Conversing and searching: the causal relationship between social media and web search

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Abstract

Purpose – It is important to measure the interaction between conversing in social media and searching on the web in order to understand the impact on electronic word-of-mouth marketing. The paper aims to discuss this issue.
Design/methodology/approach – The authors research the relationship between social media conversing and web searching concerning brands on three major social soundtrack platforms (Instagram, Twitter, and Tumblr) and on a major web search engine (Google). The authors examine the effects of changes in both volume and attitude of conversing and volume of searching for two phases (Pre and Post) concerning brands in commercials aired during Super Bowl XLIX. The authors perform Granger causality testing and panel data regression analysis to determine the causal relationship between social media conversing and web searching.
Findings – Results show that volume and attitude of social media conversing has a significant causality relationship to the volume of web searching. Each unit increase of volume on Twitter, Instagram, and Tumblr significantly increases Google search volume for the same brands by 4.7 times, 11.9 times, and 8.7 times, respectively. Each unit increase of attitude score on Twitter significantly increases web search volume 3.96 times, while for Tumblr, search volume significantly increases 0.95 times with each unit. Interestingly, search volume also has a significant causality relationship on the volume of social media postings.
Originality/value – This research seeks to understand the commercial impacts of the interaction among broadcast advertising, social media conversing, and web searching for which there is limited prior work, especially in the context of a major media event.

Keywords Online advertising, Second screen, Multi-channel attribution, Social soundtrack, Web analytics, Web searching

Paper type Research paper

1. Introduction

The integration of social media with mobile devices marks the emergence of a phenomenon that augments the delivery and consumption of online information (Google, 2012; Chyi and Chadha, 2012). This phenomenon is referred to as second screens, although there may be multiple (i.e. more than 2) screens involved. Mobile technologies provide for information sharing via different social media services, such as Facebook, Twitter, Weibo, or VK. With mobile devices for access to the online social media sites during broadcasts of in-real-life (IRL) events, the resulting stream of social media posts is what we refer to as the social soundtrack (Mukherjee and Jansen, 2014).

With the second screen phenomenon, as shown in Figure 1, the broadcast media event is shown on the primary screen (i.e. typically the largest display) where the viewing occurs, while the secondary screen is the computer device (e.g. usually a smartphone but might also be desktop, laptop, or tablet) (Newswire, 2010; Phalen and Ducey, 2012). The second screen phenomenon facilitates information sharing on one or more social media platforms, which is a common activity (Wang *et al.*, 2017). These social media platforms provide for the producing and consuming of content in online communication, creating a channel for social commentary among those watching the event. It is this combination of the secondary screen and social media technologies that allows for the creation of the social soundtrack, the online

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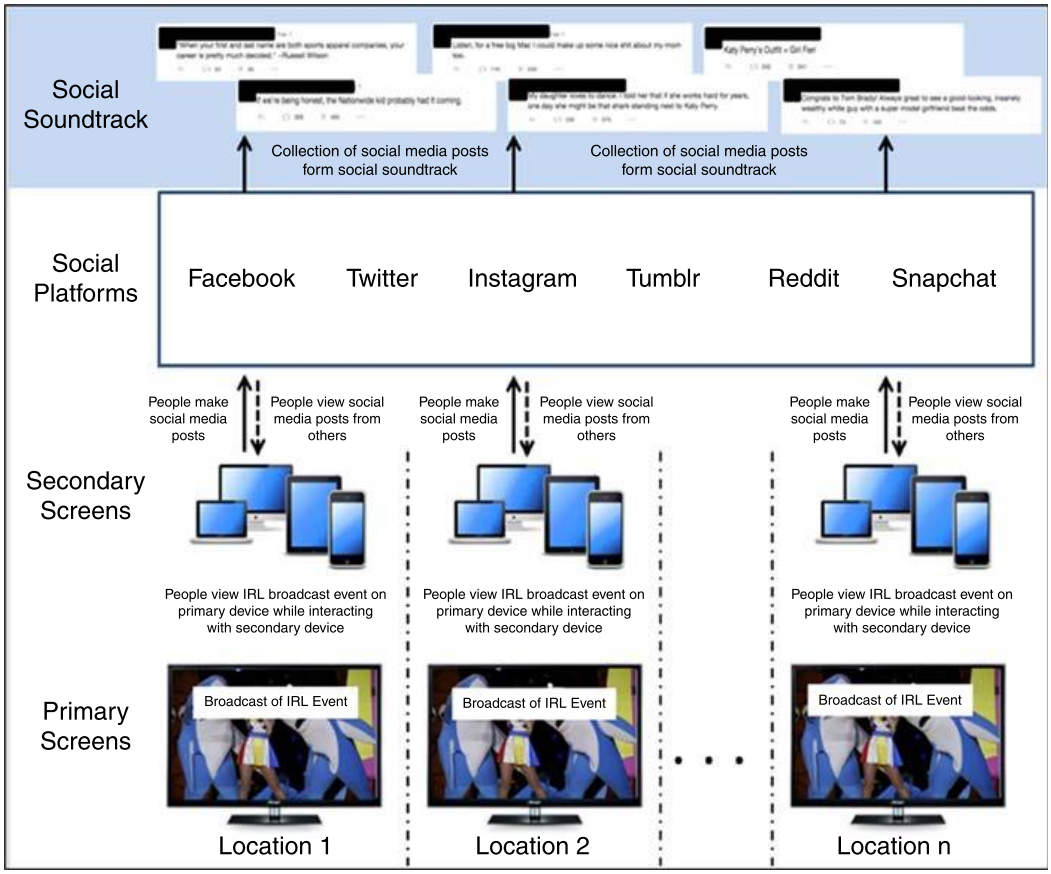


Figure 1.
Overview of the second screen phenomenon, with primary screen, computing devices, and social media sites facilitating the creation of the social soundtrack

conversation with others regarding an IRL broadcast event. These IRL broadcasts events are associated with substantial social soundtracks, as these events do not lend themselves to recording for later viewing, like a seasonal TV show.

There has been limited academic research concerning the increasingly important second screen phenomenon. As online information sharing is now a powerful marketing venue, questions remain about the commercial impacts of the interaction among broadcast advertising, social media, and web search. Using the internet simultaneously or after television (TV) consumption has been found to influence the information-seeking behavior of the audience (Kessler *et al.*, 2017). As the driver of online commerce, especially advertising, web search is a critically important economic indicator (Kulkarni *et al.*, 2012). Understanding this relationship, among broadcast advertising, social media conversing, and web searching, can provide significant business insights in managing online brand awareness and especially electronic word-of-mouth (eWOM) marketing.

In this research, we investigate the relationship between volumes and attitude in social soundtrack conversations and web search. We consider brands from Super Bowl XLIX commercials as the domain for both social soundtrack conversations across multiple social media platforms and web searching on a major web search engine. So, this research is both a multiple social media platform analysis and multiple channel analysis, as web searching is typically not analyzed in conjunction with social media.

2. Literature review

The theoretical foundation for this research is eWOM marketing. Keller and Fay (2012) claimed that social media mediums are the platforms where consumers share their opinions

about the products via eWOM communications and thereby influence product sales. Word of mouth (WOM) is the process of conveying information from person to person and plays a major role in customer buying decisions (Richins and Root-Shaffer, 1988). WOM communication functions are based on social networking and trust: people rely on families, friends, and others in their social network for product recommendations. Research indicates that people trust seemingly disinterested opinions from people outside their immediate social network (Malizia *et al.*, 2017), such as online reviews (Hu *et al.*, 2017). This is known as eWOM. Similar to earlier processes, eWOM offers a variety of means to exchange information, many times anonymously or confidentially, as well as providing geographical and temporal freedom, although the online user profile seems to effect the credibility of eWOM (Xu, 2014). As such, eWOM is seen as increasingly important by businesses and organizations concerned with reputation management.

eWOM is defined as a "statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau *et al.*, 2004, p. 39). Cheung *et al.* (2008) examined the extent to which people were willing to accept and adopt online consumer reviews and the factors that encouraged adoption. The research findings reported comprehensiveness and relevance to be the most effective components of online postings. Consumers routinely express emotion in eWOM statements (Standing *et al.*, 2016), and Park and Lee (2009) reported that negative eWOM had a greater effect than positive eWOM.

One can view eWOM as a form of information sharing, especially around an IRL event. Prior research on information sharing shows that social actions can augment the central event, which in this research is a broadcasted sporting event. For example, Alliez (2008) showed that end user enrichment enhances the social aspects of broadcast events. Liu *et al.* (2015) claimed that content and technology gratification are key factors that drive user satisfaction with social media communication. Showing that information sharing is impacted by both demographics and informational attributes, Joannah Sin (2015) investigated the variation in problematic informational outcomes (e.g. too much information, irrelevant information, conflicting information, etc.) with the use of different social soundtrack mediums between genders, with the derived user satisfaction via second screen social soundtrack conversations augmenting other social possibilities. Alpar *et al.* (2015) claimed that information recipients are influenced by the quality of information and social cues that prompt business vendors to incorporate the social aspects of the advertising message, tying eWOM with the broader information sharing (Choi *et al.*, 2017). In other research, Oh and Yeon Syn (2015) analyzed the different dimensions of motivation for using the social media to share personal experiences, again demonstrating the impact of demographics. Showing that information sharing is not always factual, Zhao *et al.* (2011) extracted sentiments about football teams by analyzing opinions in tweets.

The rapid growth of the social soundtrack as an eWOM network that augments information sharing may enable social media channels to become the primary mode of advertising (Haley, 2006; Barsamian, 2001). De Chernatony (2001) showed that when consumers become the promoters of the brand value, alongside the retailers, they participate in social conversations about the products. Zhang *et al.* (2011) showed that social media can be an effective eWOM and brand engagement (Kelley and Alden, 2016) tool. In other research, a framework was proposed to analyze the use of social media as a predictive tool in different areas such as brand sales and volatility of stock markets (Gayo-Avello *et al.*, 2013).

Advertising of brands in the social media environment generates inter-personnel connectedness by means of information sharing (Willie, 2012; Liou *et al.*, 2016). Carroll (2005) argued from the user engagement perspective that such eWOM advertisement strategies create involvement, participation, and social media distribution. Young (2014) identified that consumers using traditional and digital media simultaneously have replaced single traditional linear advertising media, such as TV. Therefore, the rapid expansion of social media usage

leads to the reinforcement of the impact of TV advertising in terms of a resurgence of its ability to develop brands (Stipp, 2011), as such connectedness facilitates eWOM brand awareness. Similarly, Micu and Pentina (2015) found that brand information in online communication, before and after ads, generated high brand attitude scores for experienced products. In a similar research, Liu (2012) analyzed sentiments to predict sales performance.

Though the aforementioned studies speak to the impact of eWOM conversations concerning brand advertisement, they do not identify the role of users' information behavior concerning web searching for brands in conjunction with conversing on social media. There are studies that hint that eWOM advertising might stimulate web searches (Rockwood, 2012; Keller and Fay, 2012). Graham and Havlena (2007) examined the relationship between WOM advertising and brand interest behavior (i.e. brand search in the web, brand website visits, etc.). Jansen *et al.* (2009) identified the relationship between attributes of search queries and the ranking of the web advertising results against those queries using a time series approach, with better ranked results getting more consumer interaction, with a follow-up study addressing revenue (Ortiz-Cordova and Jansen, 2012). Analyzing consumer's online searching behavior for multiple brands and the product attributes, Jun *et al.* (2017) found that a relationship existed among brands, and there was a brand-product attribute network that defines the relationship between specific brand and product attributes. The information searching in response to the brand advertisements may prompt consumers to turn to a search engine as their first action related to the brand communication (Lecinski, 2012). Regarding the impact of the social soundtrack on brand search, Neff (2013) claimed that social media interaction played a positive role on brand engagement, although the researcher was skeptical of its influence on short-term sales.

From our review, prior work fails to investigate the synergies among phases of an IRL event, social media platforms facilitating the social soundtrack, and web search activity in discussing the same brands. Also, prior studies have been mainly limited to one social media platform. Given this, there are several unanswered questions concerning social soundtrack conversing and web searching concerning IRL events. How do the conversations on different social media platforms affect web search? How does the media broadcast of IRL events influence web search? How does the social commentary in the phases of an IRL event stimulate web searching activity? What impact does attitude about brands have on web search concerning an IRL event? These questions are the motivation for our research.

3. Research questions

The social environment influences and shapes individual human behavior (Ashford and LeCroy, 2009). Therefore, making broadcast media events more social impacts the human communication act of information sharing in a socially mediated way that can affect people's thoughts and behaviors. Via second screens, viewers of an IRL event use one or more social media sites as channels of conversation by posting the online content about the broadcast event to build social relationships. Therefore, the social soundtrack can influence and shape the social environment around major marketing events.

For clarity, we define our key constructs:

- IRL broadcast media event – happening anchored temporally and not lending itself for delayed viewing;
- second screen – computing device used for posting social media content to the social soundtrack while the person is simultaneously engaging with media on a primary screen or event;
- social soundtrack – collection of discrete social media posts by individuals conversing about a particular event; and

- web search – act of submitting a query to a search engine in order to retrieve information about a topic.

We select three social media platforms for the social soundtrack data collection, which are Twitter, Instagram, and Tumblr. At the time of the study, Twitter was one of the most popular micro-blogging sites and was also used by brands for communication (Jansen *et al.*, 2009). Instagram is a social media medium where users perform online sharing of images and videos (Hu *et al.*, 2014). Tumblr was the second largest micro-blogging service after Twitter. It supported eight types of posts including images, videos, audios, text, answer, links, quotes, and chat (Chang *et al.*, 2014). We chose Google as the search engine, the most popular search engine at the time of the study, using Google Trends as the data collection channel for the search terms.

Our research focuses on Super Bowl XLIX, as this program was the most watched American television broadcast event in history, at the time, with an average audience of 114.4 million viewers (Wikipedia, 2015b). Due to the high level of viewership during the Super Bowl, companies pay for commercials that are televised during the broadcast. Quite expensive, the commercials are an integral aspect of the Super Bowl broadcast, and these commercials are an event in their own right. There are considerable discussions in the social soundtrack concerning Super Bowl commercials, before, during, and after the game. We term these phases of the Super Bowl event as: Pre phase, During phase, and Post phase. The Pre phase highlights the audience lead up conversation in social media and can start weeks ahead of a major event. We label the conversations on the game day as occurring in the During phase. The Post phase is the social soundtrack data beginning when the event is over until the point the data collection ends.

If the Super Bowl commercials have a branding effect, our premise is that a relationship should exist between the volume of posts via social soundtrack conversing and queries in web searching in each of the phases. In other words, an interplay among the broadcast advertising, social conversing, and web searching. Based on this insight, we formulate our research questions to evaluate the influence between social soundtrack conversing and web searching in phases of an IRL event. We evaluate the information aspect of social soundtrack conversations based on influence of both volume and attitude of social media posts to volume of web searching related to brands in the Super Bowl commercials. As in the study by Kucuktunc *et al.* (2012), we define attitude as the inclination toward positive or negative sentiments. We form two research questions based on these two aspects of information sharing in the social soundtrack about brands:

RQ1. Is there a relationship between the (a) volume and (b) attitude of social soundtrack posting and volume of web searching concerning brands?

Answers to these research questions can inform retailers and marketers of the influence of broadcast commercials on social media conversing and web searching as an information-seeking behavior pertaining to brands. As foundational research questions, we would expect, if the eWOM about the ads and the ads themselves had an effect on behavior outside of social media, we would expect to see an impact on search activity. Preliminary results from this research are presented in the studies by Mukherjee and Jansen (2015, 2016).

To examine *RQ1a*, we define the following hypotheses, each for one social media platform:

H1. There is a significant relationship between volume of social soundtrack posting on (a) Twitter, (b) Instagram, and (c) Tumblr searching on Google.

RQ1b regarding evaluation of social soundtrack attitudes on brand-related web search is examined by the following three hypotheses each for one social media platform:

H2. There is a significant relationship between attitude of social soundtrack posting on (a) Twitter, (b) Instagram, and (c) Tumblr and web searching on Google.

4. Data collection and research design

Super Bowl XLIX occurred on February 1, 2015 at University of Phoenix Stadium, Arizona, USA, with a kick-off time of 6:30 p.m. Eastern. The NBC channel broadcast the event, with an average of 114.5 million viewers, reaching 118 million viewers during the half time show (Wikipedia, 2015b). As shown in Table I, we collected data related to Super Bowl XLIX from January 10 through February 24, 2015 on each of three social media platforms. To collect data from each platform, we utilized the respective APIs and tokens for Twitter, Instagram, and Tumblr in corresponding search scripts.

The queries we used include: "superbowlxlix," "superbowl49," "superbowlcommercial," "superbowlAd," "superbowlhalftime," "superbowl2015," "2015superbowl," "sb49", and "football." The query list included the terms that occurred most frequently as social media tags (e.g. #superbowlcommercial, #superbowlxilx, etc.) in a collection of sample data for all social media platforms collected against the seed query named "superbowl." We collected the sample data for 48 hours (i.e. from January 6, 2015 to January 8, 2015) to identify the potential queries for this research, and the sample data were not included in the data set used in this research. For our hypotheses, we divide the data collection period into three phases. Table II shows the date and time of each of the periods.

We considered game day as the During phase, including the 4 hours of the game, the first 18.5 hours of the day preceding the game, and the remaining 1.5 hours of the day. The Pre phase spans from the moment the data collection for social soundtrack starts and continues till the beginning of the game day. The Post phase begins the day following game day and continues until the point data collection ends.

For our research regarding the conversing and searching relationship, we deal with brands from the 47 commercials (Staff, 2015; Anonymous, 2015) shown during the event. The list of Super Bowl commercial keywords contains the ad titles (e.g. "mercedes," "coca cola," "wix," etc.), titles of the videos for the brands (e.g. "real strength," "like a girl," etc.), the popular name of the brands (e.g. coke, burrito, etc.), hashtags associated with the spots (e.g. "#realstrength," "#likeagirl," "#itsthateasy," etc.), and the first and last names of actors participating in the Super Bowl commercial videos. We check for the presence of these keywords, extracted from relevant websites (Anonymous, 2015; Staff, 2015), in the social media posts. We generate the list of search queries based on the terms that occurred most frequently as tags in the sample data. We use the keywords list for commercials formed to determine the sub-list for each of these 47 brands, such as upcoming movie trailers (e.g. *Fifty Shades of Gray*, *Jurassic World 3D*), products (e.g. Mercedes, Skittles), services (e.g. Esurance, TurboTax), technologies (e.g. Microsoft, Mophie), mobile games (e.g. Game of War, Heroes Charge), etc. We segregate the commercial keywords list into 47 sub-lists by identifying the ad title, titles of the video, hashtags, and the names of the actors participating for each of these 47 brands. So, a social

Table I. Volume of Super Bowl XLIX data in three social media platforms

	Twitter	Instagram	Tumblr
Volume	3,112,789	811,262	51,569

Note: Volume of collected Super Bowl XLIX data by social media platforms

Table II. Start and end dates and times for Super Bowl phases

Phase	Start date time	End date time
Pre	January 10, 2015 00:00:00	January 31, 2015 23:59:59
During	February 1, 2015 00:00:00	February 1, 2015 23:59:59
Post	February 2, 2015 00:00:00	February 24, 2015 00:00:00

media post belongs to a particular brand if the post contains the corresponding keywords from the keyword sub-list concerning that brand.

We collect the search data regarding web queries from Google Trends, where the query list contains the brand names of the commercials extracted from the websites (Anonymous, 2015; Staff, 2015) (e.g. "Mercedes," "Budweiser," "Pepsi," "Skittles," "Microsoft," etc.). The brands either sponsor the championship or pay for advertisements during the media broadcast. The search data show the relative interest of users over days for those brands. The search data collection phases are the same as for the social media data.

For *RQ1a*, we segregate the count of social soundtrack posts collected on all three social media platforms for commercials into 24-hour intervals to keep the same dimensionality as that of search engine data (i.e. continuous scale). We compute relative counts of the postings in social soundtracks for all three social media platforms by using the following equation to maintain the same scale as the searching data (0 to 100). We define relative count as relative volume in our research:

$$rel\_count_j^i = \frac{Count\_of\_post_j^i}{\max_{i,j}\left(Count\_of\_post_j^i\right)} \times 100 \tag{1}$$

In Equation (1), i and j denote the day and the social media platform, respectively. For normalization, the relative count values lie in the range of 0 to 100. Max function selects the highest value from the set of frequencies for days across all three phases on jth social media platform.

For *RQ1b*, measurement of attitude involves the computation of sentiment of the postings that is carried out in two major stages. The first stage deals with mining emoticons from the postings on all three social soundtrack mediums, while the second stage determines the presence of positive and/or negative words. Beforehand, the pre-processing steps are carried out as: remove the hashtags; remove the usernames addressed by "@" and "RT" within the messages; remove the special characters such as "@," "RT," "via", and URLs; replace all contraction of verb forms to the corresponding verbs (e.g. "'ll" to "will," "'ve" to "have," and "'re" to "are"); replace all negations ("neither," "nor," "never," "no," "negative," "not," "n't," "won't," etc.) to "not"; replace a sequence of repeated characters by two characters (e.g. "coooool" to "cool," "ooooh" to "ooh," etc.); and lowercase the letters and expand each acronyms in the posts to its meaning extracted from relevant online resources (Fisher, 2012; Rouse, 2015; Howard, 2009). We execute sentence-level parsing of the texts based on the punctuations (e.g. ".", "?", "!" etc.) and/or emoticons, as used in the study by Hogenboom *et al.* (2013), before performing the stages. Once the sentence-level parsing is done, we remove the punctuation after extracting emoticons.

We extract the emoticons from the social soundtrack messages posted on all three social networking platforms by preparing two emoticon sentiment lexicons. We categorize the lexicons as positive sentiment lexicon and negative sentiment lexicon. The lexicons are prepared from available online resources (ComputerUser, 2014; Wikipedia, 2015a). We combine these online lists of positive and negative emoticons into the corresponding lexicons, while leaving out duplicate entries. We do not weigh the intensity of the emotions, but we do assign the emoticons either positive (e.g. ":-D," ":-)," ";-)," ":o," etc.) or negative (e.g. ": (," ":-(," "-_-," "v.v," "*D8*," ":c," etc.). We assign the polarity of sentences contained in Twitter texts, Instagram captions, and Tumblr blogs either as positive or negative, depending on the presence of positive and negative emoticons. We exclude neutral emoticons from our research.

Once the data cleaning and pre-processing of emoticons is complete, we implement the second stage of attitude analysis to determine the existence of positive and negative words.

We use online sentiment lexicon (Liu and Hu, 2004) employed in the study by Liu *et al.* (2005) to form our lexicons of positive and negative words, while removing the duplicating entries. In determining the attitude of the sentences by means of the presence of positive or negative words, we split the sentences into tokens and assign the polarity according to the following logic:

$$if\left(\left(\text{"not"} \in sentence_i \wedge pos\_word_j \in sentence_i\right) \wedge (index(\text{"not"}) < index(pos\_word))\right)$$

$$count\left(polarity_{neg}\right) + +;$$

$$else\ if\left(\text{"not"} \notin sentence_i \wedge pos\_word_j \in sentence_i\right)$$

$$count\left(polarity_{pos}\right) + +;$$

$$if\left(\left(\text{"not"} \in sentence_i \wedge neg\_word_j \in sentence_i\right) \wedge \left(index\left(\text{"not"}\right) < index\left(neg\_word_j\right)\right)\right)$$

$$count\left(polarity_{pos}\right) + +;$$

$$else\ if\left(\text{"not"} \notin sentence_i \wedge neg\_word_j \in sentence_i\right)$$

$$count\left(polarity_{neg}\right) + +;$$

Table III shows the polarity of example statements based on presence of positive and negative words.

Once the polarity of the social media postings related to each commercial is determined with the presence of emoticons and sentiment words, we compute the polarity score at the sentence level. Next, we aggregate the score at single tweet, caption, or blog level. Once the posting-level attitude score is computed, further aggregation is carried out on the number of messages posted within the 24-hour time window in order to determine the overall attitude for that day.

We assign a scale of rating for the emoticons and the sentiment words. We provide more positive or negative weight on positive and negative emoticons than for positive and negative words, as emoticons simulate the nonverbal cues that dominate verbal cues (Burgoon and Saine, 1978) (i.e. the text messages) and an important emotion intention indicator for viewers. The text coupled with emoticons has 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 neutral emoticons: 0. We are assigning equal weights with opposite signs for positive and negative emoticons and assign same positive and negative weight for positive and negative words but with opposite signs as in the study

Table III. Example statements and polarity

Statement	Polarity
"it is not at all worth viewing"	Negative
"the katy perry show was amazing"	Positive
"i will not miss the telecast of halftime show"	Positive
"first 15 min of the game was boring"	Negative

by Kramer (2010). So, the attitude score we compute using the following formula is for a specific category in a specific phase:

$$S_{t_k} = \frac{1}{N} \times \sum_{i=1}^{N} \sum_{j=1}^{M} \left(2 \times PosEmot_j^i + 1 \times PosWord_j^i - 1 \times NegWord_j^i - 2 \times NegEmot_j^i\right) \quad (2)$$

Here we term S_{t_k} as the average attitude score of postings aggregated in a particular 24-hour time window t_k; N is the total number of postings within t_k; $PosEmot_j^i$, $PosWord_j^i$, $NegWord_j^i$, and $NegEmot_j^i$ are positive emoticons, positive words, negative words, and negative emoticons for sentence j in posting i; and M is the count of sentences in posting i. Higher S_{t_k} indicates more positive attitudes. The steps of attitude measurement for all three social soundtracks are performed for each commercial to evaluate *RQ1b*.

Once computation of relative counts and attitude scores are done for social soundtrack conversations, we organize the social and search data as balanced panel data (Berrington *et al.*, 2006) for all three social soundtrack mediums. Each of the 47 brands has relative counts of social soundtrack posts and web queries across the total 46 days of data collection. So, the balanced panel data set can be viewed as a three-dimensional space where the dimensions are brands, time stamps, and the relative volumes or attitude score for each of the online channels (Twitter, Instagram, Tumblr, and Google). As there are three social media platforms, we have three such conversing-searching data panels. In our data set, we have a total of 2,162 records (47 brands $\times$ 46 days) each with relative counts and attitude scores for three social media platforms, along with relative counts for one search engine. Each record is the unit of analysis in our study to evaluate our hypotheses.

5. Methodology

For the research questions, we follow two separate methods. The first is the Granger causality test, a statistical hypothesis test that identifies whether one time series data are capable of forecasting the other (Granger, 1969), as the volume and attitude score of social soundtrack and the volume of web search are time series data. We also test whether the reciprocal causality exist between the time series data. If volume and attitude of social soundtrack independently cause web search, the reciprocal causality test evaluates whether web search can cause volume or attitude of social soundtrack separately.

The second method that we use is panel data regression with fixed and random effects (Schmidheiny, 2016; Bell and Jones, 2015) on individual brands to quantify the relationship between conversing on the social soundtrack and searching on the web. In the regression model, Google search data are the response variable, while the relative volume and attitude metrics of social soundtrack data are the cofactors. We conduct the Hausman specification test to determine the preferred model (fixed or random) and observe time effects on the linkage between social postings and web searching. The fixed effects model assumes that individual specific effect is correlated with the independent variable, while for random effects there is no correlation between individual specific effect and independent variables. We set the movie brand "50 shades of gray" as the baseline for brand effect in the fixed effects model, as there needs to be a reference point, and this commercial was first alphabetically. We are estimating the pure effect of web searching by controlling the unobserved heterogeneity with the addition of dummy variables for each brand in the fixed effects model.

6. Results

We apply the Granger causality test separately between volume of web search (X) and volume of social soundtrack conversation (Y) that are brand related and between volume of

web search (X) and attitudinal score of social soundtrack conversations (Z) related to brands. The number of lags is included according to the minimum Akaike information criterion (AIC). Table IV shows the optimal number of lags that generate minimum AIC values for (Y, X), and (Z, X) for Twitter, Instagram, and Tumblr.

We test whether social soundtrack volume (Y) causes brand search volume of Google (X) with optimal lags (see Table IV) for Twitter, Instagram, and Tumblr, respectively. Additionally, we also evaluate whether social soundtrack attitude (Z) causes Google search volume (X) with optimal lags (see Table IV) for Twitter, Instagram, and Tumblr, respectively. Table V shows the F-statistic with p-values of the models for all three social media platforms.

From Table V, the causality of Google search volume by social soundtrack volume is observed for all three social media platforms (p-values < 0.05), so the volume of social media posts does influence the volume of web searches. For the Granger causality test between attitude and search volume, it is also noticed from the p-values that for Twitter and Tumblr, social soundtrack attitude influences web searching, that is the attitude scores of social media postings influence the volume of web search activity. For Instagram, the null hypothesis (i.e. social soundtrack attitude does not cause Google search) cannot be rejected.

Next, we evaluate the reciprocal causation taking into account whether Google search causes social soundtrack volume and social soundtrack attitudes. Table VI represents the result of reciprocal causation done by means of the Granger causality test.

From Table VI, it is noted that Google search volume causes volume of social soundtrack conversations for Twitter and Tumblr, while the reciprocal causation is not supported for Instagram. So, web search causes an increase of posting in the social soundtrack for Twitter and Tumblr but no increase on Instagram. Regarding social soundtrack attitude, none of the

Table IV. Optimal number of lags with minimum AIC values for three social media platforms

	Twitter		Instagram		Tumblr	
	Lags	AIC_{min}	Lags	AIC_{min}	Lags	AIC_{min}
(Y, X)	8	1.429	9	1.395	8	1.347
(Z, X)	7	−0.083	7	−0.726	8	2.787

Notes: X is volume of web search; Y is volume of social soundtrack conversation; Z is attitudinal score of social soundtrack conversations

Table V. Result for granger causality for all three social media platforms

	Twitter		Instagram		Tumblr	
	F-statistic	p-Value	F-statistic	p-Value	F-statistic	p-Value
(Y, X): $Y \rightarrow X$	*3.335*	*0.0008*[a]	*5.165*	*5.87e−7*[a]	*6.7768*	*8.21e−9*[a]
(Z, X): $Z \rightarrow X$	*2.461*	*0.016*[a]	1.066	0.383	*2.01*	*0.042*[a]

Note: [a]Denotes significance causation, M → N means M Granger causes N

Table VI. Result for reciprocal causality for all three social media platforms

	Twitter		Instagram		Tumblr	
	F-statistic	p-Value	F-statistic	p-Value	F-statistic	p-Value
(X, Y): $X \rightarrow Y$	*3.920*	*0.0001*[a]	1.764	0.070	*5.736*	*2.99e−7*[a]
(X, Z): $X \rightarrow Z$	0.486	0.846	0.813	0.576	0.843	0.565

Note: [a]Denotes significance, M → N means M Granger causes N)

social media platforms supports the hypothesis that Google search volume causes social attitude about brands. So, volume has a two-way relationship (social soundtrack affects search and search affects social soundtrack), while attitude has a one-way relationship (social soundtrack affects search).

Once we have the result of Granger causality, we perform regression analysis on the panel data for each social media platform to quantify the relationship and compute the results of both fixed effects and random effects model. For panel data regression, we consider the forward direction of relationship (i.e. social soundtrack volume and attitude cause web search related to brands) as the social soundtrack volume directly causes Google search in all three social media platforms, and brand attitudes also cause Google search in the two of the social platforms in forward direction of causal relationship. In our regression equation, attitude scores and volume of the social soundtrack conversations are explanatory variables, and the Google search volume is the response. For random effects model, we use again use "50 shades of gray" as the baseline. We perform the Hausman specification test (Hausman, 1978) to choose either fixed or random effects model. The Hausman test results, displayed in Table VII, show that the *p*-values for all three social media platforms are less than 0.05, indicating the fixed effects model is preferable to use.

The results of *H1a-H2c* are displayed in Table VIII.

Table VIII shows that the estimates of relative volume for all three social media platforms are significant (p-value < 0.05). Regarding *RQ1a*, each unit increase of volume on Twitter, Instagram, and Tumblr significantly increases the Google search concerning brands by 4.7 times, 11.9 times, and 8.7 times, respectively. There is a significant relationship between volume of social soundtrack postings and web search queries regarding brands. So, *H1a-H1c* are fully supported. We tested the multicollinearity between the associated independent variables (i.e. sentiment and volume). The coefficients of individual predictors are not dramatically changed from the result given in Table VIII. This infers that multicollinearity does not exist between volume and sentiment for all three social media platforms.

Regarding the influence of social soundtrack attitude on Google search volume, Table VIII shows that for Twitter and Tumblr, the relationship between social media attitude and Google search volume concerning brands is significant. For Instagram, the attitude to search relationship is insignificant, though it is positive. For Twitter, each unit increase of aggregated attitude score significantly increases web search 3.96 times,

Table VII. Hausman specification test between fixed effects and random effects models for three social media platforms

	$F_{(46,\ >120)}$	*p*-Value
Twitter	201.27	< 2.2e−16
Instagram	162.47	< 2.2e−16
Tumblr	201.09	< 2.2e−16

Table VIII. Coefficient estimate of regression for relative counts and attitude with coefficient of determination (R^2) in different social soundtrack mediums

	Coefficient estimate		*t*-Value		*p*-Value		
	Volume	Attitude	Volume	Attitude	Volume	Attitude	R^2
Twitter	*4.723*[a]	*3.955*[a]	*3.188*	*2.153*	*0.0015*	*0.031*	0.826
Instagram	*11.862*[a]	1.143	*7.221*	0.335	*7.246e−13*	0.738	0.830
Tumblr	*8.617*[a]	*0.952*[a]	*3.676*	*2.118*	*0.0002*	*0.034*	0.827

Note: [a]Denotes significance, i.e. p-value < 0.05

while for Tumblr, the search significantly increases 0.95 times, with each unit increase of attitude scores. So, *H2a* and *H2c* are supported, while *H2b* is not.

Interestingly, 43 out of 46 brands have significant positive or negative fixed effects (i.e. p-value > 0.05), while "Terminator," "Jurassic World", and "Mophie" have insignificant effects for the conversing to searching relationship. Out of 43 brands that show significant effect, 41 brands show positive and 2 show negative effect (i.e. "Sprint" and "Nationwide"). In the interest of space, we present specifics on a subset of the brands. Table IX provides the fixed effects estimates of car-related brands. It is worth noting the "Sprint" and "Nationwide" commercials have significantly negative fixed effect on social conversing to web searching relationship concerning brands on all three social media platforms (i.e. Nationwide: Twitter-9.32, Instagram-10.89, and Tumblr-11.16 and Sprint: Twitter-6.40, Instagram-5.42, and Tumblr-5.52).

7. Discussion and implications

In this research, we evaluate the relationship between volume of social soundtrack conversing and web searching and attitude of social soundtrack conversing and volume of web searching concerning brands of Super Bowl commercials using three social networks and a major web search engine. The results of Granger causality show that the volume of brand-related postings to the social soundtrack and attitude of these postings directly influence the volume of web searching, with the exception of Instagram where the attitude does not directly influence web search. It is important to note that there exists a reciprocal causation where web searching also contribute to the volume of social media posting for Twitter and Tumblr. This overall relationship among broadcast ads, social media conversing, and web searching is illustrated in Figure 2. The theoretical implications for eWOM are very interesting. Social media postings have been considered eWOM in prior work (Jansen *et al.*, 2009), but our research findings show that web searching directly contributes to an increase in eWOM social media postings concerning the brands.

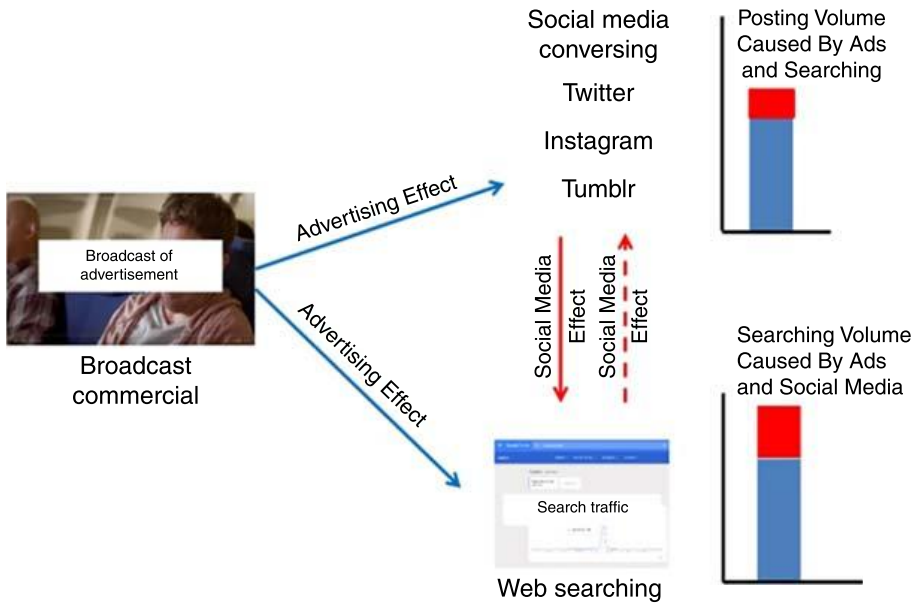
Our results from panel data regression analysis show that social soundtrack conversation significantly influences web search for the set of brands, corroborating the results from the Granger causality test. The unit increase per volume and per attitude on social media significantly increases the searching on Twitter and Tumblr. The regression model with fixed effects explains about 82 percent of the variance (R^2) in the conversing-searching relationship for all three social media platforms.

We also analyzed the brand fixed effects and time effects concerning the social conversing and web searching linkage. It is observed that "Budweiser" has the highest effect, followed by "Coco Cola" and car-related commercials, especially "BMW," "Mercedes," "Dodge," "Jeep," "Toyota," "Nissan," "Lexus", and "Kia." "Sprint" and "Nationwide" have significant negative estimates, which is corroborated by the average attitude scenario for these brands.

Table IX. Fixed effect in social conversations and web search association with respect to "50 shades of gray" on three social media platforms for ten car brands

Car brands	Twitter estimate	Instagram estimate	Tumblr estimate
BMW	67.61*	63.79*	64.58*
Dodge	63.52*	58.40*	62.53*
Jeep	61.97*	55.80*	59.13*
Kia	57.46*	50.46*	56.36*
Lexus	55.94*	55.26*	55.60*
Mercedes	65.97*	60.29*	62.87*
Nissan	63.57*	58.88*	62.70*
Toyota	59.04*	58.69*	57.75*
Fiat	35.16*	33.50*	33.35*
Chevrolet	26.18*	23.15*	26.01*

Note: *Significance, i.e., p-value < 0.05



There is a three way interplay occurring. The broadcast ads engenders both social media conversing and web searching. The increase in social conversing increases web searching. The increase in web searching increases social conversing

Figure 2. Interaction effects among broadcast commercials, social media conversing, and web searching

From the time effects, it is observed that days in Post phase have significantly positive effect on the relationship for all three social media platforms. This indicates that there are certainly individual differences for brands based on the actual commercials shown during the IRL event and consumer reaction to those commercials once the event is over. The social soundtrack conversing on all three social media platforms and the web searching concerning the commercials increases in the Post phase, perhaps with viewers engaging more on commenting and sharing about the commercials and videos pertaining to the brands on all three social media platforms relative to that in Pre phase.

There are several brands that show strong positive volume and attitude as a result of the broadcast commercials ("Budweiser," "Coco Cola," "BMW," "Mercedes," "Dodge," "Jeep," "Toyota," "Nissan," "Lexus" and "Kia," "Clash of Clans," "Microsoft," "Pepsi," "Geico," etc.) and the related social conversing on three social media platforms and associated web searching. There is certainly a relationship between conversing and searching as shown by the causality analysis, which can have a positive effect for the brands in both directions. Causality can be reciprocal in some social media platforms from the perspective of influence of web search on brand-related social media.

Regarding practical implications of these research findings, we believe that increased eWOM diffusion of information within the social soundtrack concerning these brands during and after the media broadcast of the IRL event drives an increase in web searching, one of the primary online economic drivers. Interestingly, the effect is less before the event, when the curiosity and excitement about the upcoming commercials is definitely high, showing that the broadcast commercials do have a near immediate effect on behavior with an increase in both search media post and search queries. Both web search and social soundtrack conversations significantly rise in the During phase, as shown in Figure 3.

We believe that viewers' sharing of information in terms of relative volumes and attitude toward the brands increases during the live broadcast of the event and once the event is over via social media postings. The attitude toward breweries, beverages, and car commercials is stronger compared to other products, as observed from their fixed effects

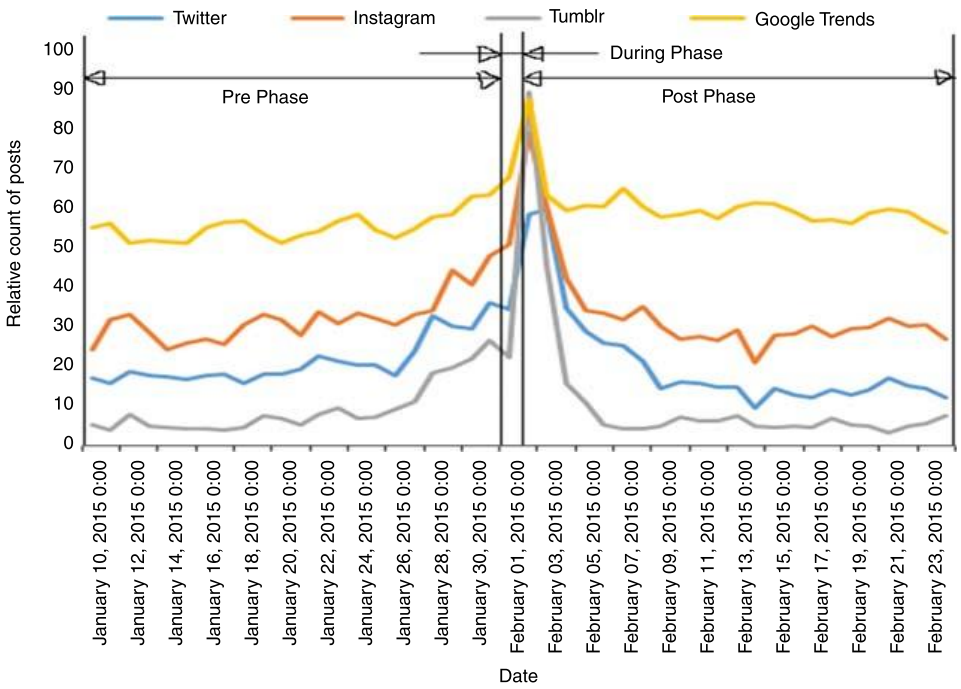


Figure 3. Patterns of social soundtrack conversations on Twitter, Instagram, and Tumble social media platforms and searching on the Google search engine aggregated over the brands

estimates during live broadcast and post-event periods, as supported by observed time effects. Before the telecast, there may be excitement or inquisitiveness as a topic of conversation, but post-event analysis of different aspects concerning the display of the ad on social media dissipates once the event has ended. People seem to be engaged more on information sharing about those brands after the broadcast in terms of expressing the attitude and social media post circulation, which brands may be able to convert to online purchases. The information sharing concerning the commercials after broadcast combined with the impact of the actual commercials may drive an increase in information seeking via web searching concerning the brand once the broadcast is over, which is most likely what a brand would strive to accomplish with such an expensive broadcast commercial.

It is also interesting to observe that average magnitude of volume of web search is considerably more in the Post phase for brands at the individual level. Retailers should monitor the brands that cause a rise in web searching and leverage such opportunities to promote their sales and by cross-selling. This points to the need for a coordinated multi-channel marketing effort across all online channels, including social, organic, and paid verticals (Jansen and Schuster, 2011).

As with most research, there are limitations. The first limitation is that we have garnered 3 million tweets, while there were 28 million tweets reportedly sent during the telecast of the Super Bowl (Gibbs, 2015). This is because we have used the public APIs to collect the data for our research for all three social soundtrack platforms instead of using the full data access. Using the firehose to collect the data may strengthen our findings. However, we do collect substantial data for our research. Also, we consider attitude of social soundtrack conversations as one of the independent variables in our research. We did not capture the actual sentimentality of the texts, as the positiveness and negativeness may neutralize each other at a sentence-level or post-level averaging.

In future work, we will focus on deriving the amount of sentiment (i.e. positive and negative) besides computing attitude, as sentimentality and attitude are different metrics (Kucuktunc *et al.*, 2012). We will also explore the relative effect of time and that of different subcategories of commercials on the relationship between social soundtrack

postings for each of the social media platforms and web search engine. Other avenues of research could include the effect of individual social network users (Riquelme and González-Cantergiani, 2016; Yang and Xie, 2016).

8. Conclusion

In our research, we evaluated the relationship between second screen conversing in the social soundtrack and web searching on a searching concerning commercials of an IRL event. The research questions are investigated from the perspective of information sharing as a form of eWOM advertising in conjunction with traditional broadcast advertising, both in terms of the volume and attitude of social soundtrack mediums conversing and web searching. We believe that our research contributes to understanding human information sharing and information-seeking behavior and interaction via social soundtracks in conjunction with viewing mass media broadcasts of IRL events in an emerging avenue of social soundtrack research for eWOM research.

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