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Title: How Do Explicitly Expressed Emotions Influence Interpersonal Communication and Information Dissemination? : A Field Study of Emoji's Effects on Commenting and Retweeting on a Microblog Platform

Year: 2016

Version: Published version

Summer 6-27-2016

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HOW DO EXPLICITLY EXPRESSED EMOTIONS INFLUENCE INTERPERSONAL COMMUNICATION AND INFORMATION DISSEMINATION?

A FIELD STUDY OF EMOJI'S EFFECTS ON COMMENTING AND RETWEETING ON A MICROBLOG PLATFORM

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Abstract

The proliferation of microblogs greatly facilitated interpersonal communication and information diffusion. Prior studies mainly examined effects of user and network characteristics on information diffusion. In this study, we examine how explicitly expressed emotions through emojis influence commenting and retweeting, two types of interactions enabled by microblogging platforms. While existent research largely focused on retweeting, we also take commenting into consideration. A distinction is made between commenting and retweeting, since commenting is more related to interpersonal communication, and retweeting is more related to information diffusion. Hypotheses are tested using data from a leading microblogging platform in China. The results show clear differences between emoji's effects on commenting and retweeting. Overall speaking, messages with more emojis receive more comments but less retweets. Specifically, positive emojis increase the number of comments, but decrease the numbers of retweets. Similarly, negative emojis increase the number of comments, but decrease the numbers of retweets. Our findings suggest explicitly expressed emotions have different influences on interpersonal communication and information diffusion. Hence, the use of emojis in social media communication shall be catered in order to achieve desired effects.

Keywords: Microblog, Emoji, Interpersonal communication, Information diffusion, Retweet, Comment, Emotion.

1 INTRODUCTION

In the recent decade, social media platforms such as microblogs have experienced significant growth. For example, founded in 2006, Twitter (NYSE: TWTR) has around 320 million monthly active users, and more than 500 million tweets were sent per day as of December 2015 (Twitter 2015). The total revenue in 2015 exceeded $2.2 billion. Weibo.com (NASDAQ: WB), the leading microblog platform in mainland China, also experienced tremendous growth. Weibo's revenue increased from $65.9 million in 2012 to $188.3 million in 2013 and further to $334.2 million in 2014. It had 175.7 million monthly active users and 80.6 million average daily active user in December 2014 (Weibo 2015).

The adoption of social media has tremendously transformed the way people interact with each other, the way they distribute and gather information. Considering the significant amount of information users generated, it is natural to ask, which messages are more likely to elicit others' responses, which messages are more likely to be further diffused?

Prior studies addressed these questions mainly through examining the effects of user characteristics and certain message characteristics. For example, user characteristics such as a user's number of followers, and Twitter account registration time were found to influence the number of retweets (Bakshy et al. 2011; Suh et al. 2010). Message characteristics such as the inclusion of URLs, the quantity of topics embedded, and the number of mentioned others @ were also found to influence the number of retweets (Yang and Counts 2009).

In this study, we examine the effects of explicitly expressed emotions through emojis in tweet message on the responses elicited. Specifically, we examine how emoji emotions (positive, neutral, and negative) embedded in tweet messages influence commenting and retweeting behaviours, in terms of the number of comments or retweets elicited by the original tweet. We consider both commenting and retweeting, as they are two important microblogging features related to social interactions. In the meantime, a distinction is made between commenting and retweeting, since commenting is more related to interpersonal communication, and retweeting is more related to information diffusion.

The research is carried out in the context of social media communication on a leading microblog platform in China. We focused on 367 crowd funding project initiators as seed users, and collect 556,419 original tweets, from their respective microblog registration date till October 31 2014. We further collected 7,842,256 corresponding retweets and 3,738,723 corresponding comments of the original tweets. The hypotheses are tested through OLS regression models, and negative binomial regression models are used for robustness check. Since there are factors other than emojis which may influence retweet and comment, we also controlled for user characteristics and message characteristics.

The results showed that explicitly expressed emotions indeed influence readers' responses to tweet messages. Overall speaking, messages with more emojis tend to receive more comments, but less retweets. Specifically, positive emojis increase the number of comments, but decreases the numbers of retweets. Similarly, negative emojis increase the number of comments, but decrease the numbers of retweets. Our findings suggest explicitly expressed emotions have different influences on interpersonal communication and information diffusion. Explicitly expressed emotions are more likely to elicit interpersonal communication through comments, but decreases retweet. To practitioners, our findings may help them cater their messages to either attract comments or effectively diffuse information.

The paper is organized as follows. In the next section we review related literatures regarding emotions' effects on social sharing, and information diffusion on social media platforms. We then lay out the theoretical backgrounds and develop hypotheses. The subsequent section describes the research methodologies, including data collection, sampling strategy, and model testing strategy. Results are then discussed, followed by a discussion of contributions from both theoretical and practical perspectives, limitations and potential future research questions.

2 RELATED LITERATURE AND RESEARCH GAP

2.1 Emotions and Sharing

The theoretical foundation of this study is related to the literature of emotion's impacts on social sharing and information diffusion. Researchers has been examining emotion related sharing in offline settings (Luminet et al. 2000; Rime 2009). Berger (Berger 2011) examined the impact of emotion valence and arousal on social transmission of information, and found that after watching videos which contained emotions that could trigger high arousal (e.g. anxiety or amusement), participants are more likely to share a piece of news with others. Kim, Kashima and Clark (Kim et al. 2009) showed that participants were more willing to share social anecdotes that of high or medium emotionality than that of low emotionality, and more willing to pass on anecdotes that trigger surprise and contempt than anecdote that triggers sadness. Luminet and colleagues (Luminet et al. 2000) found participants who watched excerpts with intense emotions did more social sharing comparing to those who watched non emotional or moderate emotion excerpts.

In addition to the above experimental studies conducted with student participants, social media enabled scholars to examine the effects of emotion in other settings. In a large field experiment conducted on Facebook, through manipulating news feeds, Kramer, Guillory and Hancock (Kramer et al. 2014) found people's sharing are influenced by the news feed they read, and when positive content was reduced from the news feed, people's own status updates became more negative. But this study did not examine how users will interact with the original post.

2.2 Information Diffusion on Social Media

Another stream of research specifically examined information diffusion on social media such as Twitter. Studies in this stream addresses questions such as which messages will be retweeted, who are the popular micro bloggers (Bakshy et al. 2011; Ghosh et al. 2012; Suh et al. 2010; Weng et al. 2010; Wu et al. 2011). Suh and colleagues (Suh et al. 2010) gathered 74 million tweets and tried to identify factors that influence retweets. They noted URLs and hashtags contained in a tweet message significantly increases the quantity of retweets the message receives. User characters, such as the number of followers, followees, and the age of the account also influences the quantity of retweets the message receives. Bakshy and colleagues (Bakshy et al. 2011) also found tweets from users who have a large number of followers, and tweets with interesting URLs are more likely to diffuse. Weng, Lim, and Jiang (Weng et al. 2010) developed an algorithm to identify influential Twitter users, called TwitterRank, and measured influence considering topic similarity between users and the link structure. Diakopoulos and colleagues (Diakopoulos et al. 2012) tried to develop new methods for filtering and assessing the information sources for news events. Researchers (Ghosh et al. 2012; Pal and Counts 2011) also investigated how to identify influential users in specific topic areas. Wu and colleagues (Wu et al. 2011) examined 260M tweets that contained bit.ly URLs, and found a great concentration of attention on Twitter, around 50% of URLs are generated by just 20K influential users. Hong, Dan and Davision (Hong et al. 2011) tried to predict whether a message will be retweeted or not, and the volume of retweets. They considered message topic, temporal information, and structural properties of the users' social network.

Though emotions are important in interpersonal interactions, to the best of our knowledge, there are few studies focusing on the effect of emotions on retweeting and commenting, though the relationship is theoretically and practically interesting. One exception is Stieglitz and Dang-Xuan (2013), they examined how tweet's sentiment influence information diffusion in the context of political communication. They found Twitter messages with negative or positive emotions are retweeted more often and more quickly as compared to messages with neutral emotions. In this study, we would like to examine the effects of emotions on retweeting and commenting, controlling for user characteristics as well as other message characteristics.

2.3 Emotions Expressed through Emojis

In the current study, we focus on emotions explicitly expressed through emoji. Emoji were first used by Japanese mobile operator NTT Docomo. The Japanese word “emoj” literally means “picture” (e) and “character” (moji). Besides expressing emotions through words, users can use emoji images to express emotions. Adoption of emojis in social media communication becomes popular world widely. In 2015, the Emoji  is chosen to be the Oxford Dictionaries Word of the Year “as the ‘word’ that best reflected the ethos, mood and preoccupations of 2015”(Oxford Dictionaries 2015). On Weibo, the leading Chinese microblog platform, emojis are also frequently used. Figure 1 illustrates some of the emojis available on Weibo.

Emojis enable users to express emotions conveniently, in a vivid manner, and can be an important component in sentence formation (Amaghlobeli 2012; Miyake 2007). Though linguists and culture researchers have been examining emoji and recognized its significant role in social media communication, to our knowledge, no study investigated the effects of emotions expressed through emojis on interpersonal communication and information diffusion. Furthermore, while prior studies mainly focused on retweets (Hong et al. 2011; Kupavskii et al. 2012; Stieglitz and Dang-Xuan 2013), we also consider commenting, as we argue the psychological motivations underlying these two behaviours are different, and hence emotions can influence commenting and retweeting in different manners.

Figure 1. Examples of emojis available on Weibo, a leading Chinese microblog platform

3 HYPOTHESES DEVELOPMENT

3.1 Differences between Comments and Retweets

At a glance, both comments and retweets are responses to a tweet. Yet they are different in terms of microblog feature and the nature of interactions. First, as microblog technical features, comments and retweets are different in their user interfaces design. When commenting, the comment appears only below the original tweet, and does not appear on the page of the commenter. Readers will not be able to read a comment unless they visit the page of the original tweeter, click and expand the comments below the focal tweet. When retweeting, the original tweet, together with new information added by the retweeter, will appear on the retweeter's page.

Furthermore, the interaction natures for commenting and retweeting are different. Commenting is commenter's response to the original tweet, and the commenter does not mean to further disseminate the comment nor the original tweet. Commenting are basically conversations among the original poster and the commenters, happened on the poster's microblog page. But retweets of the original message are easily accessible to, or actually meant to be read, by the followers of the retweeter. In this way, through retweeting, the information in the original tweet is purposely spread to others. Retweeting is thus more related to information dissemination.

To better explain the differences between commenting and retweeting, we illustrate with a real example from Weibo. On Oct 21, 2015, Apple's CEO Tim Cook visited China and he posted on Weibo, "Happy to be back in China! Started at dawn with a hike along the Wall on Chongyang Festival. Simply breathtaking."

The screen capture on the left shows the interface for commenting. Comments created are appended below Cook's original tweet, but not displayed on the commenters' pages. Commenters are talking to Cook, instead of disseminating information to the public. For example, one of the commenter asks Cook, "Why did you visit China so frequently?" Comments can thus be considered as interpersonal communications.

The screen capture on the right is the interface for retweeting. When retweeting, a pop up window appears, the retweeter can choose to add his/her own texts in addition to Cook's original tweet, and the retweet together with the original tweet will appear as a new tweet on the retweeter's page. In this way, retweeter further circulates the information. For example, one retweeter addresses the public, "Cook comes to China again, guess what he is doing this time?" This message, together with Cook's original tweet, appears on the retweeter's page. Retweeting is more related to information dissemination.

While commenting is more about interactions between specific individuals, retweeting is designed to address a larger audience group. Retweeting also associates one's own image with the original tweet, and retweets reflect retweeter's personal attitudes and tastes. Taking into considerations the differences between these two ways of responding, we develop hypotheses regarding commenting and retweeting respectively.

Figure 2. Illustration of commenting and retweeting, screen captures from Weibo

3.2 Explicitly Expressed Emotions and Their Effects on Commenting and Retweeting

Emotions may trigger higher level of cognitive involvement. Previous research has found that emotion words are associated with enhanced attention. For example, using Electroencephalogram (EEG), Kissler and colleagues (Kissler et al. 2007) noted emotion words elicited more brain responses in predominantly left occipito-temporal areas and were also better remembered than neutral words. Certain kinds of emotion (e.g. anxiety or amusement) may also trigger higher physiological arousal, i.e. activation of the autonomic nervous system (Heilman 1997), and when people are in the state of arousal, they are more active, and more likely to share (Berger 2011). Hence we propose that, overall speaking, messages containing emojis will be more likely to draw reader's attention and lead them to higher arousal, and thus more likely to receive comments and retweets.

H1. Controlling for the other factors, a tweet message which contains emoji receives more comments comparing to a tweet message which does not contain any emoji.

H2. Controlling for the other factors, a tweet message which contains emoji receives more retweets comparing to a tweet message which does not contain any emoji.

In addition to examine the overall effect of emojis, we further distinguish between the valences of emoji emotions. The emotions expressed through emojis are classified into positive, negative, and neutral. Some studies considered positive and negative emotions in tweet messages, e.g. (Stieglitz and Dang-Xuan 2013), and we note emojis can also express neutral or ambivalence emotions. Details of the classification scheme are discussed in the methodology section.

We reason that, when a user expresses positive emotions in a tweet message, he/she is publicly sharing joy. Readers, who are most likely his/her direct followers, will offer affirmation and echo his/her joy through commenting. An offline analogy scenario can be, friends applauding for one who shares with his/her friends about recent achievements with a happy smile. We thus hypothesize:

H3. Controlling for the other factors, a tweet message which contains more positive emojis receives more comments than a tweet message which does not contain any emoji.

When a user publicly expresses negative emotions in a tweet message, he/she is seeking social support. His/her direct followers are likely to offer comfort and encouragements through commenting. Therefore, we develop the following hypothesis:

H4. Controlling for the other factors, a tweet message which contains more negative emojis receives more comments than a tweet message which does not contain any emoji.

Regarding retweeting, we argue that users are willing to diffuse positive emotions, but reluctant to diffuse negative emotions. Retweets will appear on the retweeter's personal page, i.e., the retweets are then visible to the public from the retweeter's page, and the followers of the retweeter will most likely read the retweet. In this way, when retweeting a message, the retweeter is associating his/her own image with the message Retweeting message with negative emotions may make others think the retweeter is pessimistic or passive, and users will avoid to retweet posts with negative emotions, because they are concerned of how others will perceive them and will try to manage the impression they leave on others (Krämer and Winter 2008; Leary and Kowalski 1990; Rosenberg and Egbert 2011).

H5. Controlling for the other factors, a tweet message which contains more positive emojis receives more retweets than a tweet message which does not contain any emoji.

H6. Controlling for the other factors, a tweet message which contains more negative emojis receives fewer retweets than a tweet message which does not contain any emoji.

4 METHEDOLOGY

4.1 Research Context

The study is carried out using data from Weibo, a leading Chinese microblog platform. Its functionalities are similar to Twitter, including tweeting, retweeting and commenting (we used Twitter terms to ease the communication).

There are subtle differences between the retweeting features of Twitter and Weibo. Previously on Twitter, users need to manually edit a message and add @ when retweeting. Weibo provided the retweeting "button" much earlier than Twitter.

Weibo offers different sets of emojis. We consider 73 emojis which are available since the early stage of Weibo platform development. The emojis appear on the very first page of emoji selection and are frequently used.

We chose a group of microblog users as our seed users, they are crowdfunding project initiators. Microblogging platform allows crowdfunding project initiators to reach the public, and many have microblogging pages.

In this study, we sampled all crowdfunding project initiators who finished their funding campaign on a leading crowdfunding platform in mainland China from September 1, 2011 to October 1, 2013 and who have a microblog account. This yields a sample of 367 users. We then collected all the tweets since their respective microblog registration date till October 31, 2014, and in total there are 556,419 original tweets. For all these tweets, we collected all the corresponding retweets and comments, and in total there are 7,842,256 retweets and 3,738,723 comments. We also collected user information such as the number of followers and followees, the geographic location of the user, and microblog registration date. A dataset is constructed to test the hypotheses, and below we discuss the measurements.

4.2 Measurements

4.2.1 Dependent Variables

In order to investigate how the usage of emoji with embedded emotion influence users' behaviour on Weibo, we evaluate the outcome from the number of response. We distinguish between comments and retweets. Thus in all we have the following dependent variables:

- *CmtTotal* is the total number of comment a tweet receives.
- *RtwtTotal* counts the total number of comment a tweet receives.

4.2.2 Independent Variables

Variables of main interests are emotions through emoji usage.

- *TwtHasEmoji* indicates whether a tweet message contains emoji. 1 indicates the tweet message contains emoji, 0 indicates the tweet message does not contain any emoji.
- *TwtEmojiPos, TwtEmojiNeg, TwtEmojiNeu* are measured to distinguish different embedded emotions via emojis. Besides the total number of emojis used in focal tweet, we are interested in the different emotions embedded in emoji. We classified the emojis into 3 categories, positive, negative and neutral emotion.

For classification of emojis, three PhD students independently classify the emojis into positive, negative and neutral group. They are asked to classify each emoji into the most proper category. In the final classification scheme, 21 are classified as positive emotions, 25 are negative, and 27 are neutral. Examples of positive emotions are smile, love, examples of negative emojis are disappointed, sad, and examples of neutral emojis are think, shy, yawn.

4.2.3 Control Variables

Besides the variables of interests, we also controlled for other factors that may have influence on comments and retweets. Previous studies have shown that the inclusion of URLs, the quantity of topics embedded will influence retweet behaviours (e.g. Bakshy et al. 2011, Yang and Counts 2009). In addition, a user's number of followers, registration time were also found to influence retweets (e.g. Suh et al. 2010). We controlled for both tweet related factors and user related factors.

Tweet related factors:

- *TwtLength* length of a tweet message in terms of characters, emoji (s) is excluded from this length.
- *TwtHasURL* whether the tweet contains URL. 1 indicates the inclusion of URLs, and 0 indicates no URL in the tweet.
- *TwtMentd* measures the number of mentioned usernames in a tweet, e.g. @username. The @ used for making a retweet is excluded.
- *TwtTopic* counts the number of topics, i.e. hashtags ## in a tweet.
- *TwtWbLife* is the Unix timestamp difference between the time the specific tweet was created, and the tweeter's microblog registration time. The Unix timestamp uses 1970-01-01 00:00:00 UTC as reference point, and describes the number of seconds that have elapsed since the reference point. *TwtWbLife* captures at which stage of the specific users' microblog development. A small number indicates the tweet was sent when the microblog was newly created, and a larger number indicates the tweet was sent when microblog has been created for some time.

User related factors:

- *WbFans* captures the number of Weibo fans/followers a user has on the date which the tweet was posted.
- *WbPopDif* is popularity index, calculated as the number of followers / the number of followees.
- *WbProvince* is user's geographic location, an integer indicating in which province the user is. There are 31 different geographic provinces in the sample.

Table 1 presents a summary of the descriptive statistics of the variables.

Variable	Mean	Std. Dev.	Min	Max
CmtTotal	6.72	155.58	0	91166
RtwtTotal	14.09	131.54	0	40604
TwtEmojiTotal	0.15	0.65	0	69
TwtEmojiPos	0.09	0.45	0	45
TwtEmojiNeg	0.03	0.36	0	69
TwtEmojiNeu	0.03	0.25	0	39
TwtLength	3.34	1.1	0	6
TwtURL	0.16	0.37	0	1

TwtMentd	0.35	1.38	0	31
TwtTopic	0.14	0.41	0	11
WbFans	32565.6	104062.2	0	772091
WbPopIndex	726.04	6616.72	0	97428
TwtWbLife	56100000	30900000	11	139000000

Table 1 Descriptive Statistics

5 HYPOTHESES TESTING

5.1 Data Analysis

To test the hypotheses, we used OLS with clustered standard errors to control for potential heteroscedasticity. The dependant variables are the total number of comment a tweet received, and the total number of retweets a tweet received. Since the dependent variables *CmtTotal, RtwtTotal,* and certain control variables *TwtLength*, *WbFans, TwtWbLife* are overly dispersed, we log-transformed them before employing the OLS regression. Log transformation is commonly used technique when the variables are overly dispersed (Stieglitz and Dang-Xuan 2013). Model (1) is used for testing the overall number of contains emoji or not, model (2) is for testing effects of positive and negative emojis.

(1)

$$Log(DV) = \beta_0 + \beta_1{*}TwtHasEmoji + \beta_2{*}\,\mathrm{Log}\,(TwtLength) + \beta_3{*}\,TwtURL + \beta_4{*}TwtMentd + \beta_5{*}TwtTopic + \beta_6{*}Log(WbFans) + \beta_7{*}WbPopIndex + \beta_8{*}Log(TwtWbLife) + \beta_k{*}k.Dummy(WbProvince) + \varepsilon$$

(2)

$$Log(DV) = \beta_0 + \beta_1{*}TwtPosEmoji + \beta_2{*}TwtNegEmoji + \beta_3{*}TwtNeuEmoji + \beta_4{*}\,Log(TwtLength) + \beta_5{*}\,TwtURL + \beta_6{*}TwtMentd + \beta_7{*}TwtTopic + \beta_8{*}Log(WbFans) + \beta_9{*}WbPopIndex + \beta_{10}{*}Log(TwtWbLife) + \beta_k{*}k.Dummy(WbProvince) + \varepsilon$$

In the regression analysis, we used clustered robust standard errors, because it is more suitable for the data. The usual assumption is that ε_{ij} is independently and identically distributed. But this assumption is violated when the observations have groups. Observations within group i are correlated, inducing correlation in ε_{ij} within group i. In our sample, all the original tweets are from 367 users, and the tweets from the same user are correlated in some way, i.e. the ε_{ij} for tweets from a specific user i correlates in some way. The clustered error takes this into account.

Usage of a large sample may dramatically reducing the p value and bolstering the significance level of the results (Guo et al. 2014). This concern is alleviated, as we use clustered errors, the degree of freedom is calculated based on the number of users, i.e. 367, instead of the number of tweets, i.e. 556,419. This eliminate the problem of artificially increase the significance level of the results.

Specifically, using clustered robust standard errors, testing the effect of TwtHasEmoji on the number of comments, we compare the baseline model and the model with TwtHasEmoji.

Baseline Model

$Log(CmtTotal) = \beta_0 + \beta_1 * \text{Log}(TwtLength) + \beta_2 * TwtURL + \beta_3 * TwtMentd + \beta_4 * TwtTopic + * Log(WbFans) + \beta_6 * WbPopIndex + \beta_7 * Log(TwtWbLife) + \beta_k * k.Dummy(WbProvince) + \varepsilon$

Model with *TwtHasEmoji*

$Log(CmtTotal) = \beta_0 + \beta_1 * TwtHasEmoji + \beta_2 * \text{Log}\,(TwtLength) + \beta_3 * TwtURL + \beta_4 * TwtMentd + \beta_5 * TwtTopic + \beta_6 * Log(WbFans) + \beta_7 * WbPopIndex + \beta_8 * Log(TwtWbLife) + \beta_k * k.Dummy(WbProvince) + \varepsilon$

5.2 Results

For the effect of *TwtHasEmoji* on the number of comments, $F(1, 367) = 9.69$, Prob > F = 0.0020. If using robust errors instead of clustered robust standard errors, we get $F(1, 556380) = 1359.77$, Prob > F = 0.0000. Without clustered error, a larger degree of freedom leads to a much more significant p value. But we use the clustered robust standard errors, they fit the model better, and the p value is more meaningful. We then tested the additional explanatory power of emojis through more model comparisons. For the effects of *TwtHasEmoji* on the number of retweets, $F(1, 367) = 4.01$, Prob > F =0.0459. For the overall effects of *TwtEmojiPos, TwtEmojiNeg, TwtEmojiNeu* on the number of comments, $F(3, 367) = 5.65$, Prob > F = 0.0009, and the overall effects of *TwtEmojiPos, TwtEmojiNeg, TwtEmojiNeu* on the number of retweets $F(3, 367) = 2.42$, Prob > F = 0.0658. Hence, we are confident in the statistical significance of the results. The overall data analysis results based on model (1) and model (2) are summarized in Table 2.

	Log(CmtTotal)	*Log(CmtTotal)*	*Log(RtwtTotal)*	*Log(RtwtTotal)*
TwtHasEmoji	0.163***		-0.156**	
	(0.0523)		(0.0781)	
TwtEmojiPos		0.0425*		-0.0509*
		(0.0231)		(0.0291)
TwtEmojiNeg		0.0604***		-0.0521**
		(0.0201)		(0.0205)
TwtEmojiNeu		0.0867***		-0.0814
		(0.0231)		(0.0565)
Log(TwtLength)	0.196***	0.197***	0.117***	0.116***
	(0.0173)	(0.0174)	(0.0200)	(0.0202)
TwtURL	-0.249***	-0.253***	-0.0532	-0.0491
	(0.0477)	(0.0483)	(0.0595)	(0.0594)
TwtMentd	0.0521*	0.0532*	0.0614	0.0608
	(0.0307)	(0.0306)	(0.0399)	(0.0398)
TwtTopic	-0.0543	-0.0553	0.163**	0.164**
	(0.0548)	(0.0548)	(0.0729)	(0.0729)

Log(WbFans)	0.0949***	0.0949***	0.151***	0.151***
	(0.0198)	(0.0198)	(0.0265)	(0.0265)
WbPopIndex	3.20e-06	2.95e-06	1.25e-05*	1.27e-05*
	(6.09e-06)	(6.04e-06)	(6.95e-06)	(6.93e-06)
Log(TwtWbLife)	0.280***	0.282***	0.200***	0.198***
	(0.0336)	(0.0336)	(0.0376)	(0.0376)
Constant	-9.800***	-9.900***	-10.24***	-10.17***
	(2.473)	(2.478)	(3.124)	(3.120)
Number of Users	367	367	367	367
R-squared	0.272	0.271	0.424	0.424

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Due to limited space, the coefficients for the dummies variables of the geographic provinces are not included in the table.*

Table 2 Regression Results

Containing emojis has a significant positive effect on the number of comments received, H1 receives support. But containing emojis has a significant negative effect on the number of retweets received, this result is opposite to H2. The negative effect seems to suggest, containing emojis does not help with the information value of the tweet, and since retweet is more about information dissemination, users may thus be reluctant to retweet a message with emojis comparing to retweet a message without emojis, given all other factors equal.

When examining the specific emoji valence, the effects of positive emojis are marginally significant for the number of comment, and H3 receives partial support. Containing positive emojis has a marginal negative effect on the number of retweet, which is opposite to H5. This result suggests, containing positive emojis makes users less likely to retweet a message. This might be explained by the reasons that retweet is more related to information values in a tweet, instead of information contained. Containing negative emojis has a significant positive effect on the number of comments, H4 receives support. Containing negative emojis has a significant negative effect on the number of retweets, H6 receives support. Overall, the results clearly demonstrate the differences between the effects of emojis on interpersonal communication through commenting, and the effects of emojis information dissemination through retweeting.

Hypotheses	**Results**
H1 Has emoji (vs. no emoji) has a positive effect on the quantity of comment	Supported
H2 Has emoji (vs. no emoji) has a positive effect on the quantity of retweet	Opposite
H3 # of positive emoji has a positive effect on the quantity of comment	Partial support
H4 # of negative emoji has a positive effect on the quantity of comment	Supported
H5 # of positive emoji has a positive effect on the quantity of retweet	Opposite
H6 # of negative emoji has a negative effect on the quantity of retweet	Supported

Table 3 Hypotheses Testing Results

6 DISCUSSION

This paper examined how explicitly expressed emotions through emojis influence users responding behaviours. The hypotheses are tested using data from a leading microblogging platform, with 556,419 original tweets from 367 users, 7,842,256 corresponding retweets and 3,738,723 corresponding comments of the original tweets. We found that, overall speaking, messages with emojis tend to receive more comments, controlling for other factors. But contrary to H2, messages with emojis tend to receive less retweets comparing to messages without emojis, controlling for other factors. Specifically, positive emojis increase the number of comments but decrease the number of retweets. Similarly, negative emojis also have different effects on comments and retweets, increasing the number of comments but decreasing the numbers of retweets.

The study extends the existing literature in two ways. Previous research has examined the relationship between emotions and information diffusion in contexts other than social media (e.g., Berger 2011; Luminet et al. 2000). In the social media context, studies about information sharing mainly examined message characteristics such as embedded URL's, topics or user characteristics such as user position in the network, expertise in the topic area (e.g. Diakopoulos et al. 2012; Suh et al. 2010; Weng et al. 2010). Relatively few studies examined emotional aspects. Furthermore, emotions in tweet message are mainly captured through sentiment analysis. Instead, we focused on emotions explicitly expressed through emojis, not only because emojis are widely used in social media communication, but also because emotions expressed through graphics are vivid and explicit, and it is worthwhile to examine their effects.

Our findings regarding emotions' different effects on commenting and retweeting also suggest it is necessary to distinguish between these two behaviours when discussing information diffusion and users responding behaviours. To the best of our knowledge, few studies investigated commenting together with retweeting, though they both are important microblog features. Most social media studies focus on retweeting (e.g. Hong et al. 2011; Stieglitz and Dang-Xuan 2013; Suh et al. 2010) as it is directly related to information diffusion. We also consider commenting behaviours, because commenting is an important aspect of interaction among users on microblogs, which facilitates mutual understanding and relationship building.

We noted that the findings regarding negative emotions are different from prior studies. For example Berger (2011) showed negative sentiment increased retweet amount. Stieglitz and Dang-Xuan (2013) carried the study in the context of political communication on twitter. Arguably, people can be so closely associated with certain political ideologies or parties, that they are willing to diffuse even negative sentiments as long as the original tweeter is from the specific party or hold similar ideologies. In our context, the crowd funding initiators are not political figures, and the communication is not related to politics. Negative emotions decreased retweet amount in our context. This suggests it is important to consider contextual differences.

The focus of this study is expressed emotion through emoji, but it is worthwhile to take a look at the effects of the control variables. The results help us gain understanding about the tweet and user features which influence user responses. For users who have more followers, their tweets receive larger number of comments and retweets. The length of a tweet message has positive effect on both the number of comments and retweets. Interestingly, the URL contained reduces the number of comments, and has insignificant effects on retweeting. The topic included has a positive effect on the number of retweets, but insignificant effects on the number of comments. Future studies may further examine their effects on communication in social media.

The study also has implications for practitioners. Our findings suggest that microblog users shall cater the use of emoji to their desired diffusion effects in social media communication. They can potentially elicit users to interact with them through commenting with embedded positive and negative emojis. The quantity of comments can be increased. But using emojis to trigger information diffusion through retweets is more challenging. Positive emojis have insignificant impact on retweets, and negative emojis deters retweets.

The study is also subject to limitations. In this study we focused on emotions explicitly expressed through emojis. Sentiment analyses of tweet message contents can offer more information about emotions embedded in messages. We only considered the emotion valence of emoji, i.e., positive, neutral, or negative. There can be other aspects which may also influence user responses. Future research can extend our work by incorporating other aspects of emotions such as arousal.

7 CONCLUSION

Social media plays an important role in nowadays society. In this study, we investigate the impact of explicitly expressed emotions through emoji on commenting and retweeting behaviours. The study provides new insights about emotions' effects on user interactions and information diffusion. The findings also have practical implications for general microblog users as well as entrepreneurs who use social media platform for marketing.

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