International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:10, No:8, 2016

Emotions and Message Sharing on the Chinese Microblog

Yungeng Xie, Cong Liu, Yi Liu, Xuanao Wan

Abstract**—**The study aims to explore microblog users' emotion expression and sharing behaviors on the Chinese microblog (Weibo). The first theme of study analyzed whether microblog emotions impact readers' message sharing behaviors, specifically, how the strength of emotion (positive and negative) in microblog messages facilitate/inhibit readers' sharing behaviors. The second theme compared the differences among the three types of microblog users (i.e., verified enterprise users, verified individual users and unverified users) in terms of their profiles and microblog behaviors. A total of 7114 microblog messages about 24 hot public events in China were sampled from Sina Weibo. The first study results show that strength of negative emotions that microblog messages carry significantly increase the possibility of the message being shared. The second study results indicate that there are significant differences across the three types of users in terms of their emotion expression and its influence on microblog behaviors.

Keywords**—**Microblog, emotion expression, information diffusion.

I. Introduction

MICROBLOGS are the very widely used social networking platforms for users to share thoughts, express attitudes, look for news, chase idols, and so on. The most popular and earliest microblog in the English language is Twitter, which now has over 600 million registered users since its launch in 2006. Microbloggers can write a short message less than 140 characters and share it with friends, meanwhile, they can also read others' microblogs, make comments, and share them with their own friends. The 140-character feature of micro blogs makes the messages updated and distributed with a very high speed, so microblogs are timely and carry vast amount of information. Researchers are making efforts to mine the information contained in the microblogs, especially the emotions. Twitter emotions may reflect public mood over a period of time, promote the chance of the message being retweeted and shared, increase the popularity of a tweet, be made use of by some influentials to lead the opinions of their followers.

In Asia, microblogs are also widely used in various languages. Sina Weibo is known as the most popular microblog website in China with over 500 million registered users by March 2013. Sina Weibo users are equally or even more active than Twitter users, and the average feeds per day on Sina Weibo is almost 50 times of that on Twitter. See comparisons between Twitter and Sina Weibo in Table I.

On Sina Weibo, users' identities can be classified into verified enterprise users, verified individual users, and unverified users. The verified users are mainly influential individuals or enterprises, including celebrities, business executives, journalists, famous enterprises or institutes. Verified users tend to be more influential on the microblog platforms and their attitudes and advocates are much easier to be distributed.

TABLE I
Twitter and Sina Weibo Statistics by the End of 2013

	Twitter	Sina Weibo
Registered Users	600+ million	500+ million (by Mar 2013)
Monthly Active users	115 million	129 million
Daily active users	0.1 million	61.4 million
Feeds per day	58 million	2.8 billion
Revenue 2013	405 million	188 million
Revenue 2012	259 million	66 million
IPO Date	Nov 2013	Apr 2014

II. Literature Review

A. Emotions and Microblog Behaviors

At the macro level, collective microblog emotions are reflections of public mood over time. It was argued by researchers that tweets can be regarded as microscopic instantiations of mood, and a collection of tweet over a period of time would reflect public mood state and its fluctuations. The public mood on tweeter could be predicted by or even predict the fluctuations of stock market and crude oil price [1]. In the Boolen, Pepe, and Mao study [2], tweets were regarded as temporally-authentic microscopic instantiations of public mood state, and moods in tweets were classified into six dimensions, including tension, depression, anger, vigor, fatigue, and confusion according to the extended version of the Profile of Mood States (POMS) [3]. By comparing the mood analysis results with the fluctuations recorded by stock market and crude oil price indices and major events, it was found that social, political, cultural, and economic spheres have significant effect on public mood.

At the micro level, researchers have explored how emotions expressed in a message could affect the possibility of the message being shared. It was found that the arousal of certain types of emotion could increase social transmission of information [4], [5]. Through the coding of New York Times articles, researchers found that the content that evokes high-arousal positive (e.g., awe) or negative (e.g., anger or anxiety) emotions was more likely to be shared, and the transmission was driven by the level of activation induced. Psychological

Cong Liu is with the Shanghai Jiao Tong University, China (e-mail: 85318772@qq.com).

experiments also suggested similar findings. Arousal-inducing content was shared more than content that does not induce arousal, especially when the induced arousal is negative emotion, such as panics or anxiety. In Dang-Xuan and colleagues' study [6], the authors investigated how Twitter was used for political communication during election periods. The 30 mostly retweeted users during the state parliament election in Germany were analyzed with respect to the emotionality and topics. Results suggest that the emotionality of the political parties or politicians in Twitter messages are correlated with a larger retweet quantity, which implies that expression of emotions in a user's message might be a driver of information diffusion. In the study of Stieglitz and Dang-Xuan [7], it was found that emotionally charged Twitter messages tend to be retweeted more often and more quickly compared to neutral ones. Similarly, Thelwall, Buckley, and Paltoglou explored the relation between microblog emotion and social resonance by analyzing the 30 hottest events and studying whether the attention of event would increase with the increasing strength of emotion [8]. Their results showed that events with high attention usually carry stronger negative emotions.

B. Emotion/Sentiment Analysis Techniques

Sentiment analysis was usually used to automatically analyze sentiment in large amount of online texts, such as Twitter messages. Some sentiment analysis aims to classify the polarity of sentiment (i.e., positive, negative, or neutral), while other algorithms can differentiate the strength of sentiment (e.g., mild and strong) in addition to the polarity.

Full-text machine learning, lexicon-based methods, and linguistic analysis are the three common sentiment analysis approaches. In full-text machine learning, algorithms are trained with a set of human-coded texts with the polarity of sentiment, until it can detect the features of different categories of sentiment with sets of words, word pairs, or word triples. Therefore, the algorithm can then detect sentiment polarity in new texts [9], [10]. The lexicon approach uses the occurrence of lists of pre-coded words in texts to predict their polarity [11]. The linguistic analysis identifies grammatical structures of text such as context, negations, and superlatives to predict the polarity of sentiment. It is usually conjunctly used with the lexicon approach [12].

C. Gaps of Research and Current Study

There are a few research gaps in the existing studies on microblog emotion analysis. First, existing findings only indicate that the strength of emotion relates to the information-sharing behaviors. However, there is a lack in-depth studies on how emotion polarity (i.e., positive emotion or negative emotion) facilitate or inhibit information sharing behaviors on microblogs. Second, it is unclear whether different types of user identities have varieties in their microblog influences and public attention. It is also unknown whether the influentials' emotion expressions in the microblogs are the same with the noninfluentials. Additionally, it is necessary to explore whether the influentials' emotion expression influence their microblog transmission the same way as the noninfluentials. Third, studies in this area were mostly conducted in the western cultures, and it is unclear if the findings can be generated to the Asian context. Finally, previous studies on sentiment mining mostly focus on automated approaches, and the accuracy can be hardly guaranteed. Furthermore, existing sentiment analysis techniques are based on English Sentiment Dictionary such as "SentiStrength", however, there lacks Chinese sentiment corpus or dictionary for classifying sentiment.

Based on the findings in previous studies as well as the existing research gaps, the current study aims to answer the research questions through two themes of studies. The first theme centers around the relation between emotion strength and share count (i.e., retweet quantity in Twitter), and the latter is a key indicator of information diffusion. Specifically, the research questions in the first theme include:

RQ1: How does the strength of positive emotion relate to the share count and comment count?

RQ2: How does the strength of negative emotion relate to the share count and comment count?

In the second theme of study, we will focus on the user identity differences. Because the number of comments received by a microblog is an important indicator of the microblogger's popularity, so both share count and comment count will be studied with respect to its relation with emotion expression. Specific research questions include:

RQ3: What are the differences between verified enterprise users, verified individual users, and unverified users with respect to their profiles (i.e., the number of followers and number of microblogs), popularity (i.e., share count and comment count), and emotion expression (i.e., frequencies of emotion types)?

RQ4: How does the strength of emotion in a microblog related to its comment and share counts among different types of microblog users'?

III. Method

A. Materials

Based on the searching volume on the five major web portals in China (i.e., Sina, Tencent, Sohu, Netease, and People), 24 public event cases were randomly selected from the 300 hottest public events in 2013. Sina Weibo was used as the platform for sampling microblog messages. There are three steps for the message sampling. First, analyze the fluctuation of the daily microblog message volumes from the date of occurrence to the date of sampling for each of the 24 public events. Second, divide the evolution of the public events into four stages (i.e., incubation period, evolution period, outbreak period, and resolution period), and record the total quantity of microblog messages for each stage. Third, sample the microblog messages according to the total quantity of microblog messages in each stage, and make sure that the message proportions of the four stages are consistent between the sampled messages and the entire messages of the event. Approximately 300 microblog messages were randomly sampled for each of the 24 public events, and the final number of the sample microblog messages was 7114.

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:10, No:8, 2016

B. Procedure

Each of the sample messages was coded by 15 trained graduate students in Shanghai Jiao Tong University. Message coding includes emotion polarity, types of emotion, emotion strength, and microbloggers' information. Emotion polarity contains three dimensions, that is, positive emotion, negative emotion, and neutral statements. For negative emotion, detailed types were classified, which includes Panic, Doubt, Anxiety, Objection, Anger, and Sadness. Strengths of the positive and negative emotions were coded into five levels, from very mild to very strong. Neutral statements were not coded with respect to its emotion strength. Microbloggers' information includes the number of followers and number of microblogs he/she had posted. Additionally, for each microblog message, the times of the message being shared (share counts), and the day difference between the date of public event occurrence and date of sampling were recorded.

IV. Results

A. Theme One: Microblog Emotions and Message Sharing

1. Frequencies of Positive and Negative Emotion

Frequency descriptives show that positive emotion takes 4.7% of the coded messages, while negative emotion takes 41.3% of the coded messages. This is to say; there are overwhelmingly more negative emotions than positive emotions in the microblog messages about the hot public events. As shown in Table II, among all types of negative emotions, Anger (12.6%) and Doubt (11.1%) are the dominant emotions and are followed by Sadness (5.6%), Objection (5.1%), Anxiety (3.4%), and Panic (3.3%). Over half of the microblogs (54.0%) are neutral statements.

TABLE II
FREQUENCIES OF NEGATIVE EMOTION

	Types of Emotion	Frequencies
Negative Emotion (41.3%)	Panic	3.3%
	Doubt	11.1%
	Anxiety	3.4%
	Objection	5.1%
	Anger	12.6%
	Sadness	5.6%
Positive Emotion		4.7%
Neutral Statements		54.0%
Total		100%

2. Correlations between Emotion Strength and Share Count

As shown in Table III, correlation analysis between emotion strength and share and count shows that the strength of positive emotion is not significantly correlated to share count (r = .03, p = .659) while the strength of negative emotion is significantly and positively correlated to share count (r = .04, p = .043). That is to say, microblog messages that carry stronger negative emotions are usually shared more frequently than those carry weaker negative emotions, but positive emotion strength may not relate to the frequency of a microblog being shared.

TABLE III
CORRELATIONS BETWEEN EMOTION STRENGTH AND SHARE COUNT

	Share Count
Positive Emotion Strength	.03
Negative Emotion Strength	.04*

Note. * $p < .05$.

3. Regression on Share Count

First, hierarchical regression analysis was conducted on the share count of negative-emotion messages. Control variables include Day Difference, Number of Followers, and Number of Messages; Independent variable is the Negative Emotion Strength. Results (as shown in Table IV) show that Day difference is not significantly related to share count of negative emotion messages (β = -.02, p = .348), Number of Followers is significantly and positively related to share count (β = .13, p < .001), Number of Messages is significantly and positively related to share count (β = .07, p < .001). After controlling the influence of the above variables, Negative Emotion Strength is still significantly and positively related to sharing count (β = .05, p = .040). The R^2 change of the model with the control variables is .023 (p < .001), the R^2 change of the model with the independent variable is 0.001 (p = .040). It means that the control variables explain 2.3% of the variance, while the independent variable explains an additional of 0.1% of the variance.

The results indicate that among the control variables, the more followers the microblogger have, and the more messages the microblogger have posted, the more likely his/her microblog message is to be shared on the microblog. The predictor that is beyond and above these variables regarding the influence on share count is the strength of negative emotion. Regardless of the number of followers and the number of messages posted by the microblogger, the stronger negative emotion his/her message carries, the more likely it is to be shared by other users.

TABLE IV
REGRESSION ON SHARE COUNT OF NEGATIVE-EMOTION MESSAGES

	Predictors	*B*	*SE*	β	*t*
Control Variables	Day Difference	-1.85	1.97	-.02	-0.94
	No. of Followers	0.00	0.00	.13***	6.62
	No. of Messages	0.06	0.02	.07***	3.56
Independent Variable	Negative Emotion Strength	168.09	81.91	.04*	2.05

Note. * $p < .05$. *** $p < .001$.

Second, hierarchical regression analysis was conducted on the share count of positive emotion messages. Control variables include Day Difference, Number of Followers, and Number of Messages; Independent variable is the Positive Emotion Strength. Results (as shown in Table V) show that Day difference is not significantly related to share count of positive emotion messages (β = -.01, p = .793), Number of Followers is not significantly related to share count (β = -.08, p = .176), Number of Messages is significantly and positively related to share count (β = .24, p < .001). After controlling the influence of the above variables, Positive Emotion Strength is not significantly related to sharing count (β = .03, p = .558). The R^2 change of the model with the control variables is 0.05 (p =

.001), the R^2 change of the model with the independent variable is 0.001 (p = .558). It means that the control variable explains 5.0% of the variance, while the independent variable explains an additional of 0.1% of the total variance.

The results indicate that among the control variables, the more messages the microblogger have posted, the more likely his/her microblog message is to be shared on the microblog. The influence of positive emotion strength is not beyond and above that of the number of messages.

TABLE V
REGRESSION ON SHARE COUNT OF POSITIVE-EMOTION MESSAGES

	Predictors	*B*	*SE*	β	*t*
Control Variables	Day Difference	-0.93	3.55	-.01	-0.26
	No. of Followers	0.00	0.00	-.08	-1.36
	No. of Messages	0.06	0.02	.24***	4.09
Independent Variable	Positive Emotion Strength	60.12	102.43	.03	0.59

Note. *** $p < .001$.

As shown in Fig. 1, the slope between emotion strength and share count is significant for negative-emotion messages (β = .04, p = .040), but is nonsignificant for positive-emotion messages (β = .03, p = .558). It suggests that the sharing count may increase with the increase of negative emotion strength, but may not increase with the increase of positive emotion strength.

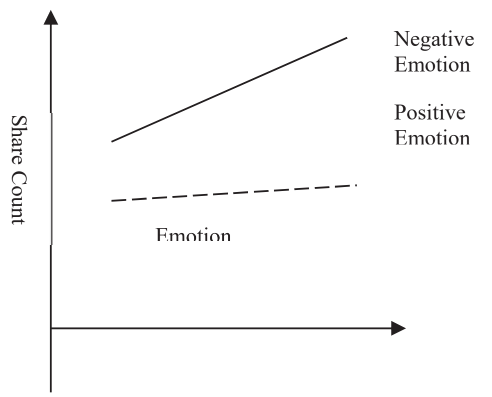

Fig. 1 Relations between emotion strength and share count

B. Theme Two: Differences between Verified and Unverified Users

1. User Identity Frequencies and Profiles

As shown in Table VI, among the 7114 microbloggers, 27.3% are verified users, among them, half are verified enterprise users and the other half are verified individual users; 72.5% are unverified users.

The verified enterprise users have the most followers than other two types of users. The average microblog followers of the verified enterprise users are approximately 1.05 million, the average microblog followers of the verified individual users are approximately 0.35 million, and the average microblog followers of the unverified users are nearly 11 thousand. There is a significant difference between the three types of microblog users in terms of follower numbers, $F(2, 7098) = 262.63$, $p <$ .001. LSD posthoc analysis showed that the verified enterprise users' followers are significantly more than the verified individual users' followers ($p < .001$), and the verified individual users' followers are significantly more than the unverified users' followers ($p < .001$).

The verified enterprise users post the most microblogs averagely than the other two types of users. The average number of microblogs posted by each verified enterprise users is 18 thousand, the average number of microblogs posted by each verified individual users is 11 thousands, and the average number of microblogs posted by each unverified users is 3.9 thousands. There is a significant difference among the three types of users' microblog numbers F (2, 7097) = 484.39, $p <$ .001. LSD post-hoc analysis showed that the verified enterprise users' microblog posts are significantly more than the verified individual users' ($p < .001$), and the verified individual users' microblog posts are significantly more than the unverified users' ($p < .001$).

TABLE VI
USER PROFILES

	No. of Followers	No. of Microblogs	Share Count	Comment Count
Verified Enterprise Users (13.7%)	1,045,025	17,956	791	279
Verified Individual Users (13.6%)	348,620	10,923	1083	658
Unverified Users (72.5%)	10,980	3,878	298	88
F	262.63***	484.39***	7.27**	14.48***

Note. ** $p < .05$. *** $p < .001$.

2. Microblog Influences

The verified individual users receive the most comments for their microblogs compared to the other two types of users (as shown in Table VI). The average comments received by the verified enterprise users' microblogs are 279, the average comments received by the verified individual users' microblogs are 658, and the average comments received by the unverified users' microblogs are 88. There is a significant difference among the three types of users' received comment numbers $F(2, 7086) = 14.48$, $p < .001$). LSD post-hoc analysis showed that the verified individual users' average comment received is significantly more than the verified enterprise users' (p = .007) and the unverified users' ($p < .001$), but there is no significant difference between verified enterprise users and unverified users in terms of received comments (p = .075).

The verified individual users' microblogs are shared most frequently compared to those of the other two types of users. The average frequency of the verified enterprise users' microblogs being shared is 791, the average frequency of the verified individual users' microblogs being share is 1083, and the average frequency of the unverified users' microblogs being shared is 298. There is a significant difference among the three types of users' microblog share count $F(2, 7088) = 7.27$, p = .001. LSD post-hoc analysis showed that the verified enterprise users and the verified individual users' microblogs are both shared significantly more frequently than those of the unverified users (p = .030; p = .001), but there is no difference between the two types of verified users' microblog share count (p = .323).

3. Microblog Emotions

As shown in Table VII, among the verified enterprise users' microblogs, 89.0% are statements without obvious emotions, and that proportion for the verified individual users was 57.8%; unverified users made the least statements (46.6%). Among the microblogs posted by the verified enterprise users, there is no dominant emotion, that is, no emotion frequency is larger than 10%; among the microblogs posted by the verified individual users, Doubt was the dominant emotion (11.9% and 10.0% respectively); among the unverified users' microblogs, Anger (15.2%) was the dominant emotions. Unverified users show the most positive emotion (5.4%), followed by verified individual users and verified enterprise users (4.6%, 1.2%).

TABLE VII
MICROBLOG EMOTION FREQUENCIES OF DIFFERENT TYPES OF USERS

	Verified Enterprise Users	Verified Individual Users	Unverified Users
Panics	0.1%	2.3%	4.1%
Doubt	3.9%	11.9%	12.3%
Anxiety	2.3%	2.1%	3.9%
Objection	0.8%	5.6%	5.8%
Anger	1.9%	10.0%	15.2%
Sadness	0.7%	5.6%	6.6%
Positive Emotion	1.2%	4.6%	5.4%
Neutral Statements	89.0%	57.8%	46.6%

4. Correlations between Emotion Strength and Share and Comment Counts

As shown in Table VIII, among the verified enterprise users, the strength of emotion expressed in a message is significantly and positively correlated to the frequency of it being shared ($r = .13$, $p = .029$), but not significantly correlated to the number of comments it received ($r = .10$, $p = .104$). Among the verified individual users, the strength of emotion expressed in a message is significantly and positively correlated to the number of comments it received ($r = .11$, $p = .011$) and also the frequency of it being shared ($r = .11$, $p = .013$).

Among the unverified users, the strength of emotion expressed in a message is significantly and positively correlated to the number of comments it received ($r = .04$, $p = .042$), but not significantly correlated to the frequency of it being shared ($r = .03$, $p = .068$).

TABLE VIII
CORRELATIONS BETWEEN EMOTION STRENGTH AND SHARE AND COMMENT COUNTS

		V1	V2	V3
Verified Enterprise Users	Emotion Strength (V1)	1		
	Comment Count (V2)	.10	1	
	Share Count (V3)	.13*	.94**	1
Verified Individual Users	Emotion Strength (V1)	1		
	Comment Count (V2)	.11*	1	
	Sharing Count (V3)	.11*	.78**	1
Unverified Users	Emotion Strength (V1)	1		
	Comment Count (V2)	.04*	1	
	Sharing Count (V3)	.03	.92**	1

Note. * $p < .05$. ** $p < .01$.

V. DISCUSSION

The first theme of study sheds light on the key mechanism of information diffusion on microblogs by studying the impact of microblog emotion on message sharing behaviors.

One of the key findings of the study is that among the microblog messages about the hottest public events, negative emotions are much more expressed than positive emotions (89.7% versus 10.3%). And among all types of negative emotions, Anger and Doubt are the dominant emotion.

Furthermore, it was found that negative emotion rather than positive emotion in a microblog message might be a key mechanism of information diffusion on microblogs. Specifically, regardless of the influence of the day difference, number of followers, and number of messages of the microbloggers, negative emotion may still facilitate readers' message sharing behavior. That is, the stronger negative emotion a message expressed, the more likely this message is being shared by the readers. However, positive emotion does not have such influence.

Findings of the second theme of study indicate that the verified users have an overwhelmingly greater number of followers than the unverified users, and the verified enterprise users have the most followers averagely than the other two types of users. Meanwhile, verified enterprise users are also the most active in posting microblogs, followed by verified individual users and unverified users.

Regarding users' microblog influences, it was found that verified individual users obtained the most attention, and their microblogs were commented and shared the most frequently than the other two types of users. Unverified users' microblogs were shared and commented the least.

With respect to microblog emotion expression, verified enterprise users are comparatively more cautious, and they usually make statements instead of expressing obvious emotions. Over half of the verified individual users' microblogs are also statements, but doubt is the mostly expressed emotion in their microblogs, if any. Unverified users are comparatively expressive, and the dominant emotions in their microblogs are anger and doubt.

Emotion strength in microblogs was found to affect the comment and share counts. Emotion strength was found to promote both comment and share counts for verified individual users. But it only promotes share count for verified enterprise users, and only promotes comment count for unverified users. Generally, emotion strength facilitates both the sharing or commenting behaviors of the followers, but in different ways among the three types of users.

The study sheds light on the influence of emotion expression and information diffusion in several aspects. First, the study explored how microblog emotion impact information transmission in the Asian context. Results in this study are consistent with the related findings in the western context. Furthermore, the study fills the research gap by including both emotion polarity and emotion strength as the predictors of information transmission (that is, share and comment counts). Second, the study compares different microblog users' identities and their emotion expression, and found that celebrities (verified individual users), enterprises (verified enterprise users) and unverified users vary with respect to their profiles, popularity, microblog influences, and emotion expression. Third, the microblog messages were coded manually rather than by the automated sentiment mining techniques. Manual coding is more reliable in capturing subtle emotions in texts, given that many microblogers may express their emotions in sarcastic ways that computers may not be sensitive enough recognize. Manual coding is also more accurate in making the judgment of emotion strengths compared to automated approaches. Fourth, implications of the findings could be meaningful to both public-health communication and business. As indicated by the results, health-related advertisements that evoke negative emotions, such as anxiety and fear, may spread faster and wider than the neutral ones. Part of the results also reminds company operators that in order to maintain the image of an enterprise or brand, it is important to actively manage the consumer-generated content about a product on social networking sites, especially those charged with negative emotion, because that information may be diffused very quickly.

REFERENCES

[1] Bollen, J., Mao, H., & Zeng, X. (2010). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*, 1-8.

[2] Bollen, J., Pepe, A., & Mao, H. (2011). Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. *Proceedings of the Fifth International AAAI Conference on Weblogs and Social MediaPaper of AAAI Conference*, *450-453*.

[3] Cheung, S. Y., & Lam, E. T. (2005). An innovative shortened bilingual version of the Profile of Mood States (POMS-SBV). *School Psychology International*, *26*, 121-128.

[4] Berger, J. (2011). Arousal increases social transmission of information. *Psychological Science, 22*, 891–893.

[5] Berger, J., & Milkman, K. (2012). What makes online content viral? *Journal of Marketing Research*, *49*, 192–205.

[6] Dang-Xuan, L., Stieglitz, S., Wladarsch, J., & Neuberger, C. (2013). An investigation of influentials and the role of sentiment in political communication on Twitter during election periods. *Information, Communication, and Society*, *16*, 795-825.

[7] Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and information diffusion in social media-Sentiment of microblogs and sharing behavior. *Journal of Management Information Systems*, *29*, 217-247.

[8] Thelwall, M., Buckley, K., & Paltoglou, G. (2011). Sentiment in Twitter Events. *Journal of the American Society for Information Science and Technology*, *62*, 406-418.

[9] Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. *Proceedings of LREC Conference*, 1320-1326.

[10] Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. *Proceedings of Conference on Empirical Methods in Natural Language*, 79-86.

[11] Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics*, *37*, 267-307.

[12] Wilson, T., Wiebe, J., & Hoffman, P. (2009). Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis, *Computational Linguistics*, *35*, 399-433.