers. Conversely, Starbucks twittered 322 times, including 77 times without replying to anyone and 245 times replying to 212 followers' tweets. Since Starbucks can only send tweets to people following it, Starbucks twittered 2.7% of its followers and replied to 20.4% people twittering it (7,751 followers, and 1,038 people twittering it). Therefore, the range of communication is rather tight, with a small number of Twitters active in the communication role and a larger number taking a more passive monitoring role. This communication pattern mirrors that in listservs and wikis, where a small number of members are very active and the majority are lurkers (Rafaeli, Ravid, & Soroka, 2004).

In terms of frequency, Table 11 informs us that Starbucks received 45.8% tweets only once from 69.9% of the people it followed and 43.5% tweets from two to four times from

TABLE 11. Twittering frequency between Starbucks and its customers.

Starbucks twittered 77 times without replying to anyone				
From Starbucks				
Twittering frequency	Follower (count)	Follower (percentage)	Tweet (count)	Tweet (percentage)
1	182	85.9%	182	74.3%
2	27	12.7%	54	22.0%
3	3	1.4%	9	3.7%
Total	212	100.0%	245	100.0%
To Starbucks				
Twittering frequency	Twitter users followed (count)	Twitter users followed (percentage)	Tweet (count)	Tweet (percentage)
1	726	69.9%	726	45.8%
2	191	18.4%	382	24.1%
3	69	6.7%	207	13.1%
4	25	2.4%	100	6.3%
5	12	1.2%	60	3.8%
6	8	0.8%	48	3.0%
7	3	0.3%	21	1.3%
8	0	0%	0	0%
9	1	0.1%	9	0.6%
10	1	0.1%	10	0.6%
11	2	0.2%	22	1.4%
Total	1,038	100.0%	1585	100.0%

27.5% of the people it followed. It was rare for people to twitter Starbucks more than four times. Starbucks twittered only once to 74.3% tweets to 85.9% of these followers.

From the twitter networking between Starbucks and followers in Figure 4, we can see that Starbucks and others usually twittered fewer than four times. Thus, both Starbucks and its customers did not interact frequently with each other during the approximately 3-month data collection period. So, at least for this company, Twitter was not an active medium for customer relationship management. There were key Starbucks followers who were active members of this brand community, which is consistent with prior work in online communities (Panzarasa, Opsahl, & Carley, 2009).

However, concerning the time aspect, Figure 5 shows a strong weekly pattern of communication. Starbucks and its customers twittered mostly during the middle of the week and less during weekend and the beginning of the week. There are three prominent spikes on the right hand, in part due to Starbucks' running a survey and an event on Twitter during these time periods. This indicates that a natural cycle of communication may exist for corporate accounts. The increase in communication for the survey and event also shows the communication reach provided by Twitter to interested potential customers.

Using the action-object approach to analyze content, we first dropped 113 tweets because they were in foreign languages or not understandable. Of the remaining, we

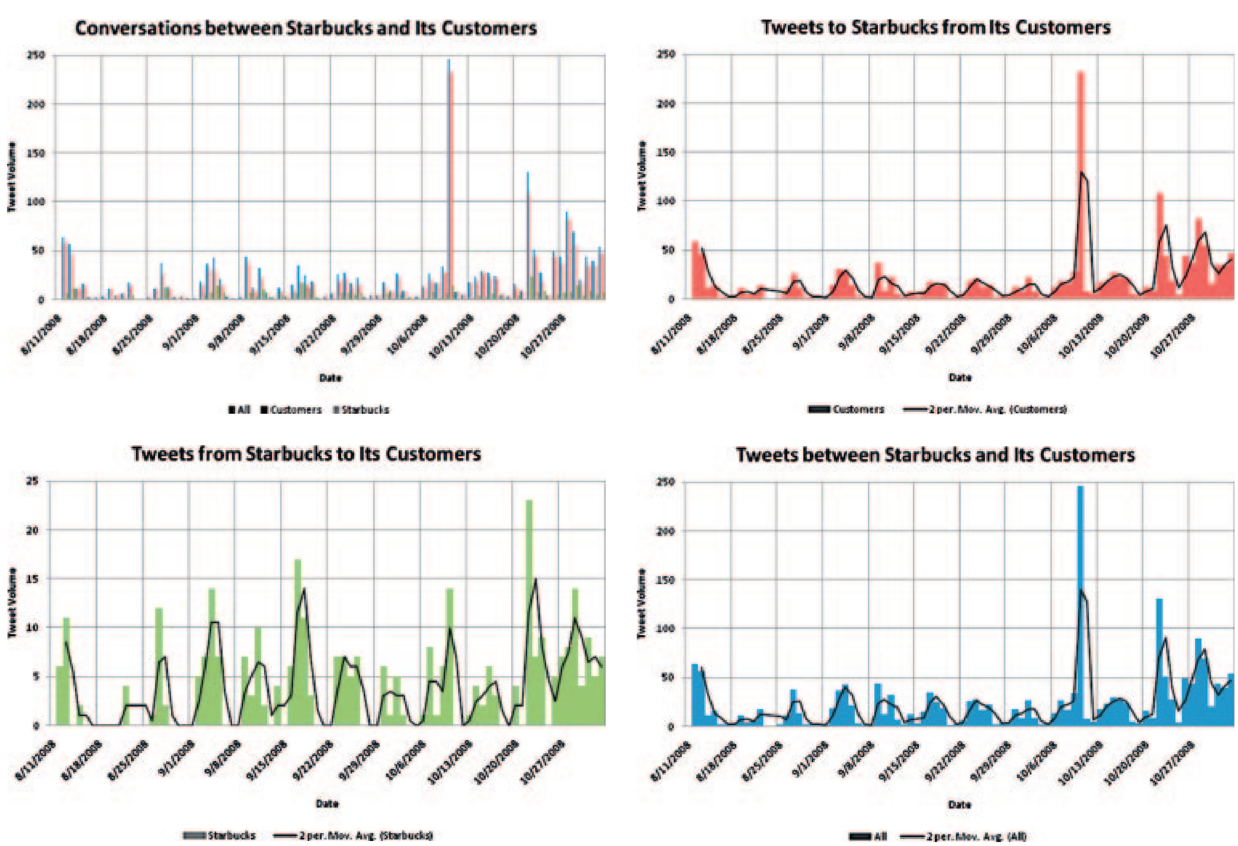

FIG. 4. Time series of tweets between Starbucks and its customers.

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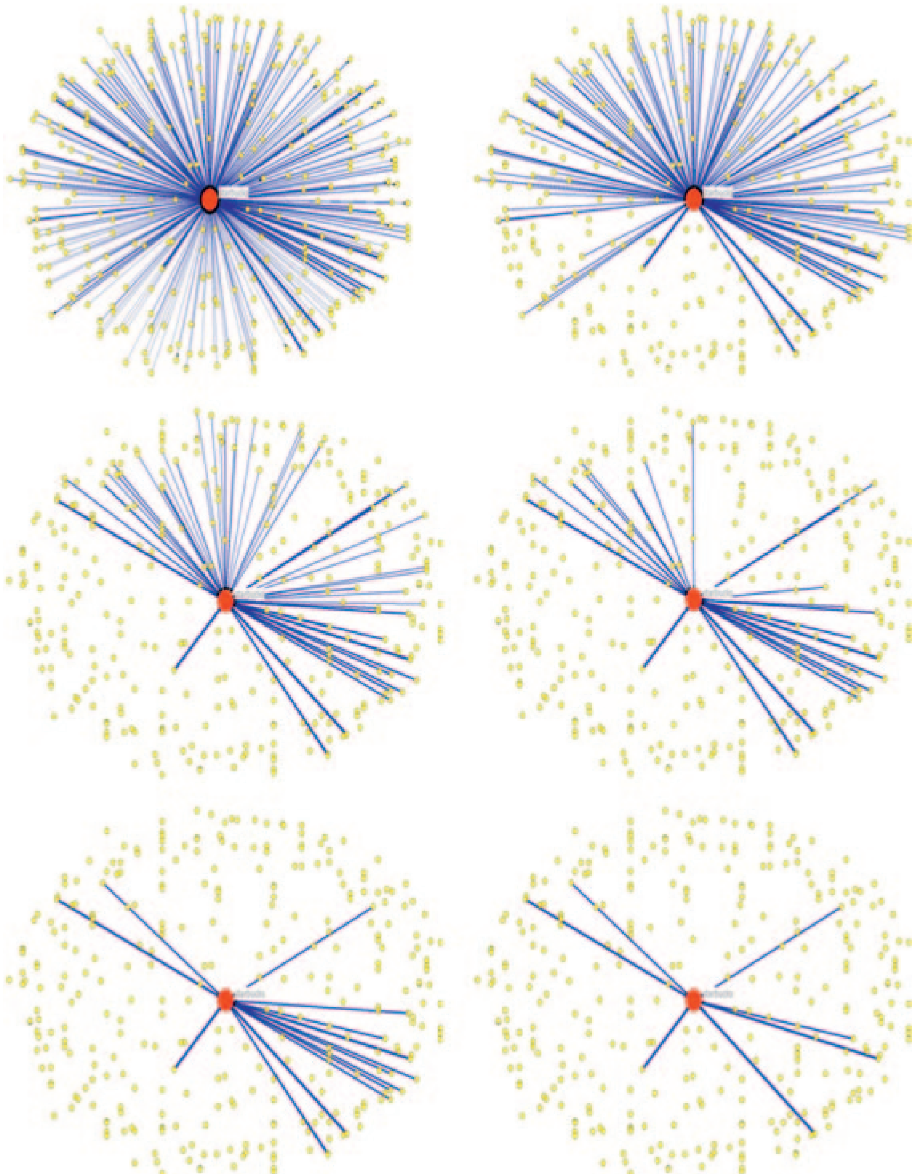

FIG. 5. Twittering network between Starbucks and its customer based on frequency (from top left to right bottom, frequency ≤>2, ≤3, ≤4, ≤5, ≤6, ≤7).[7]

identified 386 unique action-object pairs and 2,490 total action-object pairs, as shown in Table 12.

The most frequently occurring pair is a positive comment on coffee (9.6%). The fifth most frequently occurring pair is related, which is a positive comment on a noncaffeine beverage (2.8%). The second and third most frequently occurring pairs are both related to the events held by Starbucks on Twitter. One was a survey of favorite beverages, with Starbucks receiving 164 tweets responding to this survey. Starbucks followers actively responded to Twitter events sponsored by Starbucks, including Haiku on Starbucks and a trivia question competition, with an early release Starbucks Gold Card as prize. Starbucks followers were also keen on responding to promotions (2.8%).

Examining actions in Table 13, 24.8% of the actions are positive comments and 7.3% are negative comments. There are 17.6% of the actions that are responses. Also, 12.7% are questions, and 11.4% are answers to questions. Therefore, questions and answers together are 24.06% of all actions in this account. These five categories of actions (i.e., positive comments, negative comments, responses, questions, and answers to questions) altogether make 73.7%. Thus, one can view Starbucks' Twitter account as a place for a combination of customer testimony, complaining, feedback, and Q&A. This appears in line with prior customer relations research (Reinartz, Krafft, & Hoyer, 2004), so Twitter appears a viable customer relationship management channel.

[7]The red dot in the center is Starbucks, the yellow dots are people who twittered with it more than once, and the blue line indicates the communication.

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TABLE 12. Action-object pairs.

Action-object pair occurrence > 20				Action-object pair occurrence ≤ 20			
Object	Action	Total count	Percentage	Action-object pair occurrence	Count	Total Count	Percentage
Coffee	Positive comment	238	9.6%	20	1	20	0.8%
Favorite beverage	Answer	164	6.6%	19	0	0	0%
Twitter event	Response	146	5.9%	18	3	54	2.2%
Promotion	Response	70	2.8%	17	5	85	3.4%
Noncaffeine beverage	Positive comment	69	2.8%	16	2	32	1.3%
Store	Patronizing	55	2.2%	15	3	45	1.8%
Twitter	Chitchat	45	1.8%	14	2	28	1.1%
Coffee	Question	42	1.7%	13	4	52	2.1%
Coffee bean	Positive comment	33	1.3%	12	3	36	1.5%
Promotion	Positive comment	33	1.3%	11	4	44	1.8%
Twitter	Positive comment	32	1.3%	10	9	90	3.6%
Coffee bean	Question	31	1.2%	9	12	108	4.3%
Card	Question	30	1.2%	8	5	40	1.6%
Starbucks	Positive comment	27	1.1%	7	6	42	1.7%
Breakfast	Positive comment	25	1.0%	6	14	84	3.4%
Card	Response	25	1.0%	5	13	65	2.6%
Promotion	Question	25	1.0%	4	23	92	3.7%
Coffee	Order via twitter	24	1.0%	3	35	105	4.2%
Barista	Answer	21	0.8%	2	70	140	5.6%
Coffee	Negative comment	21	0.8%	1	151	151	6.1%
Twitter event	Announcement	21	0.8%	Total		1,313	52.7%
Total		1,177	47.3%	386 unique action-object pairs, 2,490 action-object pairs			

TABLE 13. Actions.

Action	Count	Percentage
Positive comment	617	24.8%
Response	439	17.6%
Question	316	12.7%
Answer	283	11.4%
Negative comment	181	7.3%
Chitchat	76	3.1%
Suggestion	68	2.7%
Comment	62	2.5%
Expecting	55	2.2%
Patronizing	55	2.2%
Announcement	54	2.2%
Request	53	2.1%
Forwarding	44	1.8%
Notification	37	1.5%
Order via Twitter	28	1.1%
Consuming	25	1.0%
Recommendation	24	1.0%
Missing	23	0.9%
Supplement	14	0.6%
Confirmation	13	0.5%
Maintenance	11	0.4%
Recommendation request	10	0.4%
Research	2	0.1%
Total	2490	100.0%

Discussion and Implications

This study offers important insights into microblogging as eWOM communications, with implications for branding for corporations, organizations, and individuals. There are also implications for the social effects that social communication services (like Twitter) are having, in terms of fostering new relationships in the commercial sector, specifically in gauging marketplace reactions (i.e., sentiment), external communication (i.e., information providing), and gathering marketplace information (i.e., information seeking). These implications are the same for both corporations and individuals. First, of the entire population of tweets, ≈19% mention an organization or product brand in some way. This is good percentage and indicates that the microblogging medium is a viable area for organizations for viral marketing campaigns, customer relationship management, and to influence their eWOM branding efforts.

Second, about 20% of all microblogs that mentioned a brand expressed a sentiment or opinion concerning that company, product, or service. Microblogging is a social communication channel affecting brand awareness and brand image, that managing brand perception in the microblogging world should be part of an overall proactive marketing strategy, and maintaining a presence on these channels should be part of a corporation's branding campaign. It is apparent that companies can receive positive brand exposure via followers and others who microblog about the company and products. Twenty percent of this fast-growing market is substantial. Additionally, with 80% of tweets mentioning a brand but expressing no sentiment suggests people are also seeking information, asking questions, and answering questions about brands via their microblogs. Thus, company microblogging accounts are probably a smart idea to both monitor brand community discussions and to push information to consumers. This information seeking and brand and product commenting seems to open the door for some type of advertising medium. Similar to search advertising, where

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FIG. 6. Example of company using microblog to improve customer service.

relevant ads are triggered via key terms in queries, it would appear that there could be a tweet advertising medium where relevant ads are triggered by keywords in tweets.

Third, the ratio of positive to negative branding tweets is about 50% to 35%, with the remaining being neutral. People have an opinion and are expressing them via microblogs. Some part of the positive tweets could be part of commercial viral marketing by corporations (i.e., hiring persons to post positive tweets about companies or products); however, given the large number of tweets examined, it would seem that this would be a small part if it existed at all. This implies that corporations could use tweets as customer feedback about products and features that are well received by the consumers. Duana et al. (2008) found that product quality had a positive impact on generating positive eWOM; therefore, businesses could generate brand awareness without large outlays on advertising and marketing. As for the 35% of negative tweets, this permits a direct customer expression of what is not going right for a product or service. Online consumer review information can be useful for identifying consumer preferences, finding out product defects, and correcting inadvertent mistakes. Duana et al. (2008) pointed out that a large amount of negative eWOM made it difficult for a business to overcome its adverse industry positioning. Corporations should then be proactive in evaluating these sentiments in the microblogging eWOM area. With microblog monitoring tools, companies can track microblog postings and immediately intervene with unsatisfied customers. Some corporations are already getting involved, as shown in Figure 6, which shows a Chrysler employee addressing a microblog posting from a customer concerning her PT Cruiser. Get Satisfaction.com (getsatisfaction.com) integrates directly with Twitter and automatically pulls in tweets of specific companies.

Fourth, there is about a 60% swing in sentiment from week to week. Assuming that this is not due to biases in classification, microblogging branding is fluid, requiring constant and continual management. Given that one can easily send a microblog via a variety of mobile devices, there is obviously an immediate expression or reaction to an individual's experiences of products or services. This immediacy at the point of purchase is a critical factor that separates microblogging from other forms of product expression, such as blogging, Websites, or product reviews. As such, eWOM requires continual and constant managing in the microblogging medium as it has closed the emotional distance between the customer and business.

Fifth, there is a statistical difference of brands within industry sectors, so the microblogging domain may be a good avenue to explore to track the trends within a given marketplace. We found brand sentiments were different in seven industries. Those corporations that fell behind relative to others in the industry segment could leverage the microblogging to improve their brand image by an analysis of these customers' posting. Those corporations ahead of others could learn from those behind and further enhance their brand image.

Sixth, the term, co-occurrence, and mutual information statistics generally conform to typical natural language usage, with some notable differences. There is obviously something (probably the technology) that is altering the normal communication patterns. This would imply, again, the need for some specialized marketing effort and methodology to analyze these microblogging posts. However, the results of the manual classification and automatic classification are not statistically different. This is particularly important given that microblogging will most likely grow and integrate itself into the overall landscape of electronic expression mediums. In order to make sense of these data and phenomena, corporations will have to rely on automated methods. Based on this analysis, it appears that one can accurately classify microblogging via our automated method.

Seventh, we see some general patterns in how companies are leveraging microblogging for eWOM branding. These efforts are providing a place for customers to express feelings, provide feedback, ask questions, and get answers. As such, there are a lot of possibilities to use Twitter and similar sites for customer relations and branding efforts. These include having multiple accounts for various areas of the corporation to accommodate the swings in customer traffic and different customer expectations of these services as a communication system (e.g., one for surveys and events, one for comments and suggestions, etc.). Considering the rapid growth and popularity of microblogging, companies should come up with a systematic way to handle customers on microblog sites to influence brand image. It would seem that microblogging can be used to provide information and draw potential customers to other online media, such as Websites and blogs. As such, monitoring and leveraging microblogging sites concerning one's own brand and the brand of competitors is a valuable competitive intelligence. Companies can get near real-time feedback by setting up corporate accounts. Companies also get valuable content and product improvement ideas by tracking microblog postings and following those people who follow their corporate accounts. Finally, companies can leverage contacts made via microblogging services to further their branding efforts by responding to comments, suggestions, or comments about the company brand.

Naturally, there are limitations to this study. First, we examined microblogs from only one microblogging site. Users of other microblogging services might differ in their usage patterns. Twitter is by far the largest and most popular of these sites, but investigations into other services will be an area for future research. Second, most of the brands that we examined are major brands, with only a small percent being minor brands like Averatec. Porter & Golan (2006) analyzed 501 advertisements, including 235 television advertisements and 266 viral advertisements. The findings showed that Fortune 500 companies created 62% of the television ads analyzed (146 ads), while non-Fortune 500 companies created 38% (89) of the television ads. However, non-Fortune 500 companies produced the majority of viral ads, with 60% (160 ads), compared to 40% by Fortune 500 companies (106 ads). It would be interesting to continue this investigation into small or even local brands. Finally, in comparing manual and automated coding, we compared the distributions of each category acquired from human coding and system coding. One could conduct a more in-depth analysis by comparing the sentiment of each tweet coded by human and by an automated system. However, the distribution of different sentiment categories can give us a fair enough description about the sentiment of tweets.

There are several strengths of the study. First, we used a number of well-known brands with major impact from a variety of industry sections. This ensured our results would have practical and influential implications. Second, we approached our analysis of microblogging from a variety of perspectives and paradigms, using a mixed methods approach and employing both quantitative and qualitative measures. This helped ensure that our findings are robust. Third, we focus on microblogging as an emerging area with potentially significant impact on eWOM and anchored this analysis in the brand knowledge and relationships that link the finding to consumer behavior. Therefore, our research is timely and has practical implications in the marketplace.

Conclusion

In this research we examined the use of microblogging for eWOM branding. Examining several datasets from a variety of angles, our research has shed light on critical aspects of this phenomenon. The implications of this research include that microblogging is a potentially rich avenue for companies to explore as part of their overall branding strategy. Customer brand perceptions and purchasing decisions appear increasingly influenced by Web communications and social networking services, as consumers increasingly use these communication technologies for trusted sources of information, insights, and opinions. This trend offers new opportunities to build brand relationships with potential customers and eWOM communication platforms. It is apparent that microblogging services such as Twitter could become key applications in the attention economy. Given the ease of monitoring any brand's sentiment, one can view microblogging as a competitive intelligence source.

The essence of eWOM communicating and customer relationship management is knowing what customers and potential customers are saying about the brand. Microblogging provides a venue into what customers really feel about the brand and its competitors in near real time. Additionally, microblogging sites provide a platform to connect directly, again in near real time, with customers, which can build and enhance customer relationships.

For further research, it would be interesting to investigate occurrences of brand hijacking on microblogging service (e.g., www.web-strategist.com/blog/2008/08/01/how-janet-fooled-the-twittersphere-shes-the-voice-of-exxon-mobil/). As with most information services on the Web, microblogging sites are susceptible to adversarial and spamming maneuvers, and brand hijacking appears to be an early form of adversarial methods. Early research in this area could reduce the susceptibility of microblogging sites to these forms of attack.

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