Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior

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ABSTRACT: As a new communication paradigm, social media has promoted information dissemination in social networks. Previous research has identified several content-related features as well as user and network characteristics that may drive information diffusion. However, little research has focused on the relationship between emotions and information diffusion in a social media setting. In this paper, we examine whether sentiment occurring in social media content is associated with a user's information sharing behavior. We carry out our research in the context of political communication on Twitter. Based on two data sets of more than 165,000 tweets in total, we find that emotionally charged Twitter messages tend to be retweeted more often and more quickly compared to neutral ones. As a practical implication, companies should pay more attention to the analysis of sentiment related to their brands and products in social media communication as well as in designing advertising content that triggers emotions.

KEY WORDS AND PHRASES: information diffusion, sentiment, social media, Twitter.

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In recent years, social media has experienced tremendous growth in user base and is said to have an impact on the public discourse and communication in society. For example, more than 1 billion people worldwide were members of Facebook as of December 2012 [20]. At the same time, Twitter counted more than 200 million accounts [35]. This mainstream adoption of social media applications has changed the physics of information diffusion. Until a few years ago, the major barrier for someone who wanted a piece of information to spread through a community was the cost of the technical infrastructure required to reach a large number of people. Today, with widespread access to the Internet, this bottleneck has largely been removed. In this context, personal publishing modalities such as microblogging, social networking sites (SNS), and weblogs have become prevalent [39].

In particular, social media has facilitated information sharing in social networks. Recent research has identified several factors that drive information diffusion such as content-related features (e.g., topics [50], URL [uniform resource locator] and hashtag inclusion [66]) as well as user and network characteristics (e.g., social capital perception [57], popularity and homophily [48]). However, little research has drawn attention to emotions as another potential driver of information diffusion in a social media setting, in particular regarding the user's information sharing behavior. As part of human communication, social media content often conveys information about the author's emotional state, his or her judgment or evaluation of a certain person or topic, or the intended emotional communication (i.e., the emotional effect the sender wishes to have on the receiver) [10], which is generally termed as "sentiment."

Given this observation and the relevance of emotions in general shown by psychology research, we seek to fill the research gap identified above by examining the potential relationship between sentiment articulated in social media content and its diffusion through online social networks. More specifically, we hypothesize that sentiment of social media content might be positively associated with information diffusion. Our reasoning is based on previous findings from various disciplines that have confirmed the relevance of sentiment in online communication. It has been shown that affective information could be transferred through computer-mediated communication (CMC) [29]. Results from studies on SNS, weblogs, discussion forums, online news portals, or other contexts indicated that the affective dimensions of messages (both positive and negative sentiment) could trigger more cognitive involvement in terms of attention (e.g., [7, 40, 62]) as well as higher levels of arousal (e.g., [8]), which in turn have an influence on feedback and reciprocity (e.g., [19, 34, 63]), participation (e.g., [38]), and social sharing behavior (e.g., [9]).

We carry out our research in the context of political communication on Twitter. Given the controversial and polarizing nature of politics, political communication exhibits a high level of sentiment associated with political topics, political parties, or politicians, particularly in times of elections [18]. Moreover, the growing relevance of political communication in social media implies a fundamental change in traditional political communication, which has usually been exclusively initiated and managed by specific actors such as politicians and journalists [15]. This phenomenon is currently observed and studied by numerous disciplines such as sociology, political science, communication studies, linguistics, and also information systems (IS) [74].

We choose to study Twitter because of its popularity along with its unique feature of "retweeting" as a powerful mechanism of information sharing. As a result, Twitter is an ideal platform for users to spread information where the original tweet is propagated to a new set of audiences, namely, the "followers" of the retweeter. By retweeting, users may not only share information but also entertain a certain audience or publicly agree or disagree with someone [11]. Twitter is increasingly used in the political context. In particular, Twitter has become a legitimate and frequently used communication channel for political institutions (e.g., parties or politicians) and citizens [71]. Besides being increasingly used for political deliberation, Twitter is said to be capable of reflecting collective emotive trends and thus might have the predictive power with regard to political events [10]. Studies have also shown that sentiment of contemporaneous tweets correlates with voters' political opinions and preferences (e.g., [51, 71]).

In this study, we specifically examine whether the affective dimensions of Twitter messages (positive and negative sentiment) associated with political parties or politicians are related to retweet behavior in terms of (1) quantity of triggered retweets and (2) speed of retweeting defined by the time lag between the original tweet and the first retweet. Moreover, we aim to give some insight into how Twitter is used for political discussions with a focus on the most influential users who have the power to influence (online) opinion-making and agenda-setting processes.

This study makes several important contributions to research and practice. First, we shed light on the role of sentiment in information diffusion in a social media setting. We show that sentiment (positive or negative) in social media–based content is correlated with information sharing not only in terms of quantity but also speed. In addition, our findings provide several practical implications for politics and business. In particular, as sentiment might have viral effects in social media communication, companies should pay more attention to the analysis of sentiment related to their brands and products in social media communication as well as in designing social media–based advertising content that triggers emotions because such content is more likely to be shared.

The remainder of this paper is organized as follows. The next section provides a literature review on microblogging with an emphasis on Twitter, particularly regarding usage and information diffusion. In the subsequent section, we lay out the theoretical background of our research, which leads to the development of our hypotheses. We then present our methodology and the results of our study. We conclude with a discussion of our results, research, and practical implications, as well as limitations and potential future work.

Microblogging and Twitter

Microblogging is a form of blogging in which entries typically consist of short content such as phrases, quick comments, images, or links to videos. Notable services include Twitter, Tumblr, Cif2.net, Plurk, Jaiku, and identi.ca. However, other leading SNS such as Facebook, Myspace, Google+, and LinkedIn also have their own microblogging feature, better known as "status updates." As microblogging services have recently gained wide popularity, users have adopted them for sharing news, promoting political views, marketing, and tracking real-time events [11, 37].

Among various microblogging services, Twitter is a very popular platform. Twitter allows users to send and read 140-character short messages known as "tweets," enabling users to share and discover topics of interest with a network of "followers" in real time. "Following" another Twitter user is a kind of subscribing to that user's tweets. The act of following is not automatically reciprocal. A user can follow any number of other users although the user being followed does not necessarily have to follow back. Modes of communication on Twitter (e.g., answering or drawing attention to external content) are signified by user-accepted norms, such as annotating their tweets with different characters. To start conversations, the @ sign is used to mark the addressee of a message. For example, posting a message including @username indicates that the message is intended for or somehow relevant to a specific user. Retweets refer to the practice of resending a tweet posted by another user and is one particular case of mentioning. When users find an interesting tweet written by another Twitter user and want to share it with their followers, they can retweet the tweet by copying the message, typically adding a text indicator (e.g., "RT," "via," or "by") followed by the user name of the original author in @username format. When retweeting, users often add more content or slightly modify the original tweet. Tweets can also include so-called hashtags, where the # character is used in conjunction with a word or phrase in order to connect the tweet to a particular theme. This use of the # sign allows users to search the "Twittersphere" for specific topics of interest and to follow certain threads of discussion.

Twitter Use

Recent studies have shed light on the user of Twitter in various contexts. Kwak et al. [42] conducted a large-scale study to analyze the topological characteristics of Twitter and reveal its power as a new medium of information sharing. From Twitter's public timeline, Java et al. [37] examined the topological and geographical properties of Twitter's social network. They identified a number of usage categories such as daily chatter, conversations, sharing information/URLs, and reporting news. Honeycutt and Herring [33] employed a grounded theory approach on their sample and found 12 distinct categories of tweets: about the addressee, announce/advertise, exhort, information for others, information for self, metacommentary, media use, opinion, other's experience, self-experience, solicit information, and others. As studies indicate, people use Twitter mostly to inform others and to express themselves. For example, Naaman et al. [49] examined the content of 3,379 tweets by manually coding the messages collected from the public timeline and found that 80 percent of the 350 users in their study posted messages relating to themselves or their thoughts, as opposed to sharing general news. By addressing the retweet practice, Boyd et al. [11] found different conversational aspects of retweeting on Twitter such as how authorship, attribution, and communicative fidelity are negotiated in diverse ways. Moreover, retweeting may be performed to entertain a specific audience, to comment on someone's tweet, to publicly agree with someone, or to save tweets for future personal access.

Recently, social media have played an important role in shaping political debates in the United States and around the world (e.g., [21, 71, 74]). Researchers have studied political microblogging use (mostly Twitter), with studies focusing on either nonparliamentary or parliamentary uses of the service. As for parliamentary uses, previous literature has dealt mostly with the United States. For example, studies found that members of the U.S. Congress use Twitter as a vehicle for self-promotion and information sharing, particularly as a part of their political campaigns [27]. Other work has focused on the use of Twitter by citizens in the political context around the world such as Iran [23], Germany [71], Sweden [45], and the United States [18, 74]. The main findings of these studies show that Twitter is extensively used for the dissemination of politically relevant information, particularly as a new outlet for speakers already affiliated with prominent positions in mainstream media or political debate in general. Furthermore, it has been shown that Twitter users are more likely to interact with others who share similar views in terms of retweeting, but they are also actively engaged with those with whom they disagree in terms of mentioning [18]. In addition, replies among like-minded individuals would strengthen group identity, whereas replies among different-minded individuals would reinforce in-group and out-group affiliation [77].

Retweeting and Information Diffusion on Twitter

The study of information diffusion in social networks has a long history in the social, physical, and computational sciences. In addition, the business and marketing literature has addressed information diffusion in terms of online word of mouth and viral marketing (e.g., [25, 46]). Information diffusion research has increasingly turned attention to different social media platforms such as SNS (e.g., [67]), weblogs (e.g., [16, 26, 73]), picture-sharing portals (e.g., [14]), as well as online communities (e.g., [17, 24]). In particular, a large number of studies have focused on Twitter (e.g., [13, 32, 42, 76]) as it provides an explicit way to mark the diffusion of information in the form of retweets. This indication of retweets reveals which links in the social network have actually played a role in the diffusion of information. Previous studies have shown quantity as well as speed of retweeting to be good indicators for message virality (e.g., [32, 76]) as well as user's influence (e.g., [13, 42]).

Another strand of literature has revealed factors behind the observed diffusion of information by retweeting practice. Nagarajan et al. [50] analyzed over 1 million tweets referring to three real-world events and the properties of the retweet behavior surrounding the most tweeted content pieces. They found that the tweets categorized as "call for action," "crowdsourcing," or "collective group identity making" generated sparse retweet graphs while tweets sharing information (e.g., containing URLs) generated a denser retweet network. In a large-scale study of 74 million tweets, Suh et al. [66] built a predictive retweet model and identified several factors affecting the quantity of retweets a Twitter message receives, including URL posting and hashtag inclusion as well as the number of followers and the age of users' accounts. Macskassy and Michelson [48] presented different retweet models evaluated on a Twitter data set consisting of over 768,000 tweets gathered from monitoring over 30,000 users for a period of one month. They found that context-specific retweet models regarding homophily or similarity are better at explaining the observed retweet behavior than generic or network-based models. Finally, based on a qualitative analysis of questionnaires and four quantitative case studies of retweets, Recuero et al. [57] showed that social capital may influence retweeting practice and how Twitter users perceive values as well as create benefits for the social network and themselves from three points of view: referrals, information access, and timing.

However, to our knowledge, there are no studies that have directly investigated a potential link between sentiment and information sharing on Twitter. Furthermore, previous research has focused only on retweet quantity as an aspect of information diffusion. However, the speed at which information disseminates through networks represents another important aspect of information diffusion [76]. Therefore, we seek to examine whether sentiment of Twitter messages has an influence on retweet behavior in terms of retweet quantity as well as retweet speed as a key feature for promoting information diffusion in (online) social networks.

Theoretical Foundation and Hypotheses Development

To set the context of our research, we draw on theories and empirical findings from prior research on emotions, particularly in the domain of social psychology and CMC. More specifically, we link the theoretical foundation of our study to the literature regarding cognitive and arousal-related effects caused by emotions, in particular by emotional stimuli in written communication. These effects, in turn, have an influence on behavioral responses in terms of sharing the emotional content. Since it has been shown that affective information could be effectively transferred through CMC (e.g., [29, 59, 72]), we argue that the cognitive and arousal effects caused by emotions and their consequences regarding sharing behavior may also apply in the CMC context and thus in social media communication such as on Twitter.

Influence of Emotions on Information Sharing

Scholars have demonstrated that general emotional appeals are effective persuasive devices. As Forgas noted, emotions "appear to influence what we notice, what we learn, what we remember, and ultimately the kinds of judgments and decisions we make" [22, p. 273]. In the context of written communication, previous research has indicated that emotional stimuli in terms of emotion words or emotional framing of messages may elicit extensive cognitive processes such as attention (e.g., [7, 40, 62]). An increased level of cognitive involvement may in turn lead to a higher likelihood of behavioral response to emotional stimuli in terms information sharing (e.g., [31, 47, 56, 58]). Furthermore, attentional processes are also shown to have an impact on emotional contagion, which is the spread of mood and affect through populations by simple exposure [30]. Research on emotional contagion has shown that emotions might spread through different kinds of social networks in various contexts, such as between people in frequent close contact such as families (e.g., [44]), during workplace interactions (e.g., [5]), or in leadership situations (e.g., [68]). Emotional contagion may in turn have an influence on individual and group-level communication behavior in terms of information coordination and sharing [5, 68].

Besides a high level of cognitive involvement, certain kinds of emotion such as anger, anxiety, awe, or amusement might also trigger a high level of physiological arousal, which is a state of mobilization, whereby low arousal or deactivation is characterized by relaxation and high arousal or activation is characterized by activity [8]. Physiological arousal has been shown to be a driver of information sharing [8, 9]. On the one hand, content that evokes high-arousal, or activating, positive (awe) or negative (anger or anxiety), emotions is more viral. On the other hand, content that evokes low-arousal, or deactivating, emotions (e.g., sadness) is less viral.

Sometimes, the spread of information may be in the form of a rumor, which is a collective transaction in which many people offer, evaluate, interpret information, and from which they predict something [52]. Rumors are driven by two important factors: importance and informational ambiguity [2]. However, the first factor, "importance," is strongly related to the emotional category "anxiety" in the way that the greater the anxiety is, the more the content of rumor is important for the rumor recipient [3, 61]. Therefore, rumor research has agreed on anxiety as a key variable of rumoring in addition to informational ambiguity. In this anxiety-based formulation, the rumor is conceptualized as a verbal outlet to release emotional pressure (anxiety or concern) by rationalizing ambiguous information [52]. Anthony [3] showed that rumors travel faster in high-anxiety groups than in low-anxiety ones. The rumor literature has also argued that rumors may spread particularly in times of conflict, crisis, and catastrophe (e.g., [52]), which are mostly characterized by negative emotions. Therefore, it can be assumed that, also in the form of rumors, information dissemination may be driven by emotions.

In sum, it can be argued that cognitive processes in terms of attention as well as arousal-related effects caused by emotions in written communication are determinants of sharing behavior as well as emotional contagion, which in turn might also influence sharing behavior.

Emotions in Computer-Mediated Communication

Previous research has indicated the effectiveness of CMC in transferring emotion-related information [29]. The CMC of emotions has been shown to have a significant effect on how the receiver processes and interprets the message [59, 72]. More specifically, Harris and Paradice [29] showed that in CMC, message receivers are able to detect the sender's emotion through verbal cues such as emotion words and linguistic markers (e.g., lexical or syntactical encoding of emotions) as well as nonverbal paralinguistic cues (e.g., emoticons). In fact, a number of recent works have revealed the impact of emotions in CMC as well as online communication. For example, Huffaker [34] showed that, in discussion forums, people who use affective language in their messages receive more feedback than those who do not. This applies to both positive and negative emotions. In a study of newsgroup participation, Joyce and Kraut [38] found that positive affect in messages reinforces a sense of community and encourages continued participation, whereas negative affect can result in feedback through hostile and insulting interactions. Other studies have found that articulated sentiment (positive or negative) in postings from different social media platforms such as SNS, weblogs, and discussion forums might diffuse in the corresponding subsequent comments or replies [19, 34, 63]. Regarding information sharing, in a study of a data set of all online *New York Times* articles published over a three-month period, Berger and Milkman [9] showed that the likelihood of articles to be shared (by e-mail) is positively related not only to the emotions expressed therein but also to the physiological arousal caused by different kinds of emotions. While content that evokes high-arousal emotions (e.g., awe, amusement, anger, anxiety) is more viral, content that evokes low-arousal emotions (e.g., sadness) is less viral.

Based on these findings, it can be assumed that the cognitive and arousal-related effects caused by emotions and their consequences regarding sharing behavior described above may also apply in the CMC context. More specifically, we argue that the expression of emotions in social media–based textual content may also lead to more attention and arousal, which in turn may positively affect information sharing behavior. This leads us to conjecture a positive relationship between sentiment articulated in tweets and their likelihood to spread through the Twitter network.

Moreover, given that exposure to information as well as information sharing nowadays are strongly facilitated by the tremendous growth of online social networks, in particular Twitter with its retweeting feature, we reason that an increased level of attention and arousal triggered by emotions might go along with sharing behavior not only with respect to quantity but also to speed (i.e., how quickly emotional content might spread through social networks), which represents another important aspect of information diffusion [76]. Until now, little research has been devoted to speed of information diffusion, particularly in the social media context. Therefore, we derive the following hypotheses:

> *Hypothesis 1: The larger the total amount of sentiment (positive or negative) a political Twitter message exhibits, the more often it is retweeted.*

> *Hypothesis 2: The larger the total amount of sentiment (positive or negative) a political Twitter message exhibits, the shorter is the time lag to the first retweet.*

Negativity Bias

Prior research in psychology and organizational studies has shown that people respond differentially to positive and negative stimuli, and negative events tend to elicit stronger and quicker emotional, behavioral, and cognitive responses than neutral or positive events (for a review, see [6, 60]). More specifically, it has been revealed that there is a general bias, based on both innate predispositions and experience, to give greater weight to negative entities (e.g., events, objects, personal traits) [60]. This phenomenon is referred to as "negativity bias" and holds across a wide range of domains [6]. In particular, negative entities are stronger than the equivalent positive entities ("negative potency") and the negativity of negative events grows more rapidly with approach to them in space or time than does the positivity of positive events ("steeper negative gradients") [60].

Recent studies of communication in the social media context such as Facebook also show that negative sentiment postings induce more feedback in terms of comments compared to those with positive sentiment (e.g., [63]). Moreover, it is more likely that negative sentiment words diffuse in subsequent comments. Drawing on these insights, we argue that the negative sentiment articulated in tweets might have a stronger effect on retweet quantity as well as the mean time to retweet. This leads us to formulate the following hypothesis:

> *Hypothesis 3: The associations between sentiment and (a) retweet quantity as well as (b) retweet time lag are stronger for tweets with negative sentiment than for those with positive sentiment.*

Data and Methodology

Data

For our empirical analyses, we employed two different data sets of politically relevant tweets that were published on Twitter's public message board. The first data set covers a period of one week spanning from March 21 to March 27, 2011, prior to the two Landtag (state parliament) elections in the German states Baden-Württemberg and Rheinland-Pfalz. Both elections took place on March 27, 2011. The second (larger) data set contains tweets collected around the state parliament election in Berlin, Germany, on September 18, 2011, covering a period of four weeks from August 29 to September 25, 2011. As there are usually also postelection Twitter activities such as discussions about election results, data collection continued seven days after the election (September 18 to September 25, 2011). In general, we chose to collect data during elections since they are characterized by a higher level of user participation in the political communication and discourse on Twitter.

We developed a Java-based software tool that uses the "Search API" provided by Twitter to gather data (see [65]). We collected all tweets that contained the names of either the six most important German parties (Christian Democratic Union [CDU], Social Democratic Party of Germany [SPD], Free Democratic Party [FDP], Alliance '90/The Greens [Green Party], The Left [Left Party], and Pirate Party of Germany [Pirate Party]) or those of the front-runners of these parties in the three elections as key words. In total, we obtained two samples of 100,000 (Baden-Württemberg and Rheinland-Pfalz) and 150,000 (Berlin) tweets. We then consolidated our data set by ruling out redundant tweets (i.e., tweets with identical Twitter IDs) as well as irrelevant tweets such as advertising tweets based on typical (German) key words that indicate advertising. We also excluded tweets in languages other than German by applying different language detection tools. As a result, from the two data sets, we obtained two samples of 64,431 (Baden-Württemberg and Rheinland-Pfalz) and 104,317 (Berlin) tweets, for our analyses. Since the second date set is larger and contains data in a later time period, its analysis can be considered a robustness check for the results from the analysis of the first data set.

Sentiment Analysis

Sentiment analysis represents a systematic computer-based analysis of written text or speech excerpts for extracting the attitude of the author or speaker about specific identities or topics. It provides a fine-grained examination that aims to establish the overall orientation (positive or negative) and intensity (weak or strong) of the sentiments expressed by statements [55].

Recent sentiment analysis algorithms are able to detect positive and negative sentiment strength in short informal texts with a reasonable degree of success [1, 54]. In our analyses, we use the tool "SentiStrength" [69, 70] to analyze the level of sentiments in politically relevant tweets. It has been proven useful to classify emotions in short informal messages from Myspace and Twitter [69]. SentiStrength uses a human-designed lexicon of emotional terms with a set of additional linguistic rules for negations (e.g., "not happy"), booster words (e.g., "very nice"), amplifications (e.g., "haaaaaaaappy"), emoticons, spelling corrections, and other factors such as word weighting. SentiStrength classifies texts for positive sentiment on a scale of 1 (neutral) to 5 (strongly positive) and for a negative sentiment on a scale of –1 (neutral) to –5 (strongly negative). Each classified text is given *both* a positive and negative score. The algorithm of SentiStrength has been shown to provide a higher accuracy rate than standard machine learning approaches for positive sentiment strength and a similar accuracy rate for negative sentiment strength [70]. Because our sample consists of only German-language postings, we processed our data by using the German version of SentiStrength, including the German dictionary and set of linguistic rules.

We first determined the sentiment polarity (i.e., emotional valence) of each tweet by adapting the following measure, which determines the direction of the sentiment as well as its strength:

$$polarity = positive + negative,$$

where *positive* denotes the SentiStrength positive sentiment score (1 to 5) and *negative* denotes the negative sentiment score (–1 to –5). As a result, the measure is defined within the range $[-4, 4]$.

We are also interested in the total amount of sentiments of tweets regardless of their polarity (i.e., positive or negative). This becomes particularly important in case a tweet contains both positive and negative sentiment words (i.e., mixed sentiment tweets). In such cases, the measure *polarity* fails to capture the degree of emotionality of the tweet because the positive and negative sentiment scores would cancel out each other (*polarity* = 0, although the tweet is actually heavily emotional and not neutral as the measure might indicate). Therefore, we introduced another measure accounting for the total amount of sentiments in a tweet:

$$sentiment = (positive - negative) - 2,$$

where *positive* denotes the SentiStrength positive sentiment score (1 to 5) and *negative* denotes the negative sentiment score (–1 to –5) as before. Note that we subtracted 2 from (*positive – negative*) to normalize the definition range from [2, 10] to [0, 8] to avoid confusion when—in the case of [2, 10]—a positive number (i.e., 2) would indicate no sentiment.

To get a feel for tweets featuring sentiments associated with political topics, political parties, or politicians, we provide the following illustrative examples, which were translated from German into English. Words that account for the classification of positive or negative sentiment are highlighted and additionally indicated by the succeeding signs "+" and "–":

- positive sentiment
  - ***Happy*** **[+]** *5th birthday, Pirate Party! Stay on target and full speed ahead!*
    - positive sentiment score: 2; negative sentiment score: –1
    - *polarity*: 1 = 2 + (–1); *sentiment*: 1 = 2 – (–1) – 2
  - *The election today is a* **victory** **[+]** *for freedom!* ***Nice!*** **[+]** ***Hurraaaaaaaa!*** **[+]** ***;-)*** **[+]**
    - positive sentiment score: 5; negative sentiment score: –1
    - *polarity*: 4 = 5 + (–1); *sentiment*: 4 = 5 – (–1) – 2
- negative sentiment
  - *I am somehow* ***disappointed*** **[–]** *that this party does not have the guts to meet challenges and answer tough questions.*
    - positive sentiment score: 1; negative sentiment score: –2
    - *polarity*: –1 = 1 + (–2); *sentiment*: 1 = 1 – (–2) – 2
  - *You guys just* **screwed** **[–]** *it up!*
    - positive sentiment: 1; negative sentiment score: –3
    - polarity: –2 = 3 + (–1); sentiment: 2 = 1 – (–3) – 2

Regression Analysis

Variables

To test H1 and H2, which postulate a positive relationship between sentiment of tweets and retweet behavior in terms of retweet quantity and time lag, we constructed the following variables for each tweet:

- number of times the tweet has been retweeted: *rt_no*;
- time lag between the tweet and the first retweet: *rt_timelag* (in minutes); and
- total amount of sentiments: *sentiment*.

Studies have shown that there are a number of other factors that also have an impact on retweet behavior on Twitter such as the quantity of hashtags, the inclusion of URLs, posting activity, as well as a user's number of followers (e.g., [66]). In particular, a user's number of followers in part represents the degree of homophily [4], which means that it is likely that the followers of the user will have similar interests and so, in terms of Twitter, are more likely to retweet contents of that user. Therefore, we also included the following variables as controls:

- number of hashtags a tweet contains: *hashtag*;
- dummy (binary) variable for whether or not a URL was included in the tweet: *url*;
- user's number of followers: *follower*; and
- number of tweets the user has posted during the sample period: *activity*.

Note that since not every tweet has been retweeted, our samples—when it comes to testing H2—were reduced to 6,159 (Baden-Württemberg and Rheinland-Pfalz) and 8,221 (Berlin) tweets, each of which has triggered at least one retweet.

In H3, we expect negative sentiment to be more strongly associated with both the retweet quantity and retweet time lag compared to positive sentiment. To test for the aforementioned negativity bias, we included a multiplicative interaction term between the total amount of sentiments and their direction (positive versus negative). For the latter, we introduced a dummy variable for whether the sentiment direction of a tweet is negative (i.e., *polarity* < 0): *negative.* The interaction term is defined as *sentiment* × *negative*.

Estimation Methods

We applied regression techniques to test H1, that is, to examine whether the total amount of sentiments of a tweet is associated with how often it is retweeted. Because the dependent variable *rt_no* represents true-event count data (i.e., nonnegative and integer based) and its standard deviation (and hence, the variance) is larger than its mean in both samples, the analysis needs to be adjusted for overdispersion. Therefore, we applied the negative binomial regression model assuming that the dependent variable follows the negative binomial distribution [12]. Negative binomial regression relies on a log-transformation of the conditional expectation of the dependent variable and requires an exponential transformation of the estimated coefficients for assessing and interpreting the effect sizes. The resulting regression model is as follows:

$$\begin{aligned}\log(\mathrm{E}(rt\_no|*)) = \beta_0 + \beta_1 sentiment + \beta_2 hashtag + \beta_3 url \\ + \beta_4 \log(follower) + \beta_5 \log(activity),\end{aligned} \tag{1}$$

where E(*rt_no*|*) is the expectation of *rt_no* conditional on the set of the explanatory variables on the right-hand side of the equation.

To test H3a, we included the negative sentiment dummy variable (*negative*) and the interaction term (*sentiment* × *negative*):

$$\begin{aligned}\log(\mathrm{E}(rt\_no|*)) = \beta_0 + \beta_1 sentiment + \beta_2 negative + \beta_3 (sentiment \times negative) \\ + \beta_4 hashtag + \beta_5 url + \beta_6 \log(follower) + \beta_7 \log(activity).\end{aligned} \tag{2}$$

In H2, we hypothesize that emotionally charged tweets would induce retweets more quickly. Since the dependent variable *rt_timelag* represents a continuous time unit, we applied regression analysis using ordinary least squares (OLS) estimation to test

H2. To account for nonnormality, we log-transformed the dependent variables before employing OLS regression. Results of the Shapiro–Wilk test for normality applied on the log-transformed variables suggest that the null hypothesis of normal distribution cannot be rejected. The regression model is as follows:

$$\log(rt\_timelag) = \beta_0 + \beta_1 sentiment + \beta_2 hashtag + \beta_3 url + \beta_4 \log(follower) + \beta_5 \log(activity) + \varepsilon. \tag{3}$$

To test H3b, we again included the negative sentiment dummy variable (*negative*) and the interaction term (*sentiment* × *negative*):

$$\log(rt\_timelag) = \beta_0 + \beta_1 sentiment + \beta_2 negative + \beta_3 (sentiment \times negative) + \beta_4 hashtag + \beta_5 url + \beta_6 \log(follower) + \beta_7 \log(activity) + \varepsilon. \tag{4}$$

Empirical Results

Table 1 shows the distribution of different formats of communication on Twitter for our two samples. The distributions are similar. As the table shows, 11.5 percent to 16.7 percent of all tweets contain an @ sign, which is in line with previous research that has also suggested that the majority of @ signs are used to direct a tweet to a specific addressee [33].[1] A more conservative measure of direct communication is direct messaging from one user to another by posting tweets that start with an @ sign. As shown in Table 1, 6.2 percent to 8 percent of the messages in our sample are direct messages, indicating that people not only use Twitter to post their opinions but also engage in interactive discussions. The share of retweets is roughly one-third of all tweets for both samples. In addition, more than half the tweets contain a link to a Web site (52.5 percent and 63.9 percent, respectively). These numbers indicate that people tend to share political information (e.g., political news) with their network of followers.

The categorization of users according to their Twitter activity is illustrated in Table 2. The table shows that, in both samples, a few highly active users (i.e., lead users) account for about one-third of all tweets. Slightly more than 1 percent of all users contribute to about 30 percent of all posted tweets. This is consistent with findings of Jansen and Koop [36] and Tumasjan et al. [71] who also found a large inequality of participation in political communication on Twitter.

Analysis of Influential Users

To gain a deeper insight into the political communication on Twitter, particularly regarding political opinion making during the time period around elections, we focus on the top 50 most influential users in each sample. Influential users or opinion leaders are individuals who have the power to influence (online) opinion-making and agenda-setting processes. As studies have suggested the quantity of retweets users receive on their original tweets to be a reasonable measure of influence or opinion leadership,[2] we consider the top 50 most retweeted users. We explore users' back-

Table 1. Formats of Communication

Format	Baden-Württemberg and Rheinland-Pfalz Number of tweets (percent)	Berlin Number of tweets (percent)
Mention (tweet that contains @ sign(s) but is not a retweet)	7,175 (16.7)	12,044 (11.5)
Direct message (tweet that starts with an @ sign)	5,148 (8)	6,469 (6.2)
Retweet	21,350 (33.1)	36,040 (34.5)
URL	33,850 (52.5)	66,634 (63.9)
Singleton*	14,537 (22.6)	15,050 (14.4)
Total	64,431	104,317

Note: The numbers might not add up to 100 percent as a tweet can be of different formats at the same time (e.g., a retweet can also contain a URL). * Singleton is a tweet without an @ sign (see [42]).

ground information and find that, interestingly, most users do have a clear political affiliation. Many of them are members of political parties. For both samples, we are able to easily identify four distinct political groups: left-, right-leaning users, green activists, and members of the Pirate Party (most of them are also Internet activists). For users whose background information is not obvious, we also employ qualitative content analysis [41] of their tweets to determine their political alignment.[3] Interestingly, both top 50 subsamples are overwhelmingly dominated by left-leaning users as well as green and Internet activists (in total, 76 percent and 68 percent, respectively), where the latter groups can also be located on the left end of the political spectrum (see Table 3). This corroborates the general impression that political discussion in social media in Germany tends to be left-leaning and more dominated by those who are critical of the government. Finally, the remaining group of politically unidentified accounts mostly consists of news posters or neutral bloggers.

As a next step, we consider expression of sentiment in tweets for the most influential users as well as the total samples. The results presented in Table 4 show that the top 50 most retweeted users tend to post more emotionally charged tweets compared to the total samples (29.2 percent versus 22.8 percent and 28 percent versus 23.9 percent of all tweets, respectively). Interestingly, for both top 50 subsamples, we find that the number of positive sentiment tweets ($polarity > 0$) is roughly twice that of the negative sentiment tweets ($polarity < 0$) (18 percent versus 10.1 percent for Baden-Württemberg and Rheinland-Pfalz and 19.2 percent versus 8.1 percent for Berlin). This also holds for the total samples (15.8 percent versus 6.3 percent for Baden-Württemberg and Rheinland-Pfalz and 16.1 percent versus 7.4 percent for Berlin).

Table 2. User Activity

User group (number of tweets during sample period)	Baden-Württemberg and Rheinland-Pfalz		Berlin	
	Number of users (percent)	Number of tweets (percent)	Number of users (percent)	Number of tweets (percent)
Infrequent (1)	8,155 (55.7)	8,155 (12.7)	10,497 (52.8)	10,497 (10.1)
Light (2–5)	4,443 (30.4)	12,512 (19.4)	6,118 (30.8)	17,361 (16.6)
Moderate (6–20)	1,554 (10.6)	15,363 (23.8)	2,312 (11.6)	23,602 (22.6)
Active (21–50)	340 (2.3)	10,143 (15.7)	587 (3)	18,203 (17.4)
Power (50+)	149 (1)	18,258 (28.3)	343 (1.7)	38,410 (36.8)
Total	14,641 (100)	64,431 (100)	19,876 (100)	104,317 (100)

Table 3. Political Alignment of Top 50 Most Retweeted Users

Political Alignment	Baden-Württemberg and Rheinland-Pfalz	Berlin
	Number of users (percent)	Number of users (percent)
Left leaning	13 (26)	9 (18)
Right leaning	2 (4)	2 (4)
Green/activist	16 (32)	2 (4)
Pirate/Internet activist	9 (18)	23 (46)
Others	10 (20)	14 (28)
Total	50 (100)	50 (100)

We are also interested in knowing more about the content of emotionally charged Twitter messages posted by the most influential users by taking a closer look at the reference to political parties or front-runners in messages. Such reference is mostly performed by annotating tweets with hashtags corresponding to political parties or frontrunners. More specifically, for each of the four identified political groups (i.e., left leaning, right leaning, green, and Pirate), we calculate the percentage of tweets

Table 4. Distribution of Emotionally Charged Twitter Messages

	Baden-Württemberg and Rheinland-Pfalz		Berlin	
	Top 50 retweeted users	Total sample	Top 50 retweeted users	Total sample
Emotionally charged tweets (sentiment > 0)	977 (29.2)	9,815 (22.8)	775 (28)	16,443 (23.9)
Positive sentiment tweets (polarity > 0)	604 (18)	6,796 (15.8)	533 (19.2)	10,964 (16.1)
Negative sentiment tweets (polarity < 0)	337 (10.1)	2,732 (6.3)	224 (8.1)	5,020 (7.4)
Mixed sentiment tweets (polarity = 0)	36 (1)	287 (0.7)	18 (0.6)	459 (0.7)
Total	3,351 (100)	43,081 (100)	2,780 (100)	68,277 (100)

Note: Only tweets (and no retweets) are considered in these figures.

(among positive and negative sentiment tweets) that contain hashtag reference to at least one of the political parties or one of the front-runners belonging to the same political group. We do the same for tweets that contain hashtag reference to at least one of the political parties or one of the front-runners related to other political groups. The results reveal that most positive sentiment tweets are annotated with hashtags of parties or front-runners belonging to the same political group while most negative sentiment tweets are associated with parties or front-runners from other groups (see Tables 5 and 6). This indicates that users tend to talk positively about their own political peers and badmouth ideologically opposed or different political groups. Some illustrative examples are given in the following:

- positive sentiment:
  - nati0n [pirate party]: *Oh yes* **[+]** ***:)*** **[+]**, *the* ***best*** **[+]** *thing with the* ***#pirates*** *is anyone can participate, with or without member ID. That's democracy!*
- negative sentiment:
  - KRABAT44 [green activist]: *When it is about* ***corruption*** **[–]**, ***illegal*** **[–]** *funding, preference of the rich, and so on, the* ***#CDU*** **[right leaning]** *is always there #s21.*

However, we also observe that, when compared to negative sentiment tweets, a much higher fraction of positive sentiment tweets also contain hashtag reference to parties or front-runners from other groups. To search for explanation, we manually analyze such tweets and find that the majority of those tweets contain not only hashtags referring to parties or front-runners from the same political group but also ideologically different parties or front-runners. This interesting result is similar to findings by Conover et al. [18], who showed that users frequently produce tweets containing hashtags that

Table 5. Hashtag References in Emotionally Charged Tweets by Top 50 Retweeted Users (Baden-Württemberg and Rheinland-Pfalz)

		Number of tweets (percent) among	
User's political alignment	Hashtag reference to	Positive sentiment tweets	Negative sentiment tweets
Left leaning	Left leaning (SPD, Left Party)	108 (68)	11 (12)
	Others (CDU, FDP, Green Party, Pirate Party)	64 (40)	76 (85)
Right leaning	Right leaning (CDU, FDP)	20 (81)	2 (5)
	Others (SPD, Left Party, Green Party, Pirate Party)	5 (20)	22 (56)
Green/activist	Green/Activist (Green Party)	149 (77)	8 (7)
	Others (CDU, FDP, SPD, Left Party, Pirate Party)	74 (38)	105 (92)
Pirate/Internet activist	Pirate/Internet activist (Pirate Party)	78 (72)	5 (8)
	Others (CDU, FDP, SPD, Left Party, Green Party)	28 (26)	45 (75)

Notes: Hashtag reference was made to at least one political party or one front-runner of the party denoted in parentheses. The percentages do not necessarily add up to 100 percent because of the possibility of multiple party hashtags in a single tweet.

target multiple politically opposed audiences, which they refer to as "content injection." The explanation behind this practice is that a user might seek to expose other users with different political alignment to information that reinforces his or her own political views. In our case, this would mean that, when users talk positively about their own political peer, they are more inclined to include hashtags of other parties or front-runners to expose ideologically different users to these (positive) messages. This might result from the fact that if those ideologically different users are not exposed to positive content by means of hashtag inclusion, they might never see such content as they are less likely to be followers of the user who wants to spread the positive sentiment tweet associated with his or her own political peer. To get a feel for this practice, we again provide some illustrative examples:

- _hdb [left leaning]: *The #Left: Things go* ***well*** **[+]***!* ***Positive*** **[+]** *tendency for the Left!* ***#cdu*** **[right leaning]** *#s21 http://bit.ly/h5xAEb*
- CDU_BW [right leaning]: *Schäuble: "****Good*** **[+]** *politics also means that you are FOR something and not always AGAINST!"* ***#greens*** **[green activists]** ***#spd*** **[left leaning]** *#ltwbw*.

Table 6. Hashtag References in Emotionally Charged Tweets by Top-50 Retweeted Users (Berlin)

		Number of tweets (percent) among	
User's political alignment	Hashtag reference to	Positive sentiment tweets	Negative sentiment tweets
Left leaning	Left leaning (SPD, Left Party)	62 (65)	4 (9)
	Others (CDU, FDP, Green Party, Pirate Party)	34 (36)	36 (81)
Right leaning	Right leaning (CDU, FDP)	15 (75)	1 (6)
	Others (SPD, Left Party, Green Party, Pirate Party)	3 (15)	12 (72)
Green/activist	Green/activist (Green Party)	15 (75)	1 (6)
	Others (CDU, FDP, SPD, Left Party, Pirate Party)	6 (30)	10 (60)
Pirate/Internet activist	Pirate/Internet activist (Pirate Party)	181 (74)	10 (10)
	Others (CDU, FDP, SPD, Left Party, Green Party)	44 (18)	69 (69)

Notes: Hashtag reference was made to at least one political party or one front-runner of the party denoted in parentheses. The percentages do not necessarily add up to 100 percent because of the possibility of multiple party hashtags in a single tweet.

Sentiment and Retweet Behavior

Descriptive statistics of variables relevant for regression analysis are presented for both total samples in Table 7. On average, a tweet is retweeted about 0.41 to 0.43 times. For the Baden-Württemberg and Rheinland-Pfalz sample, a tweet is retweeted for the first time slightly more than an hour after the posting (72 minutes) on average. For the Berlin sample, it is almost two hours (114 minutes). The average total amount of sentiments per tweet for both samples are similar at 0.31 and 0.34, respectively. A tweet contains slightly more than one hashtag on average (1.28 and 1.07, respectively). In our samples, a user has an average number of followers of 630 and 878, respectively.

Retweet Quantity

Tables 8 and 9 show the correlation matrix of the main independent variables for each sample. The results of multicollinearity tests suggest that multicollinearity is not a problem in our data. In H1, we hypothesize that the larger the total amount of sentiments a political Twitter message exhibits, the more often it is retweeted. We estimate

Table 7. Summary Statistics of Variables Relevant for Regression Analyses

	Baden-Württemberg and Rheinland-Pfalz (n = 43,081)		Berlin (n = 68,277)	
	Mean	Standard deviation	Mean	Standard deviation
Dependent variables				
rt_no	0.43	2.07	0.41	2.72
rt_timelag (in minutes)	72	291	114	695
Independent variables				
sentiment	0.31	0.65	0.34	0.69
hashtag	1.28	1.85	1.07	1.75
url (dummy)	0.53	0.50	0.66	0.47
follower	630	2,683	878	5,256
activity	4.94	33.70	6.69	17.43

Equation (1) for both total samples with *rt_no* as the dependent variable and report the results in Tables 10 and 11. We find that the coefficients of *sentiment* are positive and statistically significant in both samples ($b = 0.06$, $p < 0.01$ and $b = 0.04$, $p < 0.1$). This indicates that Twitter messages that feature a higher degree of emotionality indeed tend to trigger more retweets. H1 is therefore supported by our data. The magnitude of the effects of the independent variables on the dependent variable can be inferred from the coefficients. However, because negative binomial regression was applied, the interpretation requires an exponential transformation of the coefficients [12]. For example, the coefficient of *sentiment* of 0.06 means that a one-unit increase in the total amount of sentiments, holding all other predictors constant, is expected to trigger 1.06 times as many or 6 percent more retweets ($\exp(0.06) = 1.06$).

Following the negativity bias, in H3a, we expect the associations between sentiment and retweet quantity to be stronger for tweets with negative sentiment compared to those with positive sentiment. We estimate Equation (2) for both samples with the additional variables *negative* (dummy for negative sentiment) and *sentiment* × *negative* (interaction term). This modeling implies that sentiment polarity would moderate the relationship between sentiment and retweet quantity. For the Baden-Württemberg and Rheinland-Pfalz sample, our results show that the coefficient of the interaction term is insignificant. However, for the Berlin sample, we find the coefficient of the interaction term to be positive and significant ($b = 0.05$, $p < 0.05$), which suggests that negative sentiment tweets are associated with significantly higher retweet counts compared to positive sentiment ones. Nevertheless, these mixed findings prevent us from claiming that H3a is fully supported by our data.

For both samples, the control variables *hashtag*, *url*, and *follower* are each significantly positively related to the quantity of retweets, which is in line with findings from the literature (e.g., [66]). In particular, hashtag inclusion and followership are

Table 8. Correlation Matrix of Independent Variables (Baden-Württemberg and Rheinland-Pfalz)

	sentiment	*hashtag*	*url*	*follower*	*activity*
sentiment	1				
hashtag	0.04	1			
url	–0.05	–0.06	1		
follower	–0.03	–0.04	0.07*	1	
activity	0.00	0.15*	–0.01	–0.04	1

* Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Table 9. Correlation Matrix of Independent Variables (Berlin)

	sentiment	*hashtag*	*url*	*follower*	*activity*
sentiment	1				
hashtag	–0.01	1			
url	–0.06	–0.05	1		
follower	0.01	0.03	0.02	1	
activity	0.01	0.06*	0.08*	–0.01	1

* Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

strongly associated with retweet count. For example, a one-unit increase in the number of hashtags will lead to 38 percent more retweets on average and an increase of 10 percent in the number of followers is expected to trigger 4.8 percent more retweets (Baden-Württemberg and Rheinland-Pfalz). While users' activity is not correlated with retweet quantity for the Baden-Württemberg and Rheinland-Pfalz sample, there is a significant negative relationship between them for the Berlin sample. This indicates that posting activity does not necessarily result in a higher likelihood of being retweeted. The opposite might even hold in the light of information overload problems, particularly in social media.

Retweet Speed

The correlation matrices of the main independent variables for both subsamples when testing H2 and H3b are shown in Tables 12 and 13. Again, we perform multicollinearity tests and find no multicollinearity concerns for our data. H2 predicts that the larger the total amount of sentiments a political Twitter message exhibits, the shorter is the time lag to the first retweet. We estimate Equation (3) for both samples with *rt_timelag* as the dependent variable. Our results (see Table 14) show that the coefficients of *sentiment* are negative and statistically significant in both samples ($b = –0.05$, $p < 0.05$ and $b = –0.04$, $p < 0.01$). This indicates that emotionally charged Twitter messages—in

Table 10. Negative Binomial Regression Results (Baden-Württemberg and Rheinland-Pfalz)

	Dependent variable: *rt_no*					
	(1) H1			(2) H3a		
Independent variables	*b*	SE	exp(*b*)	*b*	SE	exp(*b*)
sentiment	0.06***	0.02	1.06	0.06**	0.03	1.06
negative				0.04	0.13	1.04
sentiment × *negative*				0.02	0.07	1.02
hashtag	0.32***	0.01	1.38	0.32***	0.01	1.38
url	0.36*	0.03	1.43	0.36*	0.03	1.43
log(*follower*)	0.48***	0.01		0.49***	0.01	
log(*activity*)	0.01	0.01		0.01	0.01	
Constant	–4.16***	0.07		–4.16***	0.07	
Pseudo R^2		0.16			0.16	
Number of observations		41,939			41,939	

Notes: b is the estimated coefficient, exp(*b*) is the exponentiated estimated coefficient, and SE is estimated robust standard errors. * Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Table 11. Negative Binomial Regression Results (Berlin)

	Dependent variable: *rt_no*					
	(1) H1			(2) H3a		
Independent variables	*b*	SE	exp(*b*)	*b*	SE	exp(*b*)
sentiment	0.04**	0.02	1.04	0.04**	0.02	1.04
negative				0.07	0.12	1.07
sentiment × *negative*				0.05**	0.07	1.05
hashtag	0.27***	0.01	1.31	0.27***	0.01	1.31
url	0.54*	0.03	1.72	0.54*	0.03	1.72
log(*follower*)	0.56***	0.01		0.57***	0.01	
log(*activity*)	–0.12**	0.01		–0.12**	0.01	
Constant	–4.36***	0.06		–4.36***	0.06	
Pseudo R^2		0.18			0.18	
# Observations		65,241			65,241	

Notes: b is estimated coefficient, exp(b) is exponentiated estimated coefficient, and SE is estimated robust standard errors. * Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Table 12. Correlation Matrix of Independent Variables (Baden-Württemberg and Rheinland-Pfalz, Reduced Sample)

	sentiment	*hashtag*	*url*	*follower*	*activity*
sentiment	1				
hashtag	0.02	1			
url	–0.05	–0.04	1		
follower	–0.05	–0.11*	0.11*	1	
activity	0.04	0.20**	–0.08*	–0.10*	1

Notes: The reduced sample contains only tweets that triggered at least one retweet. * Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Table 13. Correlation Matrix of Independent Variables (Berlin, Reduced Sample)

	sentiment	*hashtag*	*url*	*follower*	*activity*
sentiment	1				
hashtag	–0.04	1			
url	–0.07	0.03	1		
follower	–0.01	–0.01	0.06*	1	
activity	0.02	0.12*	0.02	0.01	1

Notes: The reduced sample contains only tweets that triggered at least one retweet. * Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

those cases where they have been retweeted at least once—tend to be retweeted not only more often but also more quickly compared to neutral ones. More specifically, a one-unit increase in the total amount of sentiments is expected to shorten the retweet time lag by about 5 percent (exp(–0.05) = 0.95 and exp(–0.04) = 0.96, respectively). This finding supports H2. However, we find no support for H3b, which postulates a stronger (negative) association between negative sentiment and retweet time lag. The coefficient of the interaction term *sentiment* × *negative* is insignificant for each sample.

All the controls in both samples are found to be significantly negatively correlated with the dependent variable. This implies that tweets containing a hashtag or URL, or tweets posted by users with a higher number of followers or posting activity, all tend to be retweeted more quickly. A summary of the results of all the hypothesis tests is in Table 15.

Conclusion

Findings

Several insights emerge from the results of this study. First, we found that the affective dimensions (positive or negative sentiment) of political Twitter messages are indeed significantly associated with retweet behavior in terms of retweet quantity, in

Table 14. OLS Regression Results

	Dependent variable: *rt_timelag*			
	Baden-Württemberg and Rheinland-Pfalz		Berlin	
Independent variables	(3) H2	(4) H3b	(3) H2	(4) H3b
sentiment	–0.05**	–0.05**	–0.04*	–0.04*
	(0.03)	(0.03)	(0.03)	(0.03)
negative		–0.02		–0.05
		(0.10)		(0.12)
sentiment × *negative*		–0.05		–0.03
		(0.09)		(0.10)
hashtag	–0.06***	–0.06***	–0.08***	–0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
url	–0.40*	–0.41*	–0.59*	–0.59*
	(0.05)	(0.05)	(0.05)	(0.05)
log(*follower*)	–0.11***	–0.11***	–0.15***	–0.15***
	(0.02)	(0.02)	(0.01)	(0.01)
log(*activity*)	–0.07***	–0.07***	–0.04**	–0.04**
	(0.01)	(0.01)	(0.02)	(0.02)
Constant	2.93***	2.93***	2.91***	2.91***
	(0.11)	(0.11)	(0.10)	(0.10)
Adjusted R^2	0.10	0.10	0.12	0.12
Number of observations	6,159	6,159	8,221	8,221

Notes: The reduced sample contains only tweets that triggered at least one retweet. Estimated robust standard errors are in parentheses. * Significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Table 15. Summary of Findings

Hypothesis	Description	Support?
H1	The larger the total amount of sentiments a political Twitter message exhibits, the more often it will be retweeted.	Yes
H2	The larger the total amount of sentiments a political Twitter message exhibits, the shorter the time lag to the first retweet will be.	Yes
H3a	The association between sentiment and retweet quantity is stronger for tweets with negative sentiment than for those with positive sentiment.	Partial (Berlin sample)
H3b	The association between sentiment and retweet time lag is stronger for tweets with negative sentiment than for those with positive sentiment.	No

the way that emotionally charged tweets are more likely to be disseminated compared to neutral ones. This finding shows that the impact of written expression of emotions on human information sharing behavior shown in other domains also applies to the social media context. More specifically, sentiment in social media content might also induce cognitive and arousal-related effects (e.g., attention and physiological arousal) that affect sharing behavior in social media communication.

Second, our results show that sentiment is positively related to not only retweet quantity but also retweet speed, which is defined as a shorter time lag between the original tweet and the first retweet. In other words, sentiment of tweets makes them spread more quickly through the Twitter network. This finding might be considered empirical evidence of the positive effect of increased attention and/or arousal on the speed of information diffusion. However, we found almost no support for the notion of negativity bias regarding retweet quantity and retweet speed (i.e., people do not tend to pass along negative content more and at a faster pace than positive content). A possible explanation might be that, as our results have partly shown, users in our samples tend to post many positive sentiment tweets associated with their favorite politicians or parties and other people within their political peer group (mostly their followers) are more likely to propagate (i.e., to retweet) such content. Other findings, such as those of Hansen et al. [28], have shown that negative sentiment may enhance virality more than positive sentiment, but only in the domain of news, whereas in some other nonnews domains, the opposite even may hold.

As a final note, our study revealed some interesting findings regarding the tweeting behavior of influential users in the Twitter network. First, they tend to post more emotionally charged tweets. In doing so, their influence may increase even more because their emotionally charged content would be more likely to be disseminated. Second, they are inclined to expose their content to others by hashtag reference, in particular to users with different political alignments.

Research Contribution and Practical Implications

Our study makes several research contributions. First, we extend the existing literature by examining the role of emotions in information diffusion in the social media setting. Previous research has addressed the relationship between emotions and information diffusion, but in contexts other than social media (e.g., [8, 31, 47, 56, 58]). Other work in the social media context has focused on the impact of emotions on feedback or reciprocity [19, 63], but not information sharing. Another stream of previous research identified several factors that drive information sharing such as content-related features (e.g., topics [50], URL and hashtag inclusion [66]) as well as user and network characteristics (e.g., social capital perception [57], popularity and homophily [48]). However, none of these studies have considered emotions as another source of content virality. Second, we address the impact of emotions on information sharing not only with respect to quantity but also speed. To our knowledge, our study is the first to consider this aspect of diffusion in a social media setting. Third, the findings of our study challenge the notion of negativity bias, which suggests stronger effects of negative stimuli in a wide range of settings. This indicates that the relation between affect and virality might be more complex than expected, as previously suggested by Berger and Milkman [9]; it depends not only on emotional valence but also on physiological arousal, among other things [9]. Moreover, the context and domain of the content (e.g., news or nonnews [28]) as well as specific characteristics of communication platforms might play an important role. In any case, the issue of negativity bias deserves future research attention, in particular in the context of CMC. Finally, our study sheds light on the tweeting practice of influential users in social media regarding a high level of emotion expression and exposure of others to information, which may induce more interaction (e.g., conversation, discussion) as well as diffusion.

In sum, this study contributes to several research streams, including information diffusion (information sharing by retweeting), social psychology (emotion/sentiment, negativity bias), CMC (Twitter communication), as well as IS due to the social media context. In the past few years, social networks and social media have become an important domain in IS research [53]. Because of its organization-centric and process-oriented approach, it is argued that IS research can help us understand the effects of Web 2.0 technologies and associated social media as sociotechnical systems on individuals, organizations, and society [74].

Our study has several practical implications. First, it is important for politicians and political parties to identify influential users since they are able to have an influence on political opinion-making and agenda-setting processes. More specifically, for the purpose of reputation management, political institutions are advised to analyze the background of those opinion leaders, follow the discussions among their peers, and especially detect sentiment in their content as sentiments might have viral effects in social media communication, as our study suggests.

Our study also has business implications. Companies are increasingly affected by communication in social media. Customers are now more enabled to share information and experience among each other. In particular, product- and brand-related sentiments are of central importance because they might strongly affect consumers' purchase decision processes. Because of the influence of sentiment on content virality, companies should pay more attention to the analysis of sentiment related to their brands and products in social media communication. While some consumer-generated content is positive, much is negative, and can result in consumer backlashes if not carefully managed. For these tasks, politics and enterprises might follow the approach of social media analytics to systematically monitor and analyze user-generated content in social media [64]. Moreover, because sentiment may trigger a higher speed of information diffusion, as our study shows, companies are advised not only to react but to react quickly to changes in sentiment related to their brands and products in social media.

Finally, our findings also have important (viral) marketing implications in the social media context. Recently, electronic word of mouth in social media is increasingly viewed as cheaper and more effective than traditional media. In this regard, it might be useful to feature or design social media–based advertising content that triggers emotions because such content is more likely to be shared. Considering emotions when crafting viral content might help companies maximize revenue when placing advertisements. The implication of exploiting emotions for marketing purposes in general may not be really novel, but our findings confirm that this implication also holds for social media communication specifically.

Limitations and Future Work

It is a limitation of our study that our analysis is based on Twitter data samples restricted to German political events, which may raise issues of generalizability. However, given that Twitter is a very popular social media communication platform used in many domains other than politics, the problem of generalizability may not be that severe. Nevertheless, future research could extend our analysis to other domains (e.g., business, marketing, or personal communication) and to a larger scale (e.g., longer time periods of data collection as well as other countries and languages).

As another caveat, while computerized language measures allowed us to test our hypotheses on a large data set, they cannot capture irony, sarcasm, or culture-specific contexts. In future work, we aim to back up our findings by conducting additional qualitative analyses. In addition, future research could also focus more on the content of Twitter messages in the analysis of retweet behavior. This might help identify topics that are more likely to spread through networks. Finally, future research could investigate whether there is also a relationship between sentiment of Twitter messages and the likelihood of being mentioned or directly replied.

Notes

1. Note that retweets that also contain an @ sign are excluded from these statistics.

2. There are various definitions or measures of *influence* from different scientific disciplines. Basically, an *influential user* is defined as someone who exhibits some combination of personal attributes (e.g., expertise or credibility) and network attributes (e.g., connectivity or centrality), which allows them to influence a disproportionately large number of others—also indirectly via a cascade of influence [75]. In this study, we adapt user's number of triggered retweets as a measure of user's influence, which has been shown to be a reasonable network-based proxy [13, 42].

3. Two independent coders with a broad knowledge of politics performed this task on about 1,000 tweets for both samples using a coding scheme containing four categories corresponding to the four distinct political groups previously identified as well as a category "others" for any tweets that did not fit into those four categories. Intercoder reliability (Cohen's κ coefficients) was 0.90 on average ($p < 0.05$), suggesting a high level of agreement between the coders [43].

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