Emotions in Microblogs and Information Diffusion: Evidence of a Curvilinear Relationship

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Completed Research Paper

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Abstract

How is emotional content shared on microblogging platforms? Prior work has proposed that emotionally charged content is diffused more than emotionally neutral content because it can evoke physiological arousal in platform users. Drawing on recent research in IS, we argue that the real relationship between emotions and Information Diffusion is an inverse U-shaped relationship; moderately strong emotions lead to optimal diffusion. We further theorize that this relationship is moderated by discourse context and valence of emotions. We test these hypotheses by testing a Twitter dataset that includes tweets collected from multiple conversation contexts. Results show broad support for our hypotheses and extend prior work on emotional content in microblogging.

Keywords: Microblogging, Emotional content, Information-Diffusion, Inverse U-shaped relationship.

Introduction

In today's networked public sphere, microblogs - bite-sized textual content[1] produced and shared on Social Media (SM) platforms - are one of the dominant means by which information travels through society (a process hereafter referred to as Information Diffusion (ID)). On microblogging websites, people post personal opinions about events of contemporary political, cultural, and economic world. Emotions are an integral part of how content is framed on these websites. Small texts may not capture thorough and articulate reason, but they can be ideal for capturing people's moods and feelings. The ubiquity of emotions in online public communication raises an important question: *what is the relationship between emotion embedded in microblogging content and its diffusion?*

In Information Systems (IS) literature, the seminal contribution to this question comes from Stieglitz and Dang-Xuan's (2013) study. By analyzing a dataset of over 150k tweets shared during the 2011 German election, the authors concluded that emotionally charged tweets are retweeted more than emotionally neutral tweets. While this is the sole IS study on emotions and information sharing on SM, one can draw similar conclusions from research in other disciplines. For instance, in moral-political discourse on Twitter

[1] While visual content such as memes, reels, and stories are also an integral part of online communication, our study focuses only on texts.

tweets, that include emotional words are more likely to be retweeted (Brady et al. 2017). Marketing scholars note that emotions drive the virality of SM content (Berger and Milkman 2012). Mass media studies also report that news stories loaded with emotions and sensationalist content have been shown to elicit emotional arousal and extensive sharing (Vettehen et al. 2008).

The rationale for a positive relationship between emotionally arousing content and its propagation on SM is as follows. Strong emotions have the potential to stir people into action. Emotional stimuli can psychologically arouse people, and spur them into sharing the stimulus' source (Berger 2011). Therefore, it is likely that on SM platforms emotionally charged content propagates more than emotionally neutral content (Stieglitz and Dang-Xuan 2013). While we endorse this logic in principle, we suggest that the theoretical pathway that mediates the effect of emotions on online content sharing is more nuanced. Using literature on emotional suppression, we theorize that emotions and ID follow an inverted U-shaped relationship. This might be because extremely arousing emotions can invoke the logic of censorship over of the logic of expression. There is some supporting evidence for this from recent studies of digitally-mediated communication, such as online reviews (Yin et al. 2021), and political dialogues (Wang et al. 2011). The implications of these studies lead us to believe that content with moderately strong sentiments will be shared optimally and content with too little/too-much emotions will be shared less. We further propose that this inverted U-shaped relationship is moderated by a) the valence of emotions and b) context of online discourse.

To test our propositions, we collected tweets on six different topics - three neutral and three polarizing - and analyzed their diffusion statistics. Our analysis supports the central argument that emotions relate to information sharing in an inverse U-shaped manner. Moderation tests further show the context-sensitive nature of this relationship. We find that in neutral conversation topics people suppress extreme emotions and in contentious topics they express them greatly.

Our study makes two contributions to IS literature. First, it problematizes how the SM user is conceptualized in extant studies. Current literature conceptualizes the SM user as a purely *reactive* one, whose response to emotional content is guided by autonomic processes such as psychological arousal (Stieglitz and Dang-Xuan 2013). Our findings suggest the need to incorporate a more *agentic* view of the average SM user who, we show, exercises agency in SM sharing behavior. A second contribution of our study is that it indicates norms of emotional communication vary across different online conversations. There are also practical implications of our study. Organizations of all kinds - from large businesses to fledgling content creators - depend on the power of microblogging platforms to boost the reach of their message and acquire new audiences. Such entities too can benefit from an understanding of how emotional framing relates to content sharing.

Hypotheses Development

Diffusion of Emotional content on Microblogging Platforms

Microblogging is a form of online discourse in which participants articulate opinions/information about a subject-matter using limited number of words (Java et al. 2007). With the internet becoming a household commodity in the early 2000s, people found new opportunities for self-expression and blogging became an emergent online practice. Over the last decade, the advent of interactive Web 2.0 websites, most notably Twitter, has not only made this practice more commonplace but also added a new material affordance in addition to self-expression: information sharing. Today, microblogging websites are institutionalized mediums for information sharing[2], used by public figures, brands, activist groups, and everyday users. Features such as the Retweet button has made the diffusion of information through one's network remarkably easy. The resultant ID is of both theoretical and practical value. IS scholars have therefore developed an interest in the factors that influence how information is diffused through microblogging platforms.

The question of interest in this study is how emotional stimuli contained in microblogs affects the latter's diffusion. Emotions are an expression of one's current state of mind or subjective attitudes. In both face-

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[2] We collapse various categories of articulations - personal opinions, product reviews, live commentary, news articles, entertainment posts, etc. - under the umbrella term information.

to-face and online settings, emotions are constitutive of the act of communicating. People use emotions to add greater meaning to the content of their communication. In the signal-rich settings of face-to-face communication, emotions are often detected via physical cues, such as facial expressions and bodily gestures (Daft and Lengel 1986). In the lean settings of microblogging, with its additional constraint on message size, one would expect that emotions will be difficult to express. However, as many scholars have noted, users on SM can readily detect sender emotions in texts (Harris and Paradice 2007).

The curvilinear Relationship between Microblog Emotions and Information Diffusion

Current IS perspective on how microblog emotions relate to subsequent sharing behavior draws on several literatures, such as marketing (Berger and Milkman 2012) and computer-mediated communication (Harris and Paradice 2007), to argue that microblog emotions relate positively to ID. There are several ways to support this assertion. First, emotional stimuli can draw attention (Öhman et al. 2001). In computer-mediated communication, an emotional appeal can draw more eyeballs than a dry and factual narration. On YouTube, for instance, video titles are framed using emotional words such as “DESTROYED” and “AGHAST” to grab user attention. In addition to this, emotions can also be persuasive (Forgas and George 2001). Emotions can make people believe in a cause and dictate behavioral outcomes. Indeed, the root of the word emotion is the Latin term *emovere* - meaning to move - implying that emotions have the power to set actions in motion. Finally, certain emotions can lead to a state of arousal. When people consume emotional information, they feel a state of physiological and psychological arousal, which is an activation of the autonomic nervous system. People in such a state tend to engage in information sharing behavior (Berger 2011), a fact perhaps best captured in the phrase “difficult to contain one’s excitement.” Therefore, in line with arguments of previous studies, we hypothesize that microblogs with emotionally charged content will be diffused greatly.

The above arguments summarize current literature’s logic on how emotions embedded in microblogs impact ID. Micro-bloggers embed emotions into their posts to reflect personal feelings and subjective attitudes about a subject. These posts, when subsequently read, transfers the embedded emotions to one’s follower-network, which, in a resultant state of arousal, shares the post further. Therefore, strong emotions amount to greater sharing activity, and more ID. The underlying assumption for this line of reasoning is that of arousal-transfer, that is a person’s state of arousal being transferred to another user (a follower) via digitally mediated communication. We discuss below several arguments which suggest that this assumption may not hold under the conditions of extremely strong and arousing emotions.

First, extreme emotions may be an indicator of a sender’s personal bias on a subject. Emotions are a signal about the subjective state of a person when the information was created. And the presence of extremely strong emotions can signal the author’s emotional bias (Seo and Barrett 2007). This certainly applies to extreme negative sentiments which can be classified as *ranting-and-raving*. It also applies to strong positive sentiments which can be considered a biased predisposition towards an object. Second, we can infer from related literature that extremely arousing emotional content can obfuscate meaning transfer in some microblogging contexts. Literature on online reviews - a specific type of microblogging - find that reviews that contain extremely arousing information can be perceived by readers as showing lack of effort and deliberation on the part of the author (Yin et al. 2017). In microblogs, where space limitations necessitate discretion and judgement in word allocation, the more words one uses to express emotions, the less there is for reasonable and measured expression. Above arguments suggest that the arousing feelings under whose influence an author composes a microblog may not always transfer to the readers. This, in turn, means that extreme emotions may not translate into greater sharing.

Moreover, even in cases where strong emotional arousal does transfer, there are reasons to suspect that aroused followers may not always engage in information sharing. Since microblog communication is public and merges multiple different contexts into one (Marwick and Boyd 2011), spreading emotional content can be off-putting for ones’ network. Microblog users may, therefore, have subjective norms on how emotional content is expressed on SM. Since sharing a microblog (via retweet) can be considered tacit approval of the underlying message, people may censor themselves even when feeling strong arousing feelings. Indeed, in a study of Facebook users, several users who made a post expressed regret when remembering posts that were made in an emotionally arousing state (Wang et al. 2011). There can also be evolutionary reasons can also be made about why people in an open communication platform may censor strong emotions (Cosmides and Tooby 2000). These arguments lead us to posit that at either extreme - too little or too much - emotions will translate to low diffusion levels.

H1: Emotions in microblogging content is associated with Information Diffusion in an inverse U-shaped manner, i.e., moderately strong sentiments lead to optimal Information Diffusion.

The Moderating Role of Context and Valence

In terms of discourse context, the microblogging universe isn't a monolith and different discourses may have their own norms on emotional communication. Consider, for instance, a discourse where people are engaged in a cordial everyday discussion. Such discussions are a regular feature in the microblogging sphere. Brand related discourse, commentary on live events, and sports related discussions are all examples of such a setting. In contrast to this, consider a polarizing discourse context such as Political Twitter, a colloquial term for a broad community of Twitter users who primarily discuss about events in the political world. Clearly, there are no reasons to believe that the norms around emotional conversation will be the same across both contexts. In polarizing discussions, extreme emotions may not only be expressed but can also lead to higher sharing. In polarizing blogs, the use of emotional rhetoric to reach fragmented communication networks is well documented (Adamic and Glance 2005; Brady et al. 2017). Because of such contexts may normalize expression and propagation of extreme emotions, the curvilinear effects of extreme emotions will likely be weaker in polarizing discourses as compared to neutral discourses. Therefore, we hypothesize,

H2a: Discourse context will moderate the curvilinear relationship between emotions and ID, such that the effect size will be lower in polarizing discourses.

Another moderating factor to consider is the emotion's valence. There are reasons to believe that, at extremities, both negative and positive emotions will both be censored. As discussed, even extreme positive sentiments can cause perceptions of bias in the mind of users as well as hinder meaning transfer. However, the degree of *censorship* evoked by such thoughts might pale in comparison to the degree of censorship evoked by strong negative emotions, such as anger and disgust. Clearly, a microblog user is more likely to not share a rant-and-rave blog than a blog with overdose of positive affect.

H2b: Valence will moderate the curvilinear relationship between emotions and ID, such that the effect size will be lower for extreme positive emotions than for extreme negative emotions.

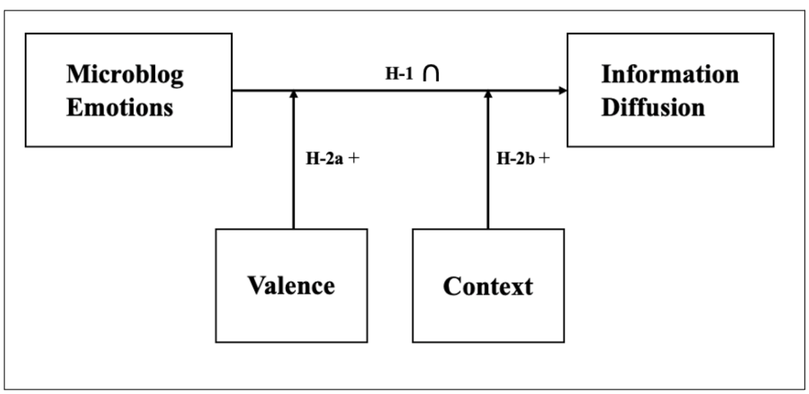

Figure 1. Research Model

Methodology

To empirically test the proposed hypotheses, we relied on observational data collected from six different discussion topics on Twitter. Each of these discussions happened between 1st September 2021 and 19th September 2021. We began harvesting tweets on 19th October and this one-month time lag between tweets' engagement and data collection ensures the completeness of our dataset. Twitter was chosen as the target platform because of its popularity in the microblogging practice. Multiple categories of SM users - brands, influencers, politicians, media celebrities, universities, and everyday content-producers/consumers - regularly contribute to discourse making and taking on Twitter. The first three topics pertained to discourses that are held on Twitter on a weekly basis. Three hashtags (#mondaymotivation, #womencrushwednesday, and #throwbackthursday) were selected, and all the tweeting-retweeting activity of a hashtag was collected over a one-week period. A one-week timeframe was chosen because even though most of the communicative activities on our focal hashtags take place on specific days of the week, some spillover activities may happen on other days. Indeed, as we noted in our data, ~8% of the overall retweets for these hashtags were recorded on days other than that indicated by the hashtag.

To create a contrast in conversation settings and to operationalize the polarizing *context*, we also collected, in the same timeframe as before, tweets relating to three contemporary polarizing discussions. The topics selected in this context were: a) California's gubernatorial recall election, b) Texas law on abortion, and c) the Biden administration's vaccine mandate. The nature of the difference between these two settings - one cordial and ordinary and one political and polarizing - allows us to test our proposition that emotions have heterogenous effects on ID based on the context of online discourse. As with the previous hashtags, tweets for each topic were gathered over a one-week time-frame. We compared the total volume of the tweets in our dataset to the total volume of tweets registered on focal hashtags over a one-month period. For instance, for California recall elections we compared total tweets collected with total tweets on the same hashtags over the period Sep 12-Oct 12. Results show that our dataset was 92% complete. The same for Texas abortion law and Biden vaccine mandate was 96% and 87% respectively. Across all six contexts, the total number of tweets collected was 459,691. Specific details about timeline of data-collection, inclusion criteria, and volume of tweets gathered is provided in Table-1.

We cleaned this dataset by first removing tweets that were replies, since reply-chains are different from diffusion-networks and thus were not relevant to our study. We also removed quote tweets from our data for the same reason. Next, we removed from the data users who may be bots, and for this we relied on the Botometer software, a popular bot-detection api. Removal of bots is particularly important in our study because automated bots have been identified as key players in the diffusion of politics-related tweets (Salge et al 2021). We then removed from the dataset users who had been suspended by Twitter or had enhanced privacy settings, as this can lead to authorization failures in subsequent data transformation. The final step in making the dataset analysis-ready was to convert individual tweets into diffusion cascades, which would serve as the unit of analysis. The diffusion cascade of a tweet represents the original tweet and all its retweets in a network form and describes the tweet's true retweet path. To create diffusion cascades, we followed Vosoughi et al's (2018) technique of leveraging Twitter's followership graphs to infer a probabilistic path a tweet may followed in traversing through Twitter's space. Thus, our original dataset was converted into the final sample of 94186 diffusion cascades. From these cascades, we generated dependent, independent, and control measures.

Topic	**Category**	**Time frame for collecting tweets**	**Hashtags**	**Volume of Tweets Collected**
Monday Motivation	Neutral	Sep 1 - Sep 7	#mondaymotivation #mondaymood #monday	31,189
Women Crush Wednesday		Sep 12 - Sep 19	#womencrushwednesday #wcw	15,903
Throwback Thursday		Sep 9 – Sep 16	#throwbackthursday #tbt	22,682
California Election Recall		Sep 12 – Sep 19	#gavinnewsom #recallnewsom	167,550

Texas Abortion Law	Polarizing	Sep 1 – Sep 7	#texastaliban #texas #abortion	286141
Covid Vaccine Mandate		Sept 9 – Sep 16	#vaccinemandate #vaccinepassport #iwillnotcomply	149756

Table 1. Data Collection Details

Dependent Variables

Three measures serve as dependent variables - Range, Scale, and Speed. To understand these measures, consider the stylized retweet graph of a tweet as shown in Figure-1. In this cascade, user U_0 is the author of the tweet, hence the root node. Users $U_{1\text{-}6}$ retweeted the tweet, either by retweeting U_0 directly or by retweeting an intermediate retweet. Range of a *node* is the distance, in degrees of separation, between itself and the root node. Thus, range of a *cascade* is the maximum range of all nodes in the cascade. Range measures how far a tweet has diffused beyond the root's ego network. In the example cascade, range equals 2. Scale refers to the number of retweeting nodes at a certain level of range. And scale of a cascade is the maximum of scales across all range levels. In Figure-1, at range-levels 1 & 2, scale = 3. Therefore, scale of the cascade equals 3. Finally, speed refers to the first instance of diffusion. It is the time lag between the origin of a tweet and the first retweet. In Figure-1, let's assume a chronological sequence of retweet times $t_{1\text{-}6}$. Then, speed of diffusion is $(t_1 - t_0)$ in seconds. Range, scale, and speed of a diffusion cascade with n nodes is formally defined as follows.

$Range = \max(r_i)\,, where\ r_i = range\ of\ node\ i, 0 \leq i \leq n$

$Scale = \max(s_i)\,, where\ s_i = number\ of\ nodes\ at\ range\ level\ i, 1 \leq i \leq Range$

$Speed = \min(t_i) - t_o, where\ t_i = time\ of\ retweet\ for\ node\ i, 1 \leq i \leq n$

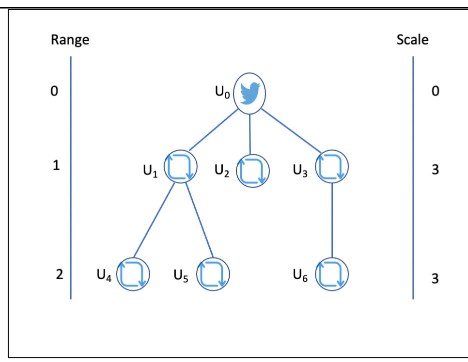

Figure 2. Range, Scale and Speed of Information Diffusion on Social Media (Vosoughi et al. 2018)

Independent Variable

The independent variable of interest is the strength of emotions embedded in a tweet. We operationalize expressed emotions using the strength of sentiment in a tweet. We calculate a measure for this using the SentiStrength software package, which uses a built-in lexicon to analyze texts and assigns them both positive and negative sentiment scores. Positive scores range from +1 (neutral) to +5 (strongly positive) whereas negative scores ranged from -1 (neutral) to -5 (strongly negative). SentiStrength has been shown to be effective at categorizing sentiments in short text messages, such as tweets (Thelwall et al. 2010) and, therefore, have been used in recent studies in IS research to calculate content sentiment (for instance (Deng et al. 2018; Stieglitz and Dang-Xuan 2013; Wu et al. 2019). To test the reliability of this software, we created a random sample of 100 tweets and used human raters to label their level of sentimentality. Comparison of human ratings with SentiStrength's polarity scores netted a kappa score of 0.64, in line with the performance expectations set by prior evaluative studies (Abbasi et al (2014)). Polarity and valence of tweets were calculated as:

$$Polarity = max(\ abs(positive), abs(negative)).$$

$$Valence = 1\ if\ (positive + negative) > 0,$$

$$-1\ if\ (positive + negative) < 0,$$

$$0\ if\ (positive + negative) = 0$$

Our measurement of sentiment polarity differs from that used by the Stieglitz and Dang-Xuan (2013) study, in which the authors aggregated positive and negative scores by adding absolute values, and then normalized the resulting scores such that polarity values ranged from [0,8]. This approach is unsuitable for our study, specifically because of our focus on extreme emotions. Consider for instance the case of two tweets that have polarity scores of [0, -4] and [2, -2]. Using the authors' approach will result in a polarity score of 4 for both tweets. However, the former tweet clearly contains much stronger negative sentiments and should not be classified as having the same level of sentimentality as the latter. Further, a tweet with polarity score of [5, -5] is unlikely to be twice more extreme than a tweet that contains a score of [0,-5]; the addition of strong positive emotions to strong negative emotions does not render the tweet twice as extreme in its polarity. Thus, our research-focus on extreme emotions required that we move away from an aggregation approach, using instead the maximum absolute value of sentiments. Summary statistics for independent and dependent is shown in Table-3. Distribution of the three dependent variables can be found in Figure-3.

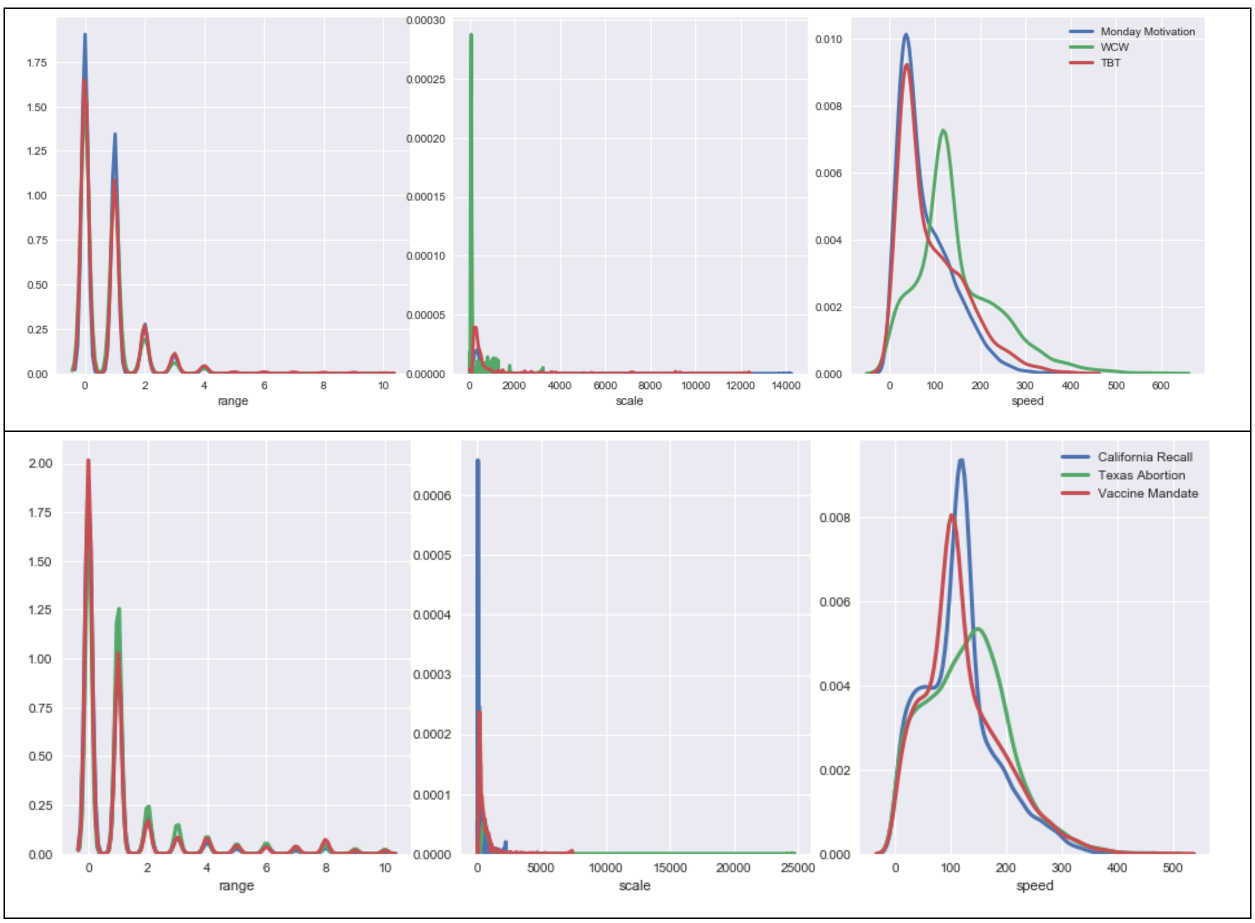

Figure 3. Distribution of dependent variables

Note: X-axis denotes absolute values for range, scale, and speed (in seconds)

	Cascades	Range		Scale		Speed		Sentiment Polarity	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Monday Motivation	19311	0.68	0.93	9.66	131.14	78.84	59.23	2.07	1.43
Women Crush Wednesday	5223	0.63	0.81	6.61	65.73	148.13	91.11	1.42	0.66
Throwback Thursday	11004	0.74	1.13	18.95	229.53	93.16	72.28	1.04	0.51
California Recall	12926	0.79	1.40	18.10	90.48	114.98	66.05	2.52	0.95
Texas Abortion	29890	1.13	1.81	49.32	305.68	130.61	74.40	2.50	0.90
Vaccine Mandate	15832	1.00	1.85	46.15	218.05	121.01	72.13	2.47	0.91

Table 2. Summary Statistics

Control Measures

To control for alternative explanations, we included several control variables in our analysis. These measures can be classified into three broad categories: a) author characteristics, b) content characteristics, and c) environmental factors. Under author characteristics, we controlled for the tweet's original author's reputation and network size using measures *isVerified* and *numFollowers*. *isVerified* is a binary variable denoting whether the root, or *any other* retweeting user in a cascade, has been verified by Twitter as influential. This is necessary because sometimes verified users may retweet unverified ones based on factors such as content quality and novelty, thus both amplifying the tweet to a larger audience and flagging it with a reputation badge. Other author characteristics controlled for include the author's network size (measured by followership metrics), the degree of clustering in her ego followership network, and the extent to which her follower base is "active" and "engaged" on Twitter.

The second category of controls corresponds to the tweet's content characteristics. In this category, we measured whether a tweet contains media or other amplificatory features such as user-mentions and hashtags. In addition, we also measured the tweet's day/time of posting since tweets that are posted during primetime window (6pm to 10pm) and during weekends could garner more attention. The final category relates to the tweet's environment. Specifically, we measured the number of other discussion topics that a focal tweet competes for attention with. The assumption underlying this inclusion is as follows. A tweet posted during a time-window when multiple concurrent topics are being discussed may have to compete harder for eyeballs, thus hampering its diffusion.

Variable-Label	**Description**	**How was it constructed**
isVerified	Binary variable measuring whether the cascade originated from a verified user or was, at some point in the diffusion cascade, retweeted by a verified user	The verification status of all users in a diffusion cascade are noted. If any user is verified, the binary variable is turned on.

numFollowers	The network size of a cascade's root	Number of followers of the root was obtained using Twitter's public metrics. Bots and Inactive users were removed using the software Botometer
networkClustering	Degree of clustering in the root's network	Network redundancy measures were calculated for the root user using Borgatti (1997).
percentHighActivityFollowers	What percent of a root user's follower base is highly active	A root user's followers were analyzed for a) total number of tweets posted (n) and b) number of days account has been active (d). If n/d > 5, then follower is classified as a high activity user. percentActiveFollowers = highActiveFollowers/numFollowers
percentPriorEngagement	What percent of a root user's follower base has engaged with them	A root user's followers' last 3200 tweets were analyzed to check if the follower has retweeted root in the past. Correspondingly, a measure was calculated that reflects what percent of a root user's followers have prior engagement with it.
percentTopicalInterest	What percent of a root user's follower base has interest in the topic of the tweet	A root user's followers' last 3200 tweets were analyzed to check if the follower has posted any tweets relevant to the topic. Correspondingly, a measure was calculated that reflects what percent of a root user's followers have prior interest in the topic.
numHashtags	Total number of hashtags in a tweet	Count(#)
numOfMentions	Total number of users mentioned in a tweet	Count(@)
hasMedia	Does the tweet contains media (such as gif, images, and videos)	Using twitter's media field
primeTime	Binary variable denoting whether the tweet originated during the prime time window?	1, if tweet was posted during 18:00 and 22:00 hrs. 0, otherwise
isWeekend	Binary variable denoting whether the tweet originated during the weekend?	1, if tweet posted on Saturday/Sunday 0, otherwise

competingTopics	Topics the focal tweet is competing for attention with	All the tweets originating in the same location as the focal tweet within a two-hour window of the tweet's posting were collected. Number of unique non-stopwords contained in these tweets was used as a proxy for the competing topics.

Table 3. Control Variables

Estimation Model

To test hypothesis-1 and 2, we use the estimation model in equation-1. The main variable of interest for hypothesis-1 is sentiment polarity (polarity hereafter), which is a positive integer between 1 and 5. For Hypothesis-2, we predicted an inverse-U shaped relationship between emotions and ID. To test this relationship, we follow prior research (cite) and include the squared term of the independent variable, $polarity^2$. Since Range and Scale are count variables that follow the Poisson distribution, we use Poisson regression to estimate the effect of polarity on both these measures. Since Speed is a continuous variable with normal distribution, we employ an Ordinary Least Squares (OLS) model. To account for non-normality, we perform a Shapiro-Wilk test. While test results indicated non-normality of data, such results are often expected in large samples. Note that because Speed is measured on an inverse scale, greater the time lag between a tweet's posting and its first retweet lower is the speed.

Because our dataset contains different clusters (six different discourse contexts), we had to ensure that clusters were not different from one another. We performed several t-tests to compare different clusters. These tests were done to ensure that clusters were not different from one another with regards to key observable characteristics, such as the proportion of verified users, bot activity, followership size, and activity rate). Based on test results we were able to conclude that groups were not different across these observables.

$$(Range|Scale|Speed) = \beta_0 + \beta_1(polarity) + \beta_2(polarity^2) + \beta_3(controls) + \varepsilon. \qquad (1)$$

Results

Main Effect

Table-4 contains results for Hypotheses-1 and 2. In models-1, 3, and 5, we regressed the variables range, scale, and speed on only polarity. The co-efficient of the main independent variable, *polarity*, has a point estimate ($p < 0.01$) of 0.105 and 0.190 for Range and Scale respectively, indicating that emotional content has a positive association with range and scale of diffusion. Interpreting coefficients in Poisson regression requires exponential transformation of the estimated coefficients. Therefore, we calculate from Table-4's point-estimates the incidence rate ratio (IRR). The IRR indicates that a one unit increase in sentiment strength is associated with a 11% increase[3] in range and 21% increase in scale of diffusion. The point-estimate for speed (model-5) is -4.075 ($p < 0.01$), which indicates that a unit increase in emotional strength of microblogs is associated with a 4 second increase in speed. Overall, these results indicate support for Hypothesis-1.

Our second hypothesis (H2) posits an inverse U-shaped relationship between our primary variable of interest, polarity, and ID. This means that sentiment strength will be positively related to ID until a threshold, beyond which the relationship reverses direction. To test the presence of this relationship in our data, we introduced the squared term of polarity in models 2, 4, and 6. The negative signs of $SentimentStrength^2$ under columns 2 and 4 indicate that tweets that contained extremely strong emotions were diffused less than those that were moderately emotional. The negative sign for $polarity^2$ under model-6 indicates that this relationship was not present in the case of speed. These results lend partial support to

[3] $e^{0.105} = 1.11$. Other IRR are calculated similarly.

hypothesis-2. Converting point estimates into IRR, at the extremities, there is a 1.4% and 1.8% decrease in range and scale respectively. These relationships are shown as a fitted plot in Figure-4.

	range		**scale**		**speed**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
polarity	0.105^{***}	0.186^{***}	0.190^{***}	0.184^{***}	-3.818^{***}	33.247^{***}
	(0.002)	(0.013)	(0.000)	(0.002)	(0.282)	(0.848)
Polarity Squared		-0.012^{***}		-0.011^{***}		-7.022^{***}
		(0.002)		(0.000)		(0.163)
numOf Followers	$7.14e\text{-}09^{***}$	$6.89e\text{-}09^{***}$	$1.14e\text{-}08^{***}$	$1.12e\text{-}08^{***}$	$4.82e\text{-}07^{***}$	$5.73e\text{-}06^{***}$
	(6.95e-10)	(6.94e-10)	(6.97e-11)	(6.96e-11)	(1.19e-06)	(1.18e-06)
network Clustering	-0.105	-0.103	0.300^{***}	0.310^{***}	-15.10^{**}	-14.95^{**}
	(0.075)	(0.075)	(0.012)	(0.012)	(5.433)	(5.386)
percentHigh Activity Followers	0.090^{***}	0.087^{***}	0.090^{***}	0.086^{***}	0.244	0.642
	(0.024)	(0.024)	(0.004)	(0.004)	(1.770)	(1.755)
percentHigh Interest Followers	0.139^{***}	0.135^{***}	0.447^{***}	0.447^{***}	1.039	1.751
	(0.024)	(0.024)	(0.004)	(0.004)	(1.767)	(1.752)
percentPrior Engagement	1.122^{***}	1.097^{***}	1.980^{***}	1.955^{***}	10.730	13.500
	(0.084)	(0.084)	(0.012)	(0.012)	(7.125)	(7.065)
isVerified	1.200^{***}	1.180^{***}	1.360^{***}	1.346^{***}	44.870^{***}	49.150^{***}
	(0.008)	(0.008)	(0.001)	(0.001)	(0.876)	(0.875)
hasMedia	0.193^{***}	0.190^{***}	0.108^{***}	0.101^{***}	3.761^{***}	3.364^{***}
	(0.007)	(0.007)	(0.001)	(0.001)	(0.499)	(0.495)
isWeekend	0.183^{***}	0.185^{***}	0.293^{***}	0.299^{***}	10.17^{***}	10.41^{***}
	(0.010)	(0.010)	(0.001)	(0.001)	(0.790)	(0.784)
primeTime	0.046^{***}	0.047^{***}	0.058^{***}	0.061^{***}	4.404^{***}	4.422^{***}
	(0.007)	(0.007)	(0.001)	(0.001)	(0.585)	(0.580)
numOfHashtags	-0.084^{***}	-0.083^{***}	-0.736^{***}	-0.731^{***}	-1.409^{***}	-1.491^{***}
	(0.001)	(0.001)	(0.000)	(0.000)	(0.065)	(0.065)

numOfMentions	0.012***	0.013***	-0.190***	-0.187***	2.743***	2.620***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.102)	(0.101)
wordCount	0.018***	0.022***	0.310***	0.316***	1.881***	1.903***
	(0.003)	(0.003)	(0.009)	(0.007)	(0.043)	(0.038)
_cons	-1.022***	-0.715***	2.934***	3.394***	51.17***	7.485***
	(0.017)	(0.023)	(0.002)	(0.004)	(1.328)	(1.702)
N	94186	94186	94186	94186	45814	45814
adj. R^2					0.049	0.066
pseudo R^2	0.164	0.165	0.406	0.407		

Table 4. Regression Results

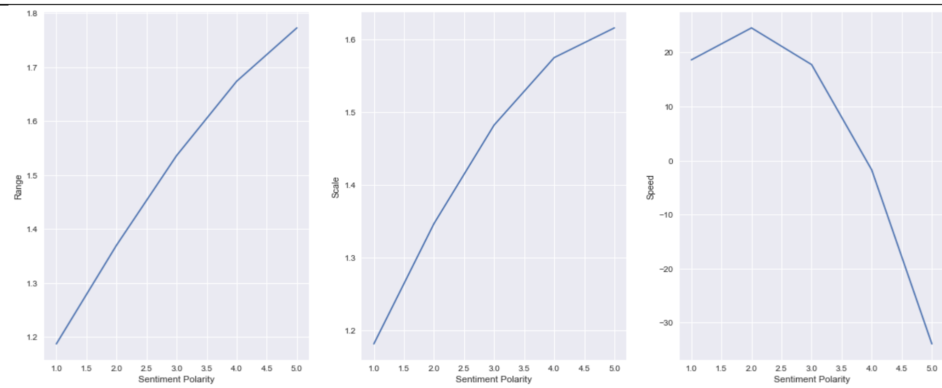

Figure 4. Relationship between Sentiment Polarity and Information Diffusion

Moderating Effect of Discourse Context and Valence

Point estimates in Table-4 and plots in Figure-4 both indicate a weak curvilinear effect of microblog sentiments. Our suspicion was that this was the result of two different discourse contexts (polarizing and neutral) mixed in the same dataset. Testing hypothesis 3a would confirm whether this suspicion was true. In hypothesis-3a, we predict that the curvilinear association between emotional content and its diffusion will be moderated by discourse context, such that polarizing tweets demonstrate weaker curvilinear effect. To test this, we created an interaction term by multiplying polarity^2 and the dummy variable discourseContext and ran the regression model specified in equation-2. Table-5 shows the output for this regression. As regression estimates show, for all three dependent measures, there is a strong and significant interaction between extreme emotions and the discourse context. To visualize this interaction, we ran two separate set of main regressions (equation-1), one on polarizing tweets and one on neutral tweets. The outcome is plotted in Figure-5. This diagram shows a clear trend. While tweets on neutral non-political discourse exhibit low diffusion levels at extreme sentiment polarity, polarizing socio-political tweets garner high retweets at extreme sentiment levels. These results show support for Hypothesis-3a.

$$(Range|Scale|Speed) = \beta_0 + \beta_1(SentimentPolarity) + \beta_2(SentimentPolarity^2) + \beta_3(SentimentPolarity^2 * DiscourseContext) + \beta_4(controls) + \varepsilon \quad (2)$$

$$(Range|Scale|Speed) = \beta_0 + \beta_1(SentimentPolarity) + \beta_2(SentimentPolarity^2) + \beta_3(SentimentPolarity^2 * Valence) + \beta_4(controls) + \varepsilon \quad (3)$$

We hypothesized in H3b that extreme negative emotions will be suppressed more than extreme positive emotions. Therefore, extremely negative tweets should display stronger curvilinear effects. To test this hypothesis, we created an interaction term by multiplying polarity^2 and the dummy variable valence, which indicates whether the tweet contains positive, negative, mixed, or no emotions (baseline), and ran the regression model specified in equation-3. The result, shown in Table-5 and plotted in Figure-6, while significant is counterintuitive. We expected that the effect of polarity^2 to be stronger in negatively valanced tweets but, instead, found the opposite. This was a perplexing result and we investigated possible reasons for this outcome. Like the previous case, our suspicion was this outcome was driven by the merging of polarizing and non-polarizing tweets in the same data. To confirm this, we ran regressions on the subset of negatively valanced tweets and separated the effects for polarizing and neutral tweets. As is clear in Figure-7, extremely negative tweets are suppressed in normal everyday discussions and shared greatly in the polarizing political discussions. Since, our dataset has an overrepresentation of political tweets (see Table-6), the effects are *pulled* in their direction. This outcome indicates the presence of a possible three-way interaction between sentiment, valence, and discourse context, something we did not originally hypothesize. The interaction was not significant for speed.

To summarize, our results indicate partial support for our main hypothesis that sentiments have strong curvilinear effects, which interact with other constructs.

	range	**scale**	**speed**
polarity	0.106***	-0.098***	42.32***
	(0.015)	(0.002)	(1.193)
polaritySquared	-0.012***	0.055***	-9.453***
	(0.00257)	(0.000)	(0.228)
discourseContext	0.343***	0.121***	-60.70***
	(0.016)	(0.003)	(1.011)
discourseContext# polaritySquared	-0.071***	-0.060***	1.250 ***
	(0.001)	(0.000)	(0.080)
negativeValence	0.028	0.016***	10.925***
	(0.198)	(0.003)	(1.436)
positiveValence	0.243***	0.443***	6.406***
	(0.197)	(0.003)	(1.470)
negativeValence # polaritySquared	-0.004**	-0.007***	-0.876
	(0.002)	(0.000)	(0.165)
positiveValence # polaritySquared	-0.003	-0.01	-0.25
	0.002	0.000	(0.165)
	(0.003)	(0.000)	(0.187)
_cons	-0.878***	3.426***	11.79***
	(0.027)	(0.004)	(1.891)
N	94186	94186	45814
adj. R^2			0.076

pseudo R^2	0.166	0.408	

Table 5. Moderating Effect of Discourse Context

Note: Estimates of control variables have been suppressed due to space considerations. No discernible differences were noted in the effect of controls.

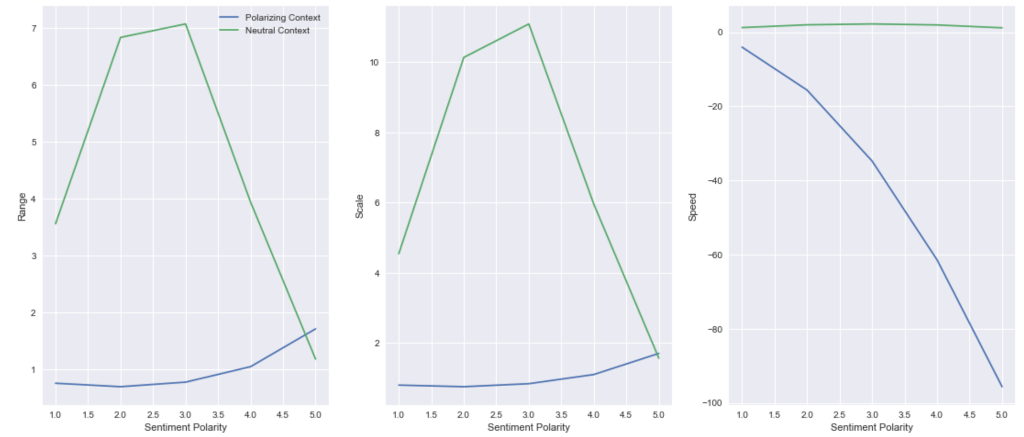

Figure 5. Moderating Effect of Discourse Context

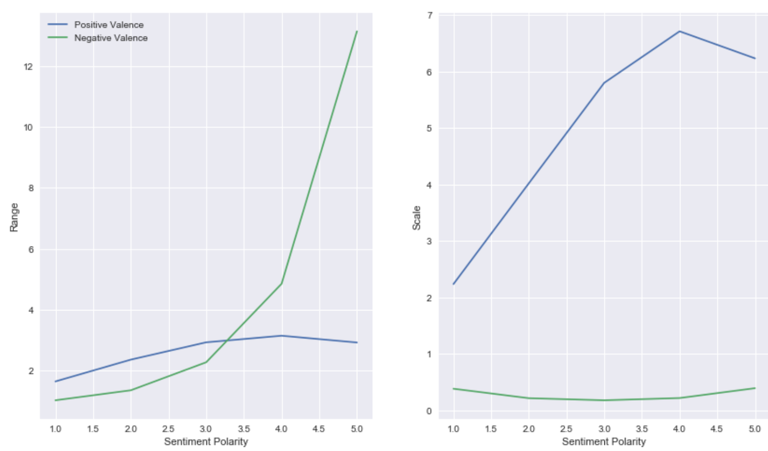

Figure 6. Moderating Effect of Sentiment Valence

Valence	Neutral Tweets	Political Tweets
Mixed	18326	20202
Positive	12555	7670
Negative	27767	7666

Table 6. Distribution of Negative and Positive Tweets Across Discourses

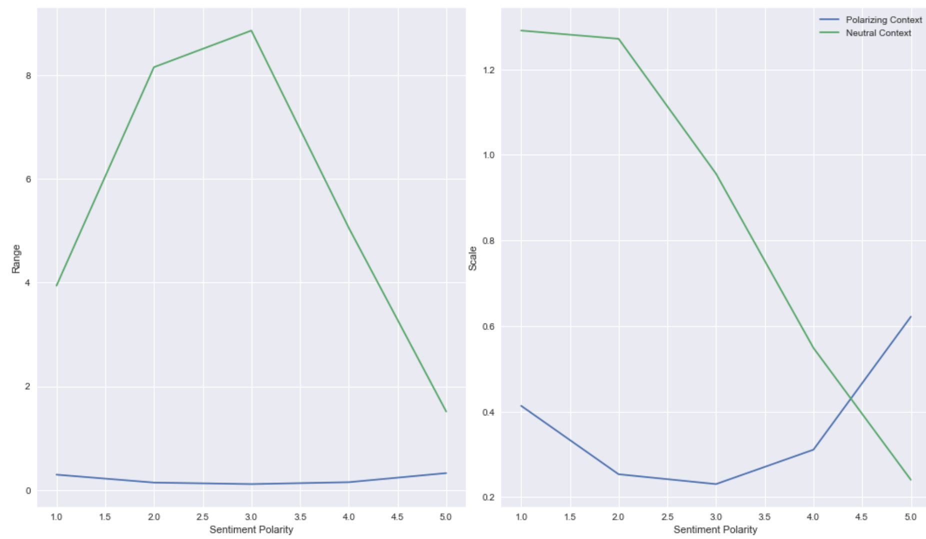

Figure 7. Three-way Interaction of Sentiment, Valence, and Discourse

Conclusion

Discussion

Microblogging uses the power of platform technologies to enable a connected world where content sharing is easier than ever. A quick retweet on Twitter is all it takes for information, opinion, and news to travel long distances. Our paper is an investigation into the role that emotions play in this practice. This is an interesting question for IS scholars, because how moods and emotions spread via computer-mediated textual communication has implications for theory. Current literature posits that strong emotions will lead to more diffusion (Stieglitz and Dang-Xuan 2013). Our paper argues and shows, partially, that there are boundary conditions and heterogenous effects in this relationship that previous studies have not addressed. Hypothesizing about these boundary conditions enabled us to a) explore a new mechanism that mediates how emotional content diffuses among micro-bloggers and b) examine the interaction of related constructs.

Three theoretical contributions emerge from our results. First, our theorizing suggests the need to include additional signals that are involved in emotional discourse on Social Media platforms. Existing explanations for diffusion of emotional SM content use Berger's (2011) psychological arousal to argue that strong emotions contain arousing signals that can activate users. Our theorizing and results indicate the presence of additional signals that can result in unexplained outcomes. When SM content contain extremely strong emotional material, it can signal that the blog's author has personal and emotional bias. It can signal a lack of effort on part of the blog's author, who composed the text in a hyper-excited state of mind (Yin et al. 2017). The inclusion of other signals allows us to show that at extreme levels emotions may produce counter-intuitive results.

Second, our study also indicates that the need to incorporate a more agentic perspective of SM users. By using psychological arousal as a mechanism, the SM user is conceptualized as a reactive actor who responds to emotional stimuli with sharing behaviors. Our results indicate that SM users exercise agency in their decision of sharing emotional content. This is in line with what scholars in the communication literature have argued about how SM's publicly visibility merges multiple contexts into one and forces the user to choose agency over arousal (Marwick and Boyd 2011). A third theoretical contribution of our study is that it foregrounds how norms for emotional communication differ across different contexts.

Finally, this study makes a modest attempt to open a communication channel between two separate streams of IS research - SM and Online Reviews. Albeit with different orientations, both streams of literature are interested in studying, among other questions, the role of emotions in digitally-mediated textual communication (Stieglitz and Dang-Xuan 2013; Yin et al. 2021). Yet, these research streams do not traditionally communicate. By showing that extremely strong sentiments can produce counterintuitive results, a result already shown by Online Reviews studies (Yin et al. 2017, 2021), our findings show consistency of outcomes across both these research streams. In doing so, our hope is to take a first step towards building a stream-agnostic cumulative tradition of IS research on emotions in online communication (Tiwana and Kim 2019).

This paper also helps inform practice. The popularity of microblogging platforms attracts multiple stakeholders - from small-time content creators to global firms and from fledgling non-profits to established political organizations. These stakeholders use these websites as a valuable organizational resource, one they use to engage with existing users as well as acquire new ones. How emotions relate to ID is also important for these stakeholders. Indeed, the use of emotions in microblogging, and other types of content, is conspicuous. Political parties make appeals based on emotions such as fear and anxiety (Brader 2006). Seekers of crowdfunding (such as those seeking funds for medical assistance) use tragic emotions to convince people to donate as well as share their message further (Xu and Wang 2020). YouTube channels use terms such as "DESTROYED" "AGHAST" to garner eyeballs. A better understanding of emotions in digital communication will enable these stakeholders to extract greater value from SM use.

Limitations and Future Directions

Our study is not without limitations. First, we relied on observational data without a strong identification technique. Therefore, we are limited in our ability to make causal claims about our relationship of interest. This, however, opens new avenues for future research which, following recent scholars (Yin et al. 2021), can work towards establishing causal linkages between emotions in online communication and ID. Second, given that gold standards for emotion detection, human raters, are difficult to employ on large datasets, we suffer from the limitations of automated sentiment detection. Finally, our research does not theorize about discrete emotions (such as anger, anxiety, happiness). As emotion theorists have noted different emotions may have different effects on behavior in interpersonal communication (Kleef 2009).This leaves room open for further research to theorize and test the effect of discrete emotions.

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