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“THEME ARTICLE”, “FEATURE ARTICLE”, or “COLUMN” goes here: The theme topic or column/department name goes after the colon.

Analyzing Attitude of Second Screen Social Media Messages

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ABSTRACT

We analyze more than 3,000,000 Twitter, 800,000 Instagram, and 50,000 Tumblr posts concerning a single major in-real-life event, Super Bowl XLIX, to determine attitude. We consider three event phases (*Pre*, *During*, and *Post*). Findings show link-based recommendations and undirected broadcast patterns positively correlate with attitude in the *Pre* and *Post* phases, respectively. The usage of these specific features highlights the differing information needs of viewers during these phases, specifically the sharing of information in the *Pre* phase and sharing of opinions in the *Post* phase. The volume of postings indicates a negative attitude for all social media platforms, demonstrating that adverse information is more likely to be shared than positive information; this finding contradicts prior findings. This second screens phenomenon research is important in identifying the of sharing information on multiple social media platforms during an in real life event.

Keywords: Second screens, dual screens, second screens, attitude, social soundtrack, panel data regression

1. INTRODUCTION

Second screens allow for information sharing via social media platforms concerning an event using mobile technologies. A broadcast media event is shown on the main (typically the largest) screen, which is where primary viewing occurs. The other screens (the second screens) are smaller personal computing devices, typically smartphones or tablets. Viewers use second screens to share information with others in disperse locations regarding the event they are watching. There are events that happen in-real-life (IRL) that are anchored temporally making them more likely to be viewed while the event is occurring versus being recording. Hence, second screen interactions about an IRL event lead to a temporally bounded social soundtrack composed of social media postings. An IRL event's popularity intuitively increases the social soundtrack volume from the perspective of posts on social media platforms. There is limited academic research concerning the second screen phenomenon for IRL events.

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2. LITERATURE REVIEW

People share opinions [1] and comments via social media about some event, often in real time (i.e., while the event occurs). These social media postings frequently contain insights into viewers' attitudes about some aspect of the event. We define attitude as the inclination toward positive or negative sentiments. In the research presented here, we determine an attitude score as an aggregation of positive and negative sentiments extracted from second screen postings. The concept of attitude has roots in prior work [2] concerning sentiment strength. Attitude detected in online content is increasingly being examined as a measure of insight across many research domains. The notion that attitude influences behavioral intentions is supported in prior work concerning advertising and technology adoption.

Determining attitudes concerning online content is challenging and has implications for identifying cultural attributes, such as individualism and long-term orientation. Social media posts reflect consumer attitude toward brands [3], with most attitudes being positive [4]. This outcome is supported by research showing that people prefer to share happy information online. In fact, prior work has shown that the attitude of a social media post affects how quickly that information is shared [5]. Mukherjee and Jansen [6] related attitude in social media posts with web searching showing that second screen interaction and web searching volumes are correlated, building on earlier findings concerning sentiment [7] and opinion mining of social media postings [8].

However, there are several unanswered questions concerning the attitude of second screen postings during IRL events. How are second screens used during the broadcast of an IRL event? How do second screens postings regarding an IRL event influence attitude toward different IRL event dimensions? How does language constructed in social media discourse affect attitude? These are some questions that motivate our research. The research reported here is part of a larger examination of second screen information behaviors with prior work investigating the volume of information sharing [9] and the effect of second screen postings on web search [6] during IRL events.

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3. RESEARCH QUESTION

We classify second screen interactions during an IRL into event sub-categories; the event is Super Bowl XLIX. Although this is a single IRL event, the temporal aspects of the relationship between the broadcasting of the event the social postings on various platforms that we are investigating are traits common to this class of events. So, we expect the results to generalizable, also this premise needs investigation. Many postings are shared on the social soundtrack before, throughout, and after the event. We label these temporal phases as a) *Pre*, b) *During* and c) *Post*. The *Pre* phase is the audience interaction beginning (sometimes) weeks ahead of an event and continuing until the event starts. The *During* phase is the period of the live broadcast of the event. The *Post* phase is the social soundtrack beginning the moment the event is over until the end of data collection. We postulate that the attitude and informational needs of the viewers are different during each of these phases. For clarity, we state our key constructs:

- **Event** – is a happening that is anchored temporally and not lending itself for delayed viewing. It usually occurs IRL and typically broadcast.
- **Event Phase** – is a distinct period of the event used for temporal classification of second screen postings.
- **Secondary screen** – is a computing device used for posting content to the social soundtrack in second screens interaction.
- **Social soundtrack** –is the collection of social media posts from second screens concerning an event.

We use three social media platforms for data collection, which are Twitter, Instagram, and Tumblr. Twitter was one of the most popular micro-blogging sites at the time of the study. Instagram is a platform where users capture and share images and videos. Tumblr was the second largest microblogging service in the U.S. after Twitter. It supports eight types of posts, which are images, videos, audios, text, answer, links, quotes, and chat. In our research, as in [10], we define attitude as the inclination toward the positive or negative sentiments and determine attitude scores as an

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aggregation of positive and negative sentiments extracted from second screens postings. Our specific research question (RQ) is:

RQ: Are there specific features of social soundtrack conversations on different social media platforms that correlate with the attitude of the social media conversations in each event phase and category?

This research question is evaluated with a linear regression method on balanced panel data using post attributes, with the overall methodology addressed in the following section.

4. DATA COLLECTION AND RESEARCH METHODOLOGY

We collected data related to Super Bowl XLIX from 10 January 2015 through 24 February 2015 on each of the three social media platforms. To collect data from each platform, we used the respective APIs and tokens for Twitter, Instagram, and Tumblr in corresponding scripts with search queries. We collected from Twitter (3,112,789 tweets), Instagram (811,262 posts), and Tumblr (51,569 posts). We segregate the data collection period into three temporal phases, *Pre* (1/10/2015- 00:00:00 - 2/1/2015-18:29:59), *During* (2/1/2015-18:30:00 - 2/1/2015-22:30:00), and *Post* (2/1/2015-22:30:01 - 2/24/2015-00:00:00).

Table 1. The phase x category for Twitter, Instagram, and Tumblr comments

Phase	**Twitter**
Pre	1593305
During	33611
Post	1195940
Phase	**Insta-gram**
Pre	415079
During	14680
Post	311198
Phase	**Tumblr**
Pre	20408
During	6317
Post	14139

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We construct a three-(phase X category) table from the distribution of the categories for second screens Super Bowl interactions on Twitter, Instagram, and Tumblr respectively, as shown in Table 1, where each cell $C^{k}_{i,j}$ gives the observed frequency of second screens interaction in Super Bowl phase *i* for Super Bowl category *j* on social network platform *k*.

4.1 Methodology

We first segregated the count of posts collected across the weeks for all three social media platforms across all three Super Bowl categories into five-minutes intervals. We selected the period to ensure that we collect a range of social media postings within the duration of the event. Prior work has employed a range of periods for rate calculations [11-14]. We then separate the categorical time-count data as *Pre*, *During*, and *Post* phases. We derive the attitude for each post, using a method similar to prior work [15] in each of these five-minute phase-category subsets by extracting emoticons followed by positive and negative words for the sentiment from messages posted in all three social soundtrack mediums using equation 1.

$$rel\_value^{j}_{i} = Score^{j}_{i} \,/\, max_{i}\,\{Score^{j}_{i}\} \qquad (1)$$

i denotes the index of the five-minute time slot within a specific phase, and *j* is the post's attitude score. For attitude, the *max* function returns the highest value of attitude score within a phase. This relative scaling is done for all three social media platforms. So, each social soundtrack has category time counts (in slots of five minutes) of attitude scores for each phase that we use as the unit of analysis in testing the two research questions.

We then organized the categorical time count data into a balanced panel data [16] for all three social media platforms where each of the three categories has relative values of the social soundtrack attributes across a total number of five-minute slots for data collection in each phase. Known as cross-sectional time series data, panel data can control for variables whose behavior cannot be observed. In our research, for each phase, the balanced panel dataset can be viewed as a three-dimensional space where the dimensions are a) the event itself, b) time stamps for each category [number of five-minute time slots, specifically 6,558, 49, and 6,534 for *Pre*, *During,* and *Post*

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phases respectively], and c) the relative attributes along with the relative attitude scores for Twitter, Instagram, Tumblr. As there are three social media platforms, we have three balanced longitudinal data panels for relative values of the attributes with attitude for each phase. In our dataset, we have a total of 19,674 (3 x 6,558) records, 147 (3 x 49) records, and 19,062 (3 x 6,354) records each with relative values of attributes for three social media platforms for *Pre*, *During*, and *Post* phases, respectively.

The act of measuring a post's attitude involves two major stages. The first stage deals with mining emoticons from the postings on all three social soundtrack mediums, and the second stage determines the presence of positive and negative words. We extract the emoticons from the social soundtrack messages posted in all three social networking platforms by preparing two emoticon sentiment lexicons. We categorize the lexicons as positive sentiment lexicons and negative sentiment lexicons. The lexicons are derived from available online resources. We combine these online lists into the corresponding lexicons, leaving out duplicate entries. The sentiment polarity of sentences contained in Twitter texts, Instagram captions, and Tumblr blogs are assigned either as positive or negative, depending on the presence of these positive and negative emoticons. We exclude the classification of neutral emoticons from our research, saving this for future research.

The second stage of analysis determines the existence of positive and negative terms. We use the online sentiment lexicon used in [17] to form our positive and negative word lexicons while removing duplicating entries from the combined list. In determining the attitude of the sentences by the presence of positive or negative words, we split the sentences into tokens and assign the polarity using a bigram approach.

$Step\ 1$: $if\ ((\text{“not”} \in\ sentence_i \wedge pos\_word_j\ \in\ sentence_i) \wedge (index(\text{“not”}) < index(pos\_word_j)))\qquad count(polarity_{neg})++;$

$Step\ 2$: $else\ if\ (\text{“not”} \notin sentence_i\ \wedge\ pos\_word_j\ \in\ sentence_i)$

$count(polarity_{pos})++;$

$Step\ 3$: $if\ ((\text{“not”} \in\ sentence_i \wedge neg\_word_j\ \in\ sentence_i) \wedge (index(\text{“not”}) < index(neg\_word_j)))\qquad count(polarity_{pos})++;$

$Step\ 4$: $else\ if\ (\text{“not”} \notin sentence_i\ \wedge\ neg_{word_j}\ \in\ sentence_i)$

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$$count(polarity_{neg})++;$$

Once the polarity of the statements was determined using the presence of emoticons and sentiment words, we computed the polarity score at the sentence level. Next, we aggregated the score at the single tweet, caption, or blog level. Once the posting level attitude score was computed, we carried out further aggregation on the number of messages posted within the 24-hour time window. We assigned a scale of rating for the emoticons and the sentiment words. We provided more positive or negative weight on positive and negative emoticons than for positive and negative words, as emoticons simulate the nonverbal cues which dominate verbal cues and hence an important emotion/intention indicator for viewers. The texts coupled with emoticons have higher sentiment than the messages without emoticons.

The weight scale we chose is as follows. Negative emoticons: -2, negative words: -1, positive words: +1, positive emoticons: +2 and 0 for neutral emoticons. We assigned equal weights with opposite signs for positive and negative emoticons and same positive and negative weight for positive and negative words but with opposite signs, as in [18]. So, the attitude scores we compute using formulas 2 through 4 for a specific category in a specific phase is.

$$\emptyset_l = (sign_i)\mathrm{w}_i.\zeta_l^+ + (sign_j)\mathrm{w}_j.\psi_l^+ + (sign_i)\mathrm{w}_i.\zeta_l^- + (sign_j)\mathrm{w}_j.\psi_l^- \qquad (2)$$

$$\varphi_{k=}\frac{1}{|l_k|}\sum\nolimits_{l\in l_k}\emptyset_l \qquad (3)$$

$$S_t = \frac{1}{|k_t|}\sum\nolimits_{k\in k_t}\varphi_k \qquad (4)$$

sign_i and *sign_j* are from {+/-} depending on positive and negative words and emoticons respectively. *w_i* and *w_j* are the magnitudes of weights assigned to the emoticons and sentiment words. The symbols ζ_l and ψ_l are the frequency of emoticons and sentiment words in sentence l. ϕ_l = weighted summation of positive and negative sentiments for sentence l (i.e., attitude score of sentence l). φ_k is the aggregated attitude score over post k where $|l_k|$ = number of sentences in post k. Here, S_t is the average attitude score aggregated over posts in a particular five-minute time win-

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dow *t*. Higher S_t indicates more positive attitude. If $S_t = 0$, the aggregated attitude in that time window *t* is neither classified as positive nor as negative (i.e. neutral). $|k_t|$ = number of posts in time window *t*. The steps of attitude measurement for all three social soundtracks are performed for each Super Bowl category.

Once done, we have the average attitude score in five-minute time counts in phase-category spaces. We extracted the social soundtrack features in addition to the count of posts that correspond to (a) pattern of viewers' conversation, (b) the number of sentences in the postings, and (c) number of unique words present in the texts of the posts. The identifiers for categories of patterns for social soundtrack conversation that are common to each of the three social media platforms are: Referral (RF) – any URL contained within the post, Response (RS) – posting intentionally engaging another specific user, and Broadcast (BC) - undirected posts not engaging a specific user. For each post attribute, we normalized since the number of posts vary among platforms and the number of features varies among posts. Using these relative numbers, after normalization, we assign each value factors and compare units of post attributes.

We use panel data regression with fixed effects on balanced panel data to evaluate the relationship between the features of social soundtrack conversations and content attitude concerning event categories, which is an approach used to investigate other aspects of postings in prior work [19]. In the regression model, relative attitude score is the dependent variable, while the relative values of social soundtrack features (i.e., volume, patterns of social soundtrack conversations, number of sentences, and number of unique words) are the cofactors. Twitter has a Retweet function that is a sharing of another's post. All cofactors and definitions are:

- Volume: Aggregated relative number of postings
- Mention: Aggregated relative number of postings with "@" symbol
- Referral: Aggregated relative number of full length or shortened URL
- Broadcast: Aggregated relative number of undirected opinions that does not contain addressing.
- Sentences: Aggregated relative number of sentences

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- Unique words: Aggregated relative number of non-repetitive words excluding hashtags and stopwords.
- Retweet: Aggregated relative number of "RT @", "via @" etc.

5. RESULTS

We present the results of the fixed effects regression model done on the panel data for Twitter in all three phases in Table 2. We find that attitude score increases by 15% and 118% in relative scale with each one-unit increase of URL recommendations, referral (RF) pattern, or number of sentences in the *Pre* phase for Twitter, while for each unit increase of other cofactors the attitude score reduces. In the *During* phase, the majority of cofactors' coefficients are large and positive, but they are not significant (p-value > 0.05) in correlating with the cofactors on social media comment attitude. Interestingly, in the *Post* phase, attitude increases by 55% and 11% with each unit increase of mention (RS) and undirected broadcast (BC) conversation patterns, respectively. It is important to note that an increased number of tweets decreases attitude significantly in the *Pre* phase, while in the other two phases, the volume effect is not significant (i.e., p-value > 0.05).

Table 2. Fixed effects model results for Twitter, Instagram, and Tumblr

		Twitter			Instagram			Tumblr		
Phase	**Co-factors**	**Coeff.**	**p-value**	**R^2**	**Coeff.**	**p-value**	**R^2**	**Coeff.**	**p-value**	**R^2**
	volume	**-1.096**	**0.000***		**-0.495**	**0.000***		**-0.915**	**0.000***	
	mention	**-0.14**	**0.002***		**-0.212**	**0.001***		0.123	0.22	
	referral	**0.152**	**0.000***		**0.449**	**0.000***		**0.477**	**0.000***	
Pre	retweet	**-0.109**	**0.009***	**0.32**			**0.41**			**0.23**
	broadcast	**-0.303**	**0.000***		**-0.294**	**0.000***		-0.016	0.873	
	sentences	**1.178**	**0.000***		**0.273**	**0.000***		**1.076**	**0.000***	
	unique words	0.159	0.102		**-0.284**	**0.000***		**-1.532**	**0.000***	
During	volume	-0.589	0.85	0.44	**-1.066**	**0.001***	0.54	-1.34	0.063	0.47

	mention	8.879	0.363		-2.277	0.317		0.665	0.522	
	referral	9.668	0.321		2.205	0.32		0.572	0.594	
	retweet	9.375	0.338							
	broadcast	9.382	0.337		-2.542	0.259		0.429	0.694	
	sentences	0.799	0.798		**0.661**	**0.001***		1.491	0.061	
	unique words	0.857	0.3		**-1.41**	**0.003***		-0.107	0.862	
Post	volume	-0.013	0.694	0.43	**-0.381**	**0.000***	0.41	**-1.114**	**0.000***	**0.25**
	mention	**0.55**	**0.002***		0.011	0.834		**-0.749**	**0.000***	
	referral	**-0.135**	**0.000***		**-0.314**	**0.000***		**-0.468**	**0.000***	
	retweet	**-0.068**	**0.000***							
	broadcast	**0.11**	**0.000***		**0.225**	**0.000***		**0.801**	**0.000***	
	sentences	-0.036	0.366		**0.231**	**0.000***		**1.282**	**0.000***	
	unique words	**-0.225**	**0.004***		**-0.385**	**0.000***		**-1.546**	**0.000***	

Table 2 represents the results of the fixed effects model on the panel data for Instagram. In the *Pre* phase, Instagram media post attitude increases by 45% and 27% for a unit increase of referral (RF) and sentences respectively in relative scale, while for a unit increase of other cofactors, the Instagram attitude is reduced, like that of Twitter in the *Pre* phase. In the *During* phase, Instagram attitude increases 66% with each unit increase of sentences in Instagram captions, while it decreases significantly by 110% and 140% with a unit increase of cofactors of unique words and volume of comments, respectively. The social soundtrack conversation patterns do not have any significant effect on attitude in the *During* phase. In the *Post* phase, among the social soundtrack features, the unit increase of undirected broadcast (BC) and the number of sentences elevate the Instagram attitude by 22.5% and 23.1%. The positive effect of mention (RS) on attitude is insignificant (i.e., p-value > 0.05). The volume of posts significantly reduces social soundtrack attitude in all three phases.

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Table 2 represents the results of the fixed effects model on the panel data for Tumblr in all three phases. From Table 5, in the *Pre* phase, it is observed that URL recommendation or referral (RF) and the number of sentences has the positive effect on Tumblr attitude. Each unit increase of referral pattern and number of sentences increases the attitude score by 48% and 108% respectively. In the *During* phase, the relation between social soundtrack attitude and none of the social soundtrack features are significant, while in the *Post* phase, it is the undirected broadcast and number of sentences that show the positive relation with Tumblr attitude. Each one unit increase of broadcast and number of sentences results in an 80% and 128% growth in attitude. Other social soundtrack conversation features are negatively related with attitude in a relative scale. The increase in post volumes reduces the attitude score on Tumblr, as was seen on Twitter and Instagram.

6. DISCUSSION AND IMPLICATIONS

The increased rate of communication via second screens during IRL events leads to the amplified exchange of feelings about different categories of the main event by sharing, publishing, and commenting on social media platforms. Those concerned about such interests can monitor the social soundtrack for information, insights, and reactions to the viewers. In one of the few multi-platform analysis of social media postings, the results of our fixed effect panel analysis show that the structure of posts has significant explanatory effect concerning the attitude of the posts.

Findings also show that this relationship between attitude and post structure changes over the phases of an event, most probably driven by the shifting informational needs of the event viewers. Specifically, the relationship between the attitudes of second screens interactions and second screens postings features, our findings show that URL-based recommendation has a positive relationship on attitude in social media posts in the *Pre* phase. We suppose that people engage more on expressing feelings by viewing event advertisements and videos trailers published weeks before the actual broadcast and focus on a sharing of additional information, such as that pointed to by the links. The implications are that brands can contribute to this information sharing by providing pre-event information for viewers. Tapping the mention and response (RS) interaction among viewers in the *Post* phase indicates that viewers are now less interested in additional information

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gathering, instead focused on opinion sharing and responding to the opinions of others. This may also facilitate retailers in identifying the attitude of viewers about the products and hence get insight into the respective brand strengths or weaknesses. Interestingly, the increased rate of communication via second screens during live broadcast media events does not always lead to increased attitude about different event categories, as it is seen that increased post volume reduces the attitude scores. This may lead to greater insight concerning a spectrum of human information behaviors during actual IRL events.

As in all research, there are limitations. First, we have collected 3 million tweets, which is a sample of the overall tweets concerning the event. This is because we used the public APIs to collect the data for our research for all three social soundtrack platforms instead of using full data pipeline, which may overcome the limitations of the public APIs for collecting data. Using the Twitter firehose to collect the data may strengthen our findings; however, even with this limitation, we collected a substantial amount of data for the research reported here. Secondly, there may be spam messages or automatically generated messages that may affect our results. Our present study did not filter out such spam or bots, which we will focus on future work. Thirdly, we consider only the attitude of the social soundtrack, and we did not capture the actual sentiment of the texts as the positiveness and negativeness may neutralize each other at some sentence level or post level averaging. Finally, we focus on only a single IRL event, so future work should analyze other events. Also, we will focus on deriving a number of sentiments (i.e., positive and negative) besides computing attitude, as sentiment and attitude are different metrics. Future work may focus on attributes of the poster along with the post [20], as prior work shows that this perspective has impact [1]. Another interesting avenue for research would be an analysis of the images and videos, along with the text. Despite these limitations, we believe our research findings present significant insights in identifying the temporal relationship between feature attributes and the attitude of second screen content-based social media conversations, along with a temporal shift in content aspects concerning IRL event categories.

7. CONCLUSION

In our study, we analyze research regarding second screens interactions from Super Bowl XLIX, a major IRL event across multiple social media platforms over an extended period. These questions are examined from the perspective of human information processing in terms of attitude expressed in the social soundtrack comments. Our research provides contributions concerning understanding user information sharing using second screens from a temporal perspective for IRL events, which is an emerging avenue of social soundtrack research that can potentially impact numerous fields, including the role of viewership in pop culture. In future research, we will analyze the relationship between the temporal subjectivity of posts and the different features of second screens interactions on more social media platforms to compare the estimates of fixed, random, and mixed models in the phase-category space of IRL events.

8. AUTHOR BIOS

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9. REFERENCES

1. F. Zarrinkalam, M. Kahani, and E. Bagheri, "Mining user interests over active topics on social networks," *Information Processing and Management,* vol. 54, pp. 339-357, 2018.
2. M. Thelwall and K. Buckley, "Topic-based sentiment analysis for the Social Web: The role of mood and issue-related words," *Journal of the American Society for Information Science and Technology,* vol. 64, pp. 1608–1617, 2013.
3. B. Schivinski and D. Dabrowski, "The effect of social media communication on consumer perceptions of brands," *Journal of Marketing Communications,* vol. 22, pp. 189-214, 2016.
4. B. J. Jansen, M. Zhang, K. Sobel, and A. Chowdury, "Twitter power: Tweets as electronic word of mouth," *Journal of the American Society for Information Science and Technology,* vol. 60, pp. 2169-2188, 2009.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/MIS.2018.2886665, IEEE Intelligent Systems

5. C. Wang, Z. Zhou, X.-L. Jin, Y. Fang, and M. K. O. Lee, "The influence of affective cues on positive emotion in predicting instant information sharing on microblogs: Gender as a moderator," *Information Processing & Management,* vol. 53, pp. 721-734, 2017.

6. P. Mukherjee and B. J. Jansen, "Conversing and searching: the causal relationship between social media and web search," *Internet Research,* vol. 27, pp. 1209-1226, 2017.

7. E. Cambria, S. Poria, A. Gelbukh, and M. Thelwall, "Sentiment Analysis Is a Big Suitcase," *IEEE Intelligent Systems,* vol. 32, pp. 74- 80, 2017.

8. E. Cambria, B. Schuller, Y. Xia, and C. Havasi, "New avenues in opinion mining and sentiment analysis," *IEEE Intelligent Systems,* vol. 28, pp. 15-21, 2013.

9. P. Mukherjee and B. J. Jansen, "Information Sharing by Viewers via Second Screens for In Real Life Events," *ACM Transactions on the Web,* vol. 11, p. Article 1, 2017.

10. O. Kucuktunc, B. B. Cambazoglu, I. Weber, and H. Ferhatosmanoglu, "A Large-scale Sentiment Analysis for Yahoo! Answers," in *Proceedings of the Fifth ACM International Conference on Web Search and Data Mining (WSDM '12),* Seattle, Washington, USA, 2012, pp. 633-642.

11. S. Asur and B. A. Huberman, "Predicting the Future with Social Media," presented at the Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology - Volume 01, 2010.

12. A. Mollgaard and J. Mathiesen, "Emergent User Behavior on Twitter Modelled by a Stochastic Differential Equation," *PLoS ONE,* vol. 10, p. e0123876, 2015.

13. A. Marcus, M. S. Bernstein, O. Badar, D. R. Karger, S. Madden, and R. C. Miller, "Twitinfo: aggregating and visualizing microblogs for event exploration," presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 2011.

14. D. Ramasamy, S. Venkateswaran, and U. Madhow, "Inferring user interests from tweet times," presented at the Proceedings of the first ACM conference on Online social networks, Boston, Massachusetts, USA, 2013.

15. E. Cambria, "Affective Computing and Sentiment Analysis," *IEEE Intelligent Systems,* vol. 31, pp. 102-107, 2016.

16. C. Hsiao, "Panel data analysis - advantages and challenges," *Test,* vol. 16, pp. 1-22, 2007.

17. B. Liu, M. Hu, and J. Cheng, "Opinion Observer: Analyzing and Comparing Opinions on the Web," in *Proceedings of the 14th International Conference on World Wide Web (WWW'05),* Chiba, Japan, 2005, pp. 342-351.

18. A. Kramer, "An Unobtrusive Behavioral Model of "Gross National Happiness"," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI'10),* Atlanta, USA, 2010, pp. 287-290.

19. B. Suh, L. Hong, P. Pirolli, and E. H. Chi, "Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network," presented at the Proceedings of the 2010 IEEE Second International Conference on Social Computing, 2010.

20. M. Malik and A. Hussain, "An analysis of review content and reviewer variables that contribute to review helpfulness," *Information Processing and Management,* vol. 54, pp. 88-104, 2018.