Managing the uncontrollable: Empirical studies of user-generated content online

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CHAPTER 4

HOW SOCIAL INFLUENCE SHAPES POPULARITY: EMOTION AND OPINION FORMATION IN ONLINE COMMENTING[1]

ABSTRACT

Why are some topics more widely and positively discussed than others in online communities? Based on social impact theory and attribution theory, we investigate individual commenting in online communities and its influence on popularity. Data from an online community suggest that users are influenced by both the immediately preceding comments, i.e., the immediacy of sources, and the comments of the majority, i.e., the number of sources. Individual comments tend to mimic the emotions of and express opinions similar to preceding comments. Concurrently, the popularity of topics is shaped by the content of these comments, rather than the content of the initial information alone. Discussions that are highly emotional and in agreement with each other are less likely to be popular. On the other hand, discussions that have high variance in opinions and emotions are more likely to be popular. This study suggests that, due to sequential influence, the first comments play an important role in how conversations are formed and in the resulting popularity of the online discussion.

[1] This chapter is based on a paper that is to be submitted to an international journal (with W. van Dolen as second author).

4.1 INTRODUCTION

Commenting or expressing opinions is an important aspect of online interaction, because these activities create and add value to online communities (Hennig-Thurau et al., 2004). In communications about specific products, the volume of comments reflects the popularity of the brand (de Vries, Gensler and Leeflang, 2012) or product, which can have a direct influence on sales (Liu, 2006). Therefore, companies establish online communities to directly engage with consumers and encourage discussion. Online marketing researchers have studied extensively how to motivate participation in online communities (e.g., Brodie et al., 2013; Burton and Khammash, 2010; Smith, Fischer and Yongjian, 2012; Sweeney, Soutar and Mazzarol, 2008). However, increased overall participation does not guarantee popular and favorable discussions, and little is known about why certain discussions are more popular or more positive/negative than others.

Recent research on online reviews stresses that to understand how people comment on a topic, it is important to analyze the dynamic process of commenting, rather than treating all comments as static entities (e.g., Ludwig et al., 2013). A few studies on product reviews illustrate a pattern in reviews, such that product characteristics, ratings of all preceding reviews (e.g., Godes and Silva, 2012; Li and Hitt, 2008), and number of preceding reviews (Duan, Gu and Whinston, 2008) influence the content and number of subsequent reviews. To date, this dynamic process has not yet been explored in the context of online communities, which exhibit a higher level of interactivity among members than do product review sites. Interactivity in communities highlights the importance of understanding the influence of preceding discussions during the individual commenting process. However, it remains unclear whether the content of preceding comments influences subsequent comments, and whether the content of all comments influences the total number of comments, i.e., the popularity of discussion threads.

To address this research gap, we turn to the social influence literature and to social impact theory, which explain the mechanism and strength of this influence in a social context. We distinguish the three sources of influence on how people comment, namely, initial information (the thread starting post, i.e., the first message), descriptive norms (majority of other users' comments), and immediacy of information sources (immediately preceding comments). Studies suggest that information with high immediacy, i.e., sources that are close in time or space proximity, and high quantity, i.e., number of repeated pieces of information, exhibits stronger social influence on the receivers of that information (e.g., Latané, 1996). Specifically, the number of information sources has been examined using the concept of descriptive norms, under whose influence people tend to follow what the majority of others do (e.g., Huang and Chen, 2006). Accordingly, users may be more likely to make comments in agreement with the majority of others' comments. Based on the influence of immediacy, we argue that immediately preceding comments, i.e., the last comments made right before, would have a stronger influence on subsequent commenting behavior than all other comments. Besides the influence of others, initial information is shown to influence reader behavior (e.g., Berger and Milkman, 2012). Considering such distinctions, we aim to identify which information sources play a key role in shaping subsequent user comments.

Since the number of comments in an online discussion thread is actually the aggregated outcome of individual comments, we examine whether and how the content of these collective comments contributes to the popularity of a discussion thread. Attribution theory asserts that people try to make sense of others' behaviors by assessing the locus of causality of events. According to Kelley's covariation principles, individuals attribute the cause externally when the information has high consensus, consistency and distinctiveness (Kelley, 1973). Internet users are more likely to be convinced that the original information is indeed favorable (unfavorable) when the comments have congruent in positive (negative) emotions and opinions. Conversely, when the variance among preceding discussions is high, subsequent users tend to attribute the content to personal opinions and are more likely further to express their own opinions. Research also suggests that moderately controversial topics are more interesting to discuss and are more likely to generate responses online, particularly when people are anonymous to each other (Chen and Berger, 2013). Consequently, we argue that discussions that are in consensus are less likely to be popular. On the other hand, when variance is high, indicating opposing views in prior discussions, the thread is more likely to continue to attract comments, leading to high popularity. We aim to use this notion to shed light on the formation of popular threads.

Specifically, we focus on the valence and agreement/disagreement of the comments. Emotions, positive or negative, form the valence of a post, and are known to influence viewer interpretation of the piece of information (Kim and Gupta, 2012) and its virality (Berger and Milkman, 2012). Concurrently, along with emotions, users may express opinions on whether they agree or disagree with the piece of information. The degree of agreement between user posts is found to influence subsequent user response (Chiou and Cheng, 2003). Hence, in this research, we aim to understand to what extent the valence and opinions from comments are influenced by emotions in the initial message, the emotions and opinions of the majority of others and/or of the immediate predecessors, and to what extent collective emotions and opinions influence thread popularity.

In particular, this study is guided by the following research questions: a) to what extent are emotions and opinions from online comments influenced by prior information, including initial messages and preceding comments? b) How, if at all, does consensus or variance of emotions and opinions from comments contribute to formation of popular discussion threads? In answering these questions, we hope to provide a theoretical framework on the formation of threads in online communities and to deepen understanding of what drives online conversations. Study of the popularity of online information poses a fruitful and central issue for scholars and marketers interested in shaping and driving online discussions.

4.2 A SOCIAL INFLUENCE FRAMEWORK OF ONLINE COMMENTING

The popularity of discussion threads represents the aggregated outcome of multiple individual commenting behaviors. While the number of times a piece of information is transmitted or discussed is known to be influenced by the characteristics and content of this initial information (e.g., Berger and Schwartz 2011; Berger and Milkman 2012), studies on why people respond positively or negatively to a topic online are still scarce. Such processes of online discussion formation have recently received increased attention, particularly in online product reviews (e.g., Godes and Silva, 2012; Li and Hitt, 2008; Moe and Schweidel, 2012; Moe and Trusov, 2011; Moon, Bergey and Lacobucci, 2010). From these studies, there is considerable evidence that reviews are written not only based on the characteristics of the initial information or independent judgments, but are also influenced by the opinions of others (Moe and Schweidel, 2012). Specifically, it is established that online users adjust their ratings in accordance with others (Schlosser, 2005). Thus, the factors that influence review formation can be identified at two levels, the characteristics of the initial information source, and the reviews that have already been submitted. To date, however, research on how individual posts are influenced by others' posts is limited to product ratings, and has not been investigated in the context of online communities.

Differing from product rating scenarios, where reviewers give scores to each product, comments in online communities are often in a text format. Users can express their comments as emotionally positive or negative, e.g., happy or unhappy and/or with opinions, such as agreeing or disagreeing. In this study, we thus distinguish between valence, or the emotional content, and agreement/disagreement, or the cognitive content of comments. Research on online discussions stresses that the development of individuals' "public" opinions is heavily affected by social influence (Ho and McLeod, 2008). More importantly, the effect of social influence could be even stronger due to the highly interactive nature of online communities of likeminded individuals. To understand how prior discussions influence current comments, we build our conceptual framework on informational social influence and social impact theory. Informational social influence suggests that people perceive others' behavior as an information source that indicates reality in an uncertain environment. Much of this influence is achieved through observation and imitation, whose mechanism is rooted in social impact theory (Argo, Dahl and Manchanda, 2005). Social impact theory asserts that individuals' emotions and beliefs can change due to "the real, implied, or imagined presence or actions of other individuals" (Latané, 1981: 343). Accordingly, we argue that individuals' commenting behaviors are affected by the presence of others' comments, though the persons who made these comments may not be online at the time.

Research drawing on social impact theory suggests that individuals infer cues from others to make their own judgments (Latané, 1996). In particular, individuals are most likely to be biased toward information that has immediate proximity and high quantity, especially when the social status of others is unknown (Mangleburg, Doney and Bristol, 2004). Studies on online discussions tend to focus on identifying which users are more likely to be influential, and conclude that opinion leaders (Iyengar, van den Bulte and Valente, 2011), light users, customers that are less loyal to specific products (Godes and Mayzlin, 2009), and the critical mass (Watts and Dodds, 2007) are likely to influence fellow users' online behavior. However, online commenting actually has the characteristic of being anonymous. User profiles rarely indicate information on personality, values, and motivations (Sukumaran et al., 2011). In this situation, influence based on user status may not be as effective. This ambiguous situation, in which the "power" of others cannot be determined, may lead to higher dependency on other informational cues, such as the proximity and amount of information. With regard to immediacy, in online discussions, the order of comments determines their relative proximity to each other. Comments made immediately before new ones have the highest immediacy and should have the strongest impact in terms of social influence.

Immediacy of information has also been found to influence the effectiveness of information integration and belief formation. In the context of information transmission, information that is more recent appears to have greater influence on consumer perceptions (van Hoye and Lievens, 2007). Research suggests that online users tend to anchor on the most recently acquired online word of mouth (Christodoulides, Michaelidou and Argyriou, 2012); as a result, the valence of their evaluation of information would be similar to that of their anchor (Cohen and Reed, 2006). In other words, subsequent comments are likely to express similar emotions and opinions as those of the immediately preceding comments. To help individuals make evaluations, many online review sites, such as Amazon.com, present user comments according to their recency. This implies that in online conversations, comments that occur immediately prior to new comments may have greater impact than those further away. We thus posit Hypothesis 1 as follows:

H1a: Comments are more likely to be positive (negative), when the immediately preceding comments are positive (negative).
H1b: Comments are more likely to agree (disagree), when the immediately preceding comments agree (disagree).

With respect to number of sources, it is argued that individual behaviors are biased toward what the majority of others say or do (Banerjee, 1992), which often serves as an indicator of what is the "correct" thing in a given situation and is described as a "descriptive norm" (Cialdini, Reno and Kallgren, 1990). People are often influenced by descriptive norms through observational learning; people disregard their own information and act on information provided by predecessors after observation (Bikhchandani, Hirshleifer and Welch, 1992). This is because individuals tend to believe that others have better information, especially when one has limited resources to evaluate a situation (Duan, Gu and Whinston 2009). In the context of online discussions, when the direction of discussions is unclear and the criteria for making "good" comments are unknown, we argue that it is likely that people are influenced by descriptive norms and will converge to the majority of others' comments.

The impact of descriptive norms suggests that people purchase or review items that are more popular and already have more comments, regardless of intrinsic product features (e.g., Chen 2011; Duan, Gu and Whinston, 2008; Huang and Chen, 2006; Oh and Jeon, 2007). This influence can be both emotional and cognitive. With respect to emotion, prior studies suggest that people have a tendency to imitate other people's emotions and that a group will reach emotional convergence during this process (e.g., Small and Verrochi, 2009). This suggests that users observe emotions expressed by the majority of others and consciously or subconsciously express the same emotions in their own comments. Similarly, when Internet users make comments in a discussion thread, whether agreeing or disagreeing, descriptive norms of opinions may also be influential. We propose that when there are few other reference points available, people are more inclined to mimic others' opinions. Online users have a tendency to express and transmit certain information that is more "desirable" to the social goal of the group in computer-mediated communications (Lin and Peña, 2011). As a result, the comments are more in line with what the majority of others have already said. We thus propose that:

H2a: Comments are more likely to be positive (negative) when the majority of the preceding comments are positive (negative).
H2b: Comments are more likely to agree (disagree) when the majority of the preceding comments agree (disagree).

Lastly, research suggests that the initial source of information influences how people react to a piece of information (Berger and Milkman, 2012). While opinions toward each topic of discussion (i.e., agreement/disagreement) may be individually different and difficult to predict, the emotions embedded in the initial message may provide cues about the direction of comments. Studies on word of mouth have found that emotions play a key role in how people react to received information. Part of the mechanism by which word of mouth information influences consumers is that the emotions embedded in the message can directly trigger similar emotions in readers' minds (Bickart and Schindler, 2001; Howard and Gengler, 2001; Pugh, 2001). These findings suggest that reading positive information can lead to positive reactions, whereas negative information can result in negative responses. In other words, when the initial message is more positive or more negative, the comments become more positive or negative, respectively. We thus posit that:

H3: Comments are more likely to be positive (negative), when the initial message is positive (negative).

4.3 DISCUSSION THREAD POPULARITY

It is important for companies to create a topic or item to spur the interest of Internet users and trigger a significant amount of online discussion, because online popularity often indicates brand popularity in general (e.g., de Vries, Gensler and Leeflang, 2012). Scholars used to assume that a high volume of online conversation resulted from product characteristics, in particular, the popularity of the product itself (Lee, Lee and Shin, 2011; Zhu and Zhang, 2010). The more popular a product is, in terms of sales and reputation, the more reviews it receives. However, many online discussions are not directly related to products. To understand the popularity of online conversations, one may consider informational cues other than product characteristics. Content characteristics, such as emotions, along with topics and authors, appear to influence whether a piece of information is shared (Heath, Bell, and Sternberg 2001). Previous research on online WOM suggests that messages that elicit emotions are more likely to be shared (Dobele et al., 2007). Positive valence embedded in the initial information, in particular, is more likely to trigger information transmission (Berger and Milkman, 2012; Lin and Peña, 2011). These findings suggest that positive emotions appear more likely to activate individuals. Thus, we argue that in online discussions, positive posts are more likely to result in commenting behavior, which leads to higher popularity for a discussion thread. Therefore, we hypothesize that:

H4: Volume of comments is more likely to be high (low) when initial message is positive (negative).

Though these studies help to address the question of why certain information is more popular than other information, it is important to note that when users participate in an online discussion, there may be multiple information sources. Once the content characteristics of the initial message lead to the first comments, subsequent commenters are exposed to all preceding comments, along with the initial message.

When a user first joins a discussion thread, the aggregated preceding comments, along with the initial message, create a commenting climate which represents overall discussion thread characteristics. Prior research indicates that such a so-called climate of opinions could influence user willingness to post a message (Yun and Park, 2011). Therefore, it is important to consider overall discussion thread characteristics when evaluating the popularity of each discussion. Research drawing upon attribution theory suggests that when the emotional elements of preceding reviews are in consensus, this helps users attribute the emotions externally to the products, rather than internally to the reviewer's personal disposition. In particular, reviews that express convergent positive and negative emotions are deemed to have higher information value and to help users make judgments (Kim and Gupta, 2012). Attribution theory asserts that individuals tend to assign causal explanations to the experienced events and respond accordingly; the consensus of emotions in observations helps individuals to validate attributions (Freling and Dacin, 2010). Accordingly, we argue that when all preceding comments express similar emotions, whether negative or positive, individuals share the same emotions and attribute these emotions to the initial messages. In other words, subsequent users may feel the same emotions and that there is no need to further comment. Consequently, convergent emotions result in lower volume of overall comments, and hence less popularity.

Similarly, when all preceding comments express similar opinions, whether agreeing or disagreeing, individuals are more likely to experience the same opinions and believe that they themselves should think like previously expressed opinions. This pattern is also observed in the relevant literature. "Silence" behaviors in online discussions often result from users feeling that there is nothing more for them to contribute (e.g., Ballantine and Stephenson, 2011), as they share the same opinions and feelings with other participants. If individuals feel that whatever they say does not make a difference to the outcome of the discussion, since consensus has already been reached, they choose not to express themselves (e.g., Morrison and Milliken, 2000). This is to say that when consensus is high, subsequent users are less likely to comment, which eventually results in lower popularity. Therefore, we hypothesize:

H5a: Volume of comments is more likely to be low when discussion threads have high emotional consensus.
H5b: Volume of comments is more likely to be low when discussion threads have high consensus of opinion.

Research suggests that "interesting" topics are more likely to create buzz online (Berger and Milkman, 2012). In particular, a controversial topic that triggers diverse responses is more likely to be discussed (Chen and Berger 2013). In the same vein, we argue that high variance among comments indicates diverse opinions and emotions in prior discussions and could lead to even more comments. These diverse comments may provide little informational value (Godes and Silva, 2012), which suggests an uncertain situation requiring further discussion. According to attribution theory, consensus information is needed to determine whether the observed events can be attributed to persons or entities (Kelley, 1973). When diversity in comments is high, i.e., low consistency and consensus in prior comments, users are likely to attribute the cause of these variations in emotions and opinions to prior individual commenters as their personal opinions instead of responses that are caused entirely by the initial messages. Consequently, the emotion and opinion climate of the discussion threads would suggest that there is still room for further discussion. Previous research also suggests that an argumentative opinion climate elicits greater participation (Rafaeli and LaRose, 1993). The high variance of prior discussions seems to suggest a more tolerant comment environment more welcoming to participation. Accordingly, we hypothesize:

H6a: Volume of comments is more likely to be high when discussion threads have high variance of emotion.
H6b: Volume of comments is more likely to be high when discussion threads have high variance of opinion.

4.4 METHODOLOGY

4.4.1 Data

To test our hypotheses, we extracted data from a brand community, Dell IdeaStorm. Dell officially launched IdeaStorm in February 2007, as an attempt to utilize online crowdsourcing. Internet users can create a free account and submit ideas or write comments about others' ideas. We chose a co-creation community as our research platform for the following reasons. First, the layout of the community makes a clean distinction between the initial message and subsequent comments. This structure makes it easier to detect what information sources one person has accessed prior to making comments. Second, in co-creation forums, comments are made in response to conceptually described ideas instead of an existing product. This avoids potential bias from pre-existing knowledge and experience of product usage, as in product review platforms. Lastly, IdeaStorm is well established and is considered one of the best crowdsourcing practices, providing abundant discussion threads to analyze.

All discussion threads within a four-year time-span since the site launch were extracted from the site, including initial ideas, comments, author aliases, author profiles, and their timestamps when available. Over the study period, excluding the posts archived and removed from the site by the site company, 14,404 ideas were documented, among which 10,178 (70.66%) attracted more than one comment; 9,436 unique individuals were recorded, for a total of 84,784 valid comments. Among these unique users, 91 were Dell employees, and they contributed 3,730 (4.40%) comments. Since we investigate only genuine user comments, comments by Dell employees were excluded from analysis, except when they preceded comments to others. The average number of comments per idea was 65.42. However, comment distribution was positively skewed (Skewness=3.93) and the median number of comments per idea was nine.

4.4.2 Variables and Coding Process

Based on our hypotheses, the variables were divided into two main dimensions, valence and agreement/disagreement. Summary descriptions for all variables are listed in Table 4.1. We labeled each variable with each associated comment made as idea *k* at order *i* in the threads. We computer-coded the valence, using Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth and Francis, 2007), as applied in a previous online information transmission study (Berger and Milkman, 2012). We coded all comments based on their use of positive and negative emotional words. $POSITIVE_{ki}$ was coded according to the percentage of positive emotional words listed in the comments, and $NEGATIVE_{ki}$ was coded based on the percentage of negative words. Similarly, the percentage of positive and negative emotional words in the initial messages, idea post *k*, was coded $IDEA\_POSITIVE_{k}$ and $IDEA\_NEGATIVE_{k}$, respectively. The valence of the majority of comments was calculated using the moving average and moving variance of the preceding comments. The moving average of positive valence of the preceding comments until comment order *i* was noted as $MVPOSITIVE_{ki-1}$, and the moving variance was calculated based on standard deviation and labeled as $VAPOSITIVE_{ki-1}$. Similarly, negative valence and its variance were labeled $MVNEGATIVE_{ki-1}$ and $VANEGATIVE_{ki-1}$, respectively. The overall valence and variance of a discussion thread initiated by idea *k* were calculated as the overall mean of positive and negative, which were labeled $POSITIVE_{k}$ and $NEGATIVE_{k}$. The overall variance of valence of each thread was calculated and marked as $VAPOSITIVE_{k}$ and $VANEGATIVE_{k}$.

The second dimension, opinions of comments, i.e., agreement/disagreement, was human-coded. We coded opinions of comments toward the initial messages with the label "agree," "disagree," "neutral," or "unclear." In our analysis, only agree and disagree were included. Similar to how user-generated content was coded in the literature (Smith, Fischer and Yongjian, 2012), comments on idea *k* at order *i* were coded $AGREE_{ki}$, $DISAGREE_{ki}$, $NEUTRAL_{ki}$, or $UNCLEAR_{ki}$, based on the overriding positions in response to the previous messages. Due to the large number of overall comments, three independent coders who did not participate in the hypothesis development process coded the comments separately. Each coder coded 10% of randomly selected discussion threads to verify the coding scheme and to test intercoder reliability. Selection of the subsample was considered sufficient (Li, Daugherty and Biocca, 2001) to establish the validity of the scheme. Ultimately, 8,429 comments from 1,017 discussion threads were tested. Intercoder reliability was sufficient. Average Cohen's Kappa among the three coders was .90, and the percentage of agreement was 94.09%. Differences in coding were discussed and resolved before the remainder of the comments were coded. The opinions in the majority of the preceding comments were then calculated in accordance with how the valence was calculated, and labeled $MVAGREE_{ki-1}$, $MVDISAGREE_{ki-1}$, $VAAGREE_{ki-1}$, or $VADISAGREE_{ka-1}$. Opinions of the overall discussion thread initiated by idea *k* were calculated as the overall average opinion and noted as $AGREE_k$ or $DISAGREE_k$. Overall variance in agreement and disagreement of each thread was calculated by their standard deviations, and labeled $VAAGREE_k$, or $VADISAGREE_k$.

Finally, the number of comments for each idea thread was extracted directly from the community and labeled $COMMENTS_k$. An idea thread *k* was considered popular if it had more comments than the mean plus one standard deviation of comments per thread for the entire forum (Aggarwal et al., 2012); we created dummy variable $POPULARITY_k$ to label this. This represents only 2.36% of all discussion threads.

To control for other factors that may influence the content and number of comments, we included various control variables in our models. The topics of idea *k* were distinguished based on categorization by the community, namely, $TOPIC_k$, $DELL_k$, and $PRODUCT_k$. In addition, we included WORD $COUNTS_k$ of the idea posts, $VOTES_k$ that it received, and the $DURATION_k$ of time the idea remains posted on the community. We also established the baseline of user *j*'s usual emotional tendency by calculating their average $POSITIVITY_j$ and $EMOTIONALITY_j$. The former was calculated based on the difference between the percentage of positive words and the percentage of negative words in comments posted by the same users. Emotionality, on the other hand, was calculated as the sum of these two percentages. The formula was used to calculate content characteristics of news articles (Berger and Milkman, 2012). Based on a similar logic, we defined $OPINIONATED_j$ as the average of agree and disagree comments among all comments made by the user, and $CONFORMITY_j$ as the difference between agreeing comments and disagreeing comments. Users who posted only once were excluded from the analysis, as their baselines would be the same as that one comment. Moreover, we controlled for activity levels of individual users by calculating the $FREQUENCY_j$ of their activities on the community. We took the average number of posts made by the person since the first time they appeared on the community until the day the data were extracted. Finally, we added dummy variables for each comment under idea *k* at order *i* for whether it was published during $WEEKEND_{ki}$ and which year between 2007 and 2011, as control variables.

Table 4.1 Description of Variables

Variables	Coding Methods	Coding Unit	Label	Description and Measures
Main Variables				
Valence of comments	Coded through textual analysis (LIWC)	Comment	$POSITIVE_{ki}$	Percentage of positive emotional words per comment to idea k at order i
			$MVPOSITIVE_{ki-1}$	Moving average of POSITIVE of idea k until order i
			$VAPOSITIVE_{ki-1}$	Moving standard deviation of POSITIVE of idea k until order i
			$NEGATIVE_{ki}$	Percentage of negative emotional words per comment to idea k at order i
			$MVNEGATIVE_{ki-1}$	Moving average of NEGATIVE of idea k until order i
			$VANEGATIVE_{ki-1}$	Moving standard deviation of NEGATIVE of idea k until order i
		Thread	$POSITIVE_{k}$	Average POSITIVE of idea k
			$VAPOSITIVE_{k}$	Standard deviation of POSITIVE of idea k
			$NEGATIVE_{k}$	Average NEGATIVE of idea k
			$VANEGATIVE_{k}$	Standard deviation of NEGATIVE of idea k
Opinions of comments	Manually coded	Comment	$AGREE_{ki}$	A dummy variable measuring whether the comment to idea k at order i agrees with idea k
			$MVAGREE_{ki-1}$	Moving average of percentage of AGREE of idea k until order i
			$VAAGREE_{ki-1}$	Moving standard deviation of AGREE of idea k until order i
			$DISAGREE_{ki}$	A dummy variable measuring whether the comment to idea k at order I disagrees with idea k
			$MVDISAGREE_{ki-1}$	Moving average of percentage of DISAGREE of idea k until order i
			$VADISAGREE_{ki-1}$	Moving standard deviation of DISAGREE of idea k until order i
		Thread	$AGREE_{k}$	Percentage of AGREE comments of idea k
			$VAAGREE_{k}$	Standard deviation of AGREE of idea k
			$DISAGREE_{k}$	Percentage of AGREE comments of idea k
			$VADISAGREE_{k}$	Standard deviation of DISAGREE of idea k
Characteristics of the initial messages	Coded through textual analysis (LIWC)	Idea post	$IDEA\_POSITIVE_{k}$	Percentage of positive emotional words of idea k
			$IDEA\_NEGATIVE_{k}$	Percentage of positive emotional words of idea k
	Captured by WebCrawler		$COMMENTS_{k}$	Total number of comments of idea k
			$POPULARITY_{k}$	A dummy variable measuring whether idea k has above-mean plus one standard deviation of COMMENTS

Control Variables				
Characteristics of the users	Coded through textual analysis (LIWC)	Registered user	$POSITIVITY_j$	Difference between POSITIVE and NEGATIVE of all comments from user j
			$EMOTIONALITY_j$	Sum of POSITIVE and NEGATIVE of all comments from user j
	Manually Coded		$CONFORMITY_j$	Difference between percentage of AGREE and DISAGREE of all comments from user j
			$OPINIONATED_j$	Sum of percentage of AGREE and DISAGREE of all comments from user j
	Captured by WebCrawler		$FREQUENCY_j$	Number of comments made by user j from its first appearance until 10 May 2011
			$EMPLOYEE_j$	A dummy variable measuring whether user j is an employee
Characteristics of ideas	Captured by WebCrawler	Idea post	$TOPIC_k$	A dummy variable measuring whether idea k is tagged with topic-related subjects
			$DELL_k$	A dummy variable measuring whether idea k is tagged with Dell-related subjects
			$PRODUCT_k$	A dummy variable measuring whether idea k is tagged with product-related subjects
			$VOTES_k$	Final score of votes received by 10 May 2011
			$DURATION_k$	Time-span between publish date and 10 May 2011 of idea k
			$WORD\ COUNTS_k$	Total word counts of idea k
			$COMMENTS_{ki}$	Total number of comments of idea k at order i
Time	Captured by WebCrawler	Comment	$WEEKEND_{ki}$	A dummy variable measuring whether a comment on idea k at order i was published during the weekend
			$YEAR_{ki}$	A dummy variable measuring which year a comment on idea k at order i was published, between 2007 and 2011

4.4.3 Models

To understand how individual comments were formulated, we analyzed the impact of initial messages and their preceding comments in three different stages. We first examined the initial comment made in each thread. Then, we examined the second comments, when there was only one preceding comment along with the initial message. Finally, we examined the remainder of the comments. We separated the models as such because the first two stages had only one comment, whereas the final stage included multiple comments for the outcome variables. The impacts of preceding information sources, whether ideas or comments, on $POSITIVE_{ki}$ and $NEGATIVE_{ki}$ were analyzed with ordinary least square regressions, and $AGREE_{ki}$ and $DISAGREE_{ki}$, due to their categorical nature, were analyzed via logistic regressions. On the other hand, in the last stage, each discussion thread had multiple observations on dependent variables, which gave the data a panel structure. Thus, for the third stage, we employed a generalized least squares random model to calculate the impact of valence, and random effect logistic models to calculate the impact of opinions, which fits longitudinal data with binary output. We report standard errors that are robust to heterogeneity.

To explore what contributed to forming a popular thread, we analyzed the influence of thread characteristics and their impacts on the volume of comments. We employed the Poisson-Logit Hurdle regression model (PLHR) (Mullahy, 1986), as applied in the literature (Hinz et al., 2011). The model is separated into two stages of calculation. PLHR first predicts the impact of the idea-specific variables on the chances that an initial message receives any comments at all, and then predicts the impact of these variables on the total volume of comments. Due to the high variance in the number of comments, we then fitted the model with a negative binomial regression to check the impact of both idea-specific and comment-specific characteristics on the total volume of comments. Finally, to verify the negative binomial model results of the impact on the volume of comments, we further conducted a logistic regression analysis to check whether the identified variables made the cutoff point for establishing a popular idea. All analyses were performed using the statistical software STATA.

Table 4.2 Descriptive Statistics and Correlation Matrix of Key Variables

(a) Correlations **Variables**	1	2	3	4	5	6	7	8	9	10
1 POSITIVE$_{ki}$	1									
2 NEGATIVE$_{ki}$	-.05***	1								
3 AGREE$_{ki}$	.20***	-.02***	1							
4 DISAGREE$_{ki}$	-.12***	.06***	-.51***	1						
5 IDEA_POSITIVE$_{k}$	.03***	-.01	.04***	-.01***	1					
6 IDEA_NEGATIVE$_{k}$	-.00	.04***	-.01*	-.00	-.06***	1				
7 MVPOSITIVE$_{ki}$	.50***	-.02***	.14***	-.09***	.06***	-.01	1			
8 MVNEGATIVE$_{ki}$	-.02***	.51***	-.02***	.05***	-.00	.11***	-.04***	1		
9 MVAGREE$_{ki}$	.11***	-.02***	.58***	-.33***	.06***	-.02***	.24***	-.04***	1	
10 MVDISAGREE$_{ki}$	-.07***	.04***	-.32***	.59***	-.02***	-.00	-.16***	.08***	-.57***	1
11 VAPOSITIVE$_{ki}$	.37***	-.01	.08***	-.08***	.04***	.00	.85***	-.01	.16***	-.17***
12 VANEGATIVE$_{ki}$	.00	.37***	-.02***	.02***	-.01	.07***	.01***	.86***	-.04***	.04***
13 VAAGREE$_{ki}$	.04***	-.00	.22***	-.17***	.01***	-.00	.12***	-.01**	.43***	-.32***
14 VADISAGREE$_{ki}$	-.03***	.02***	-.14***	.19***	-.02***	.01***	-.08***	.05***	-.27***	.38***
Descriptive Statistics										
Mean	4.66	1.29	.34	.34	3.08	.88	4.57	1.27	.35	.35
SD	9.19	3.50	.47	.48	2.85	1.64	3.56	1.46	.25	.26
Min	0	0	0	0	0	0	0	0	0	0
Max	100	100	1	1	100	50	68.75	50	1	1

	11	12	13	14
11 VAPOSITIVE$_{ki}$	1			
12 VANEGATIVE$_{ki}$	.09***	1		
13 VAAGREE$_{ki}$	.16***	.05***	1	
14 VADISAGREE$_{ki}$	.00	.08***	.20***	1
Descriptive Statistics				
Mean	6.29	2.28	.39	.39
SD	5.94	2.55	.20	.20
Min	0	0	0	0
Max	70.71	70.71	.71	.71

(b) Correlations **Variables**	1	2	3	4	5	6	7	8	9	10	11
1 COMMENTS$_{k}$	1										
2 IDEA_POSITIVE$_{ki}$	-.01	1									
3 IDEA_NEGATIVE$_{ki}$	.00	-.05***	1								
4 POSITIVE$_{k}$	.01	.05***	-.00	1							
5 NEGATIVE$_{k}$	.01	-.01	.10***	-.04***	1						
6 AGREE$_{k}$	.00	.01	.02	.24***	-.00	1					
7 DISAGREE$_{k}$	.00	-.01	-.00	-.13***	.07***	-.55***	1				
8 VAPOSITIVE$_{k}$	.07***	.03**	-.00	.86***	-.01	.17***	-.13***	1			
9 VANEGATIVE$_{k}$	.06***	-.01	.07***	-.01	.90***	-.05***	.08***	.05***	1		
10 VAAGREE$_{k}$	.07***	.00	.02*	.09***	-.02	.36***	-.28***	.12***	.02	1	
11 VADISAGREE$_{k}$	.06***	-.02	.00	-.10***	.02*	-.30***	.40***	-.02	.06***	.18***	1
Descriptive Statistics											
Mean	5.89	3.21	.89	4.50	1.26	.34	.36	5.45	1.96	.36	.36
SD	27.03	3.24	1.57	4.63	1.87	.29	.29	6.78	2.95	.25	.25
Min	0	0	0	0	0	0	0	0	0	0	0
Max	1383	100	50	67.59	50	1	1	70.71	70.71	.71	.71

Table (a) includes key variables used in models estimating valence and agreement/disagreement; Table (b) includes variables used in models estimating presence of a popular discussion thread. *, ** and *** indicate significance at the *p*<.05, *p*<.01 and *p*<.001 level, respectively.

4.5 RESULTS

4.5.1 Influence of Immediately Preceding Comments

Descriptive data and correlations among key variables are listed in Table 2. We first examine how individuals formulate their emotions and opinions under the influence of preceding information. Table 4.3 depicts estimated results for valence of subsequent comments, whereas Table 4.4 displays estimated results for opinions in subsequent comments. The results suggest that $POSITIVE_{ki}$ are found to be positively influenced by the preceding $POSITIVE_{ki-1}$ ($\beta_{ki=2}$=.0324, *p*=.019; $\beta_{ki>2}$=.0232, *p*<.001), while $NEGATIVE_{ki}$ are found to be positively influenced by the preceding $NEGATIVE_{ki-1}$ ($\beta_{ki=2}$=.0482, *p*=.005; $\beta_{ki>2}$=.0269, *p*<.001). H1a is accepted. Similarly, the results suggest that if the preceding comments are $AGREE_{ki}$ comments, the subsequent comments are also more likely to agree ($\beta_{ki=2}$=.578, *p*<.001; $\beta_{ki>2}$=.265, *p*<.001) and less likely to disagree ($\beta_{ki=2}$=-.437, *p*<.001; $\beta_{ki>2}$=-.191, *p*<.001). Likewise, when the preceding comments are $DISAGREE_{ki}$ comments, the subsequent comments are also more likely to disagree ($\beta_{ki=2}$=.604, *p*<.001; $\beta_{ki>2}$=.578, *p*<.001) and less likely to agree ($\beta_{ki=2}$=-.437, *p*<.001; $\beta_{ki>2}$=-.330, *p*<.001). Thus, H1b is confirmed.

4.5.2 Influence of Majority of Others' Comments

The results, the last two columns of Table 4.3 and 4.4 (i>2), indicate that subsequent comments are indeed influenced by the valence and opinions of the majority of others. When the $MVPOSITIVE_{ki-1}$ is high, the $POSITIVE_{ki>2}$ of subsequent comments are likely to be high (β=.0815, *p*=.018). Conversely, the $MVNEGATIVE_{ki-1}$ are found to have a positive impact on $NEGATIVE_{ki>2}$ (β=.207, *p*<.001). However, this effect is diminished if $VANEGATIVE_{ki-1}$ is high (β=-.259, *p*<.001). Therefore, H2a is accepted. Similarly, when the majority of others' comments agree ($MVAGREE_{ki-1}$), subsequent comments are more likely to agree (β=.703, *p*<.001). On the other hand, when the majority of others disagree ($MVDISAGREE_{ki-1}$), subsequent comments are not only more likely to disagree (β=.848, *p*<.001), but also less likely to agree (β=-.237, *p*=.001). Variance of agreement ($VAAGREE_{ki-1}$) or disagreement ($VADISAGREE_{ki-1}$) of preceding comments has no impact on subsequent comments. H2b is accepted.

4.5.3 Influence of Initial Messages

$IDEA\_POSITIVE_{ki}$ has a positive impact on $POSITIVE_{ki=1}$ (β=.0793, *p*=.003) and $POSITIVE_{ki>2}$ (β=.0390, *p*<.05). $IDEA\_NEGATIVE_{k}$ has a longer-lasting impact on $NEGATIVE_{ki}$ ($\beta_{ki=1}$=.164, *p*<.001; $\beta_{ki=2}$=.0968, *p*<.024; $\beta_{ki>2}$=.0562, *p*<.001). Thus, H3 is partially confirmed.

Table 4.3 Estimated Results for Valence of Subsequent Comments

	i=1		*i*=2		*i*>2	
	$POSITIVE_{ki}$	$NEGATIVE_{ki}$	$POSITIVE_{ki}$	$NEGATIVE_{ki}$	$POSITIVE_{ki}$	$NEGATIVE_{ki}$
	Control Estimates are Reported in Appendix A					
$IDEA\_POSITIVE_k$	.0793**	.0289	.0844	-.0104	.0390*	-.00269
	(.0263)	(.0283)	(.0486)	(.0114)	(.0175)	(.00931)
$IDEA\_NEGATIVE_k$	-.0213	.164***	-.0581	.0968*	.000981	.0562***
	(.0465)	(.0366)	(.0582)	(.0429)	(.0229)	(.0149)
$POSITIVE_{ki-1}$			.0324*	.00551	.0232***	.000810
			(.0138)	(.00815)	(.00701)	(.00176)
$NEGATIVE_{ki-1}$			.0152	.0482**	.0110	.0269***
			(.0419)	(.0170)	(.0120)	(.00599)
$MVPOSITIVE_{ki-1}$					.0815*	-.0143
					(.0344)	(.0145)
$VAPOSITIVE_{ki-1}$					-.0183	.0154
					(.0187)	(.00871)
$MVNEGATIVE_{ki-1}$					-.0138	.207***
					(.0660)	(.00831)
$VANEGATIVE_{ki-1}$					.0109	-.259***
					(.0357)	(.0290)
Intercept	.167	-.0999	.306	-.224	.0747	.477***
	(.472)	(.241)	(.722)	(.305)	(.261)	(.132)
Number of Comments	7653	7653	6098	6098	52225	52225
Number of Ideas	7653	7653	6098	6098	5639	5639
Adjusted R^2	.123	.0672	.0777	.0618		
Within R^2					.0733	.0297
Between R^2					.146	.134
Overall R^2					.0919	.0450
RMSE	7.134	3.221	8.818	3.472	9.158	3.525

Generalized least squares regression models above examine the factors influencing emotional expression in subsequent comments. Results indicate a clear impact of the valence in preceding comments, which increase the level of the same valence of subsequent comments. Controlling variables for these models are listed in Appendix A. Standard errors are shown in parentheses. *, ** and *** indicate significance at the *p*<.05, *p*<.01 and *p*<.001 level, respectively.

Table 4.4 Estimated Results for Opinions in Subsequent Comments

	i=1		*i*=2		*i*>2	
	$AGREE_{ki}$	$DISAGREE_{ki}$	$AGREE_{ki}$	$DISAGREE_{ki}$	$AGREE_{ki}$	$DISAGREE_{ki}$
	Control Estimates are Reported in Appendix B					
$IDEA\_POSITIVE_{k}$	.000915	.0115	.0105	-.0114	-.000610	-.0000622
	(.00786)	(.00777)	(.00909)	(.00934)	(.00407)	(.00429)
$IDEA\_NEGATIVE_{k}$	.0132	-.0176	-.00388	.0275	-.00184	-.00144
	(.0164)	(.0161)	(.0169)	(.0170)	(.00666)	(.00701)
$AGREE_{ki-1}$			.578***	-.437***	.265***	-.191***
			(.0705)	(.0728)	(.0275)	(.0291)
$DISAGREE_{ki-1}$			-.460***	.604***	-.330***	.578***
			(.0738)	(.0674)	(.0287)	(.0272)
$MVAGREE_{ki-1}$					.703***	-.0850
					(.0709)	(.0754)
$VAAGREE_{ki-1}$					.00523	-.0378
					(.0664)	(.0694)
$MVDISAGREE_{ki-1}$					-.237**	.848***
					(.0684)	(.0689)
$VADISAGREE_{ki-1}$					-.0269	.0356
					(.0663)	(.0650)
Intercept	-2.672***	-2.248***	-2.415***	-2.068***	-2.266***	-2.611***
	(.182)	(.168)	(.195)	(.189)	(.0891)	(.0928)
Number of Comments	7708	7708	6175	6175	53107	53107
Number of Ideas	7708	7708	6175	6175	5670	5670
Chi^2	1003.0	840.2	803.3	831.8	5423.3	5856.1
Log Likelihood	-4305.1	-4700.6	-3523.7	-3687.6	-29738.9	-30168.9
Correctly Classified	71.41%	64.95%	70.49%	66.20%		

Logistic regression models above examine the factors influencing position statements in subsequent comments. Results indicate that opinions in subsequent comments are influenced by opinions in the preceding comments. Control variables for these models are listed in Appendix B. Robust standard errors are in parentheses. *, ** and *** indicate significance at the p<.05, p<.01 and p<.001 level, respectively.

4.5.4 Thread Characteristics and Popularity

The final purpose of this research is to investigate the cause of the popularity of particular discussion threads. As indicated in Table 4.5, the logistic regression portion of the PLHR shows that positive emotions embedded in the idea have no impact on the odds of having at least one comment. It appears that only content-specific factors, such as the topic concerned, have an influence. In the second step, in which we fit the model to estimate the number of comments, it appears that the positive emotions in the initial idea posts have a positive impact on the number of comments received (β=-.0197, *p*=.041). This implies that when the percentage of positive words increases by 1% in the initial idea, the expected number of comments decreases by 1.9. This effect, however, is not observed when we fit the model with the comments' characteristics. Thus, we reject H4.

We then include comment characteristics in our model to investigate how these result in different volumes of comments in each discussion thread. The models that fit with either $POPULARITY_k$ or $COMMENTS_k$ show similar results. The result suggests that comment characteristics have better predictive power in identifying popular threads than do the initial messages. Both the increase in $POSITIVE_k$ and $NEGATIVE_k$ decrease the chances of having a popular thread (POPULARITY: $\beta_{positive}$=-.409, p<.001, $\beta_{negative}$=-.399, p<.001; COMMENTS: $\beta_{positive}$=-.0849, p<.001, $\beta_{negative}$=-.310, p<.001). H5a is confirmed. Similarly, when the majority of comments agree, the volume of comments also decreases (POPULARITY: β_{agree}=-1.216, p=.020; COMMENTS: β_{agree}=-.389, p=.013). However, we find no significant result with disagreement; thus, H5b is partially accepted. On the other hand, we find that when comments have diverse valence, they are more likely to be popular (POPULARITY: $\beta_{positive}$=.231, p<.001; $\beta_{negative}$=.243, p<.001; COMMENTS: $\beta_{positive}$=.0701, p<.001; $\beta_{negative}$=.239, p<.001). Likewise, when comments have diverse opinions, they are more likely to be popular (POPULARITY: β_{agree}=2.270, p<.001; $\beta_{disagree}$=1.918, p<.001; COMMENTS: β_{agree}=.814, p<.001; $\beta_{disagree}$=.700, p<.001). These results were as expected. Consequently, H6a and H6b are accepted.

Table 4.5 Estimated Results for Having a Popular Thread

Model	a		b	c
Variables	$COMMENTS_K$		$POPULARITY_K$	$COMMENTS_K$
	Logit	Poisson	Logit	Negative Binomial
$IDEA\_POSITIVE_k$	.00193	-.0197*	.0260	-.0116
	(.00621)	(.00964)	(.0155)	(.00604)
$IDEA\_NEGATIVE_k$	.00486	.0233	.0416	.0228
	(.0144)	(.0142)	(.0379)	(.0125)
$POSITIVE_k$			-.409***	-.085***
			(.0416)	(.00750)
$NEGATIVE_k$			-.399***	-.310***
			(.0738)	(.0225)
$AGREE_k$			-1.216*	-.389*
			(.524)	(.157)
$DISAGREE_k$			-.721	-.177
			(.412)	(.154)
$VAPOSITIVE_k$			.231***	.0701***
			(.0215)	(.00515)
$VANEGATIVE_k$			.243***	.239***
			(.0368)	(.0191)
$VAAGREE_k$			2.270***	.814***
			(.358)	(.0555)
$VADISAGREE_k$			1.918***	.700***
			(.254)	(.0586)
$PRODUCT_k$	-.170*	-.161	-.471	-.176**
	(.0694)	(.0961)	(.298)	(.0630)
$DELL_k$	-.182**	.0904	.174	.0186
	(.0643)	(.0862)	(.292)	(.0468)
$TOPIC_k$	-.133	-.283**	-2.159**	-.194**
	(.0963)	(.0906)	(.735)	(.0598)
WORD $COUNTS_k$	.000313	.0000959	.000948*	.000267
	(.000163)	(.000203)	(.000422)	(.000159)
$VOTES_k$	.00184***	.0000438***	.000348***	.0000107***
	(.000319)	(.00000233)	(.0000398)	(.00000201)
$DURATION_k$	.000594***	.000832***	.00123***	.000347***
	(.0000461)	(.0000644)	(.000297)	(.0000569)
Intercept	.147	1.153***	-6.185***	1.347***
	(.0897)	(.132)	(.532)	(.159)
Number of Ideas	14273		7366	
Pseudo R^2			.292	.452
Chi^2	300.0		403.2	1733.88
AIC	187217.8		1488.1	46301.109
BIC	187354		1605.5	46425.392
Log Likelihood	-93590.9		-727.1	-23123.555
Correctly Classified			97.3%	

Model a uses Poisson-logit Hurdle regression to examine the effect of the characteristics of the initial messages on volume of comments. Results indicate that the valence of initial messages does not increase the chance of attracting comments. Model b uses logistic regression to estimate popularity based on characteristics of the discussion threads. Model c uses negative binomial regression to examine the effect of the same factors on volume of comments. The two models yield similar results. Discussions having comments that are emotional or in agreement were less likely to be popular. The variance of valence and opinions, on the other hand, increases the chance of having more comments. Robust standard errors are in parentheses. *, ** and *** indicate significance at the $p<.05$, $p<.01$ and $p<.001$ level, respectively.

4.6 DISCUSSION AND IMPLICATIONS

The emergence of social media has increased interest in understanding what contributes to the popularity of certain online discussions. It is clear that consumers often comment on online information, but less is known about why consumers comment emotionally or opine about particular topics, and why certain content becomes more popular. Analysis of four years of discussion threads in an online community sheds light on what types of discussions are more popular and why. Contributing to the growing literature on online conversation development, our results demonstrate that individual comments are influenced by multiple factors, including the initial messages, the immediately preceding comments, and the majority of others' comments. When the perceived information is more positive (negative), subsequent comments are more likely to be positive (negative). Likewise, when the preceding comments express agreement (disagreement), the subsequent comments are more likely to agree (disagree) and less likely to disagree (agree). These findings are consistent with our hypothesis on how preceding comments influence subsequent commenting behavior. In other words, the first comments influence the overall comment characteristics that follow.

This research links social influence theory to the study of online discussions. Previous studies focus on individual motivations for participating in online discussions (e.g., Brodie et al., 2013; Smith, Fischer and Yongjian, 2012). However, individuals do not make comments in isolation. The results support our hypothesized process, indicating two separate forces of social influence, namely, the immediacy and the amount of information, reinforcing findings from online review studies. Confirming previous empirical evidence that subsequent raters and their ratings may be influenced by preceding reviews (e.g., Godes and Silva, 2012), we provide a theoretical explanation that individual comments are heavily affected by informational social influence. It is important to note that though the valence of initial messages does still have an impact on individual comments, this effect is reduced when other comments are present. These results highlight the importance of considering social influence from other comments in online discussions.

The influence of the immediacy and number of preceding comments on subsequent comments is demonstrated in our study, and is as suggested by social impact theory. Immediately preceding comments can influence the content of subsequent comments, because users anchor their comments on the most recent preceding comments, and imitate their emotions and opinions. For the reason that people are likely to be influenced by immediately preceding information, once the majority of opinions and emotions are formed following such sequential behavior, discussion is then likely to follow the more prominent opinions and emotions. However, it is worth noting that the effect of immediacy is reduced when the majority of others voice the same valence or opinions. This influence from the majority of others is effective for both emotions and opinions, and is found to be dominant among all information sources. These results suggest that, in the context of online discussions, the number of information sources, measured by the majority of others' comments in our study, has stronger impact on influencing behavior than the immediacy of information. In other words, once the direction of discussion is set by the first group of comments, it is difficult then to change it toward an opposite direction. Even if a new comment expressing different opinions and emotions is added, it may take several persistent followers to turn the tide.

It is important to note, however, that discussions that are in consensus with the emotions, whether positive or negative, and in agreement with the initial messages, are less likely to be popular. Variance in emotions and opinions is positively linked to popularity. The results suggest an impact from the commenting climate different from the literature. Studies on product reviews indicate that when past reviews are more positive, products are more likely to attract a high volume of subsequent reviews (Moe and Schweidel, 2012). In contrast to this, in the online community, when the majority of comments appears to be leaning toward one direction, whether positive, negative or in agreement, we find that few users make new comments. Drawing on attribution theory, we argue that this may be because a consensus has already been reached within the discussion thread. The informative value provided by the discussions is enough for the users to attribute the cause of such consensus to the initial ideas and to convince subsequent users with the convergent arguments. When all the prior comments share similar emotions and opinions, it may suggest that the original ideas trigger these emotions and opinions. This is opposed to the situation when the comments are diverse. The high variance in the comments indicates that the original ideas do not necessarily result in one specific emotion or opinion. The cause of the various opinions and emotions thus lies in prior commenters' personal views. Our findings confirm that controversial topics are more likely to trigger discussion (Chen and Berger, 2013). In particular, previous research on online user behavior suggests that those who are incongruent with the rest tend not to voice their opinions (Yun and Park, 2011), and those who are congruent with the rest believe there is no need to repeat the same thing. Conversely, high variance in emotions and opinions indicates a climate that welcomes diversity and that results in a higher volume of comments.

In this study, we observe that people are motivated to contribute (from the high variance) but are inclined to imitate others' opinions, which highlights the dual motivations that drive user participation. Research on consumer decision making suggests that the need for uniqueness and conformity co-exists in consumers' minds (Papyrina, 2012). While in the public environment people are more likely to conform, offline sequential choice studies find that in the consumption context, the need for uniqueness often drives people to choose products that are different from others (e.g., Ariely and Levav, 2000). We argue that the switch between these two motivational drives may also be triggered depending on how others' comments are formed. High variance in preceding comments may result from a high degree of "variety seeking," but could also lead to an even higher level of variety seeking. When the consensus in preceding comments is high, the opinion climate may indicate that it is not welcoming for variety seeking and the pursuit of being unique. As a result, users who feel they are suppressed may not comment, and when they do, they choose to conform.

The popularity of a discussion thread, then, is not influenced only by the content of the initial messages, but also by comments contributed during the discussions. The valence of the initial message has a direct impact on the emotions of the first comments, which then in turn influence the valence of the whole discussion thread. This is because these online discussions may be biased due to social influence. Later comments are prone to mimic earlier comments, both the majority of others' comments and the immediately preceding comments. Thus, the first comments seem to have a significant impact on the direction of the overall discussion. These results offer an alternative explanation for how popular topics can be created and how online buzz can be influenced. Different from the ongoing debate on whether opinion leaders (Iyengar, van den Bulte and Valente, 2011), light users (Godes and Mayzlin, 2009), or the critical mass (Watts and Dodds, 2007) are more likely to be influential, our study suggests that the first persons making comments appear to be most critical to shaping online discussions and their popularity.

4.6.1 Managerial Implications

Our study sheds light on how companies can create or identify potentially popular discussions. Since consumers are influenced by other users' comments in a thread, their comments may be biased. Relatedly, companies should interpret emotions and opinions in popular threads with caution because such emotions and opinions are not simply a function of the post itself, but also a function of other comments. The popularity of a topic or the volume of comments should also be evaluated carefully. In particular, an idea that gains a large number of agreeing comments is not necessarily plausible, as the reaction may stem from the overall mood rather than the idea. This is also true for ideas that receive overly disagreeing comments. As the number of comments observed could simply result from social influences, people might not be making comments based on their own independent thinking. Topics that have more comments may not be better or worse, but are more diverse and have not reached a consensus. Conversely, topics that receive fewer comments may have reached consensus and/or everyone is mimicking their predecessors. This presents a dilemma for companies in managing online discussions. To generate popularity, one would need to ensure and embrace diversity in discussions. It may be the case that controversial topics (Chen and Berger, 2013), or topics that trigger opposing emotions and opinions, generate a higher volume of discussion. In other words, companies may have to compromise between having popular vs. having favorable discussions. Topics that lead to positive emotions and opinions are more likely to be shared (Berger and Milkman, 2012) than commented on.

Further, since the first comments have such a strong impact in shaping overall discussions, it may be wise to secure a seeded word-of-mouth campaign when the intention is to spread positive opinion. However, in an online community setting, companies may be forced to rely on users to make the first move. Though users who participate more frequently seem to be more critical, they also appear to have a greater likelihood of being the first to make a comment. This emphasizes the importance for companies of keeping knowledgeable users as frequent users, to increase the likelihood of securing good-quality first comments. Interestingly, we find in our study that if company employees wrote the preceding comments, users are more likely to respond emotionally positive but express disagreement. This finding can serve as a starting point for companies to develop online discussion management strategies.

4.6.2 Limitations and Future Research

Despite the encouraging results of this study regarding how online community users make comments that result in popular discussion threads, further research is required in a number of directions. Our investigation is limited to one brand community with a very specific focus and structure. It may be useful to study such a sequential effect on other communities and forums. In particular, social-oriented communities and well-connected networks may yield an even stronger effect or higher social influence, since users are more tightly bound together. Moreover, as we do not investigate interactions between emotions and cognitive elements, future studies could examine under what condition emotions moderate the effect of opinions. Literature suggests the possibility that emotions embedded in information influence viewer judgment of that information (Kim and Gupta, 2012). It would be interesting to investigate whether the valence of comments affects perceptions of preceding opinions when making new comments.

Many aspects remain to be examined in the theoretical development of online discussions. In particular, it is noteworthy that the biggest influence on user comments found in our study is rooted in individual differences. The results suggest that users who tend to agree with others and/or express more positive emotions are more likely to continue doing so in their comments, regardless of social influence from others. Similarly, those who tend to conform may also be different users from those who tend to differ, thereby changing the direction of discussions. It is thus important to continue investigating the underlying individual-level psychological processes that shape commenting behavior. We show that social influence theories can explain the phenomenon to a certain extent. Research to understand how these mechanisms work at the personal level is still needed. Future research might also examine how personal motivation to participate in communities and discussions affects susceptibility to social influence.

In addition, the literature suggests that people who perceive themselves to be "experts" tend to be more negative (Schlosser, 2005). Our results indicate a similar pattern, in which people who are more active in the community show a tendency to disagree, and when they are the first to comment they tend to be less positive. However, it is important to note that active users are not necessarily real experts. People may perceive themselves as being influential when they are actually not (Iyengar, van den Bulte and Valente, 2011). It is essential to clarify this issue in future research before confirming what effect "expertise" has on how opinions are expressed (Moe and Schweidel, 2012). Our study highlights the necessity of taking the heterogeneity of individual characteristics into consideration when investigating online discussions. It may also be interesting to investigate whether those who have higher tendency to fulfill the need for uniqueness, i.e., those who express different ideas than those of preceding comments, are the same individuals who are often perceived as experts or opinion leaders. Although this study has limitations, we hope that it will serve as a basis for further research in understanding the way people herd when writing online comments to express their opinions.