Information Sharing by Viewers Via Second Screens for In-Real-Life Events

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The use of second screen devices with social media facilitates conversational interaction concerning broadcast media events, creating what we refer to as the social soundtrack. In this research, we evaluate the change of the Super Bowl XLIX social soundtrack across three social media platforms on the topical categories of commercials, music, and game at three game phases (*Pre*, *During*, and *Post*). We perform statistical analysis on more than 3M, 800K, and 50K posts from Twitter, Instagram, and Tumblr, respectively. Findings show that the volume of posts in the *During* phase is fewer compared to *Pre* and *Post* phases; however, the hourly mean in the *During* phase is considerably higher than it is in the other two phases. We identify the predominant phase and category of interaction across all three social media sites. We also determine the significance of change in absolute scale across the Super Bowl categories (commercials, music, game) and in both absolute and relative scales across Super Bowl phases (*Pre*, *During*, *Post*) for the three social network platforms (Twitter, Tumblr, Instagram). Results show that significant phase-category relationships exist for all three social networks. The results identify the *During* phase as the predominant one for all three categories on all social media sites with respect to the absolute volume of conversations in a continuous scale. From the relative volume perspective, the *During* phase is highest for the music category for most social networks. For the commercials and game categories, however, the *Post* phase is higher than the *During* phase for Twitter and Instagram, respectively. Regarding category identification, the game category is the highest for Twitter and Instagram but not for Tumblr, which has dominant peaks for music and/or commercials in all three phases. It is apparent that different social media platforms offer various phase and category affordances. These results are important in identifying the influence that second screen technology has on information sharing across different social media platforms and indicates that the viewer role is transitioning from passive to more active.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**

Additional Key Words and Phrases: Social soundtrack, IRL events, Super Bowl, second screens, social media, ANOVA, cross screens, dual screens, multiple screens

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1. INTRODUCTION

Given the near-ubiquitous use of online social media sites combined with access to mobile technology, online conversations related to broadcast media events have greatly increased, as the synergy of these technologies permits viewers to engage in connected

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social dialogues. The combination of social media platforms and mobile technology permits online conversations [Abdulla et al. 1998] that convey feelings of togetherness and communication among people who are often in dispersed locations. Social media platforms and mobile technologies are embedded alongside broadcast mediums, facilitating the creation of a social soundtrack among networked viewers for the event.

The social soundtrack is an interesting conversational form with dispersed networked viewers focused on a specific event anchored in time. The social soundtrack affords information sharing that can be both real time (i.e., during the live broadcast) and non–real time (i.e., before or after the live broadcast). The social soundtrack concerning such events can happen on various social media platforms. The integration of these social media platforms in conjunction with communicating about in-real-life (IRL) events using mobile devices marks the emergence of a phenomenon that greatly augments prior social aspects of the broadcast medium. This technology affordance for online conversation for a broadcast event is referred to as the second screen phenomenon, although there may be multiple (i.e., more than two) screens involved.

In the second screen phenomenon, the broadcast media event is shown on the base device where the viewing occurs (i.e., usually the largest screen), whereas the secondary screens are the computing devices (e.g., tablet, smartphone) that facilitate the conversation. It is the secondary screen that allows for the creation of what we refer to as the social soundtrack, the online conversation with others regarding a real-life event. The social soundtrack participants, which are the viewers of the event, exchange social media comments via second screen devices in terms of sharing of messages [Mukherjee and Jansen 2014]. The interchange of information can happen live (i.e., *during* the event) or when the event is not live (i.e., *before* or *after* of the event, relative to the start and end of the event). The content of posts in the social soundtrack may contain different aspects such as actors, directors, costumes, characters, and themes for a show; players, coach, and style if the event is a sporting event; or brand, sale, or customer preferences if the event is an advertisement. TV broadcasts of the events that happen IRL (e.g., Super Bowl, Academy Awards, Music Video Awards, Grammys, sports, broadcast of natural disasters) are unique happenings with substantial social soundtracks, as these events do not lend themselves to recordings for later viewing, unlike, for example, a seasonal TV show.

Therefore, the second screen interactions about an IRL broadcast event leads to a social soundtrack that is fixed in duration with the period bounded by the event's *Pre* and *Post* phases, including the event's *During* phase. The popularity of an IRL event intuitively increases the volume (i.e., number of posts) of social soundtrack from the perspective of commentary left on social media platforms. For this research, we consider Super Bowl XLIX as one such IRL broadcast media event. It happens once a year and is a major event, especially in the United States.

Aside from being just a sporting experience, the Super Bowl involves multiple topical subevents of interest, which we label as categories. For the game itself, the teams, coaches, and players are important for viewer engagement. Super Bowl commercials also hold distinct appeal for many viewers and have become a cultural phenomenon alongside the game itself. The music performances conducted during the halftime show are also an important facet of the Super Bowl. In this research, we investigate the social soundtrack for each of these three categories (game, commercials, music).

There has been limited academic research concerning the increasingly important second screen phenomenon and little systemic practitioner investigation. In this research, we investigate the use of secondary screens during the *Pre*, *During*, and *Post* phases of Super Bowl XLIX, specifically examining if viewer interactions concerning commercials, game, and music categories differ in the *Pre*, *During*, and *Post* event phases. We selected three popular social media platforms (Twitter, Instagram, and Tumblr) as our data collection sites to research the changes in second screen interactions throughout the phases of Super Bowl XLIX.

This research is important in highlighting mobile devices' roles in the changing nature of the viewer, moving from a passive to a more active, participatory, and involved role. This is important practically as the degree and manner of secondary screen usage in conjunction with IRL broadcast media events can facilitate retailer, broadcaster, and artist management of branding and advertising campaigns by using their understanding of the relationship among phase-category pairs and different social media platforms via social soundtrack conversations. Finally, findings shed light on social communication in relationship to the schedule of IRL broadcast media events, the social interaction in cross-technology usage for second screens, and the effect of the social soundtrack on pop culture and human information processing.

The rest of the article is organized as follows. Section 2 introduces the background research from the perspective of information sharing via the social soundtrack, the integration of TV and secondary screens, and media broadcast of IRL events. Section 3 provides a detailed explanation of our research questions and hypotheses. Section 4 presents the data collection and research design in detail. Section 5 demonstrates the methodology to evaluate the research questions and hypotheses; it is followed by the results, along with discussion and implication in Sections 6 and 7, respectively. Section 8 concludes the article.

2. LITERATURE REVIEW

There has been prior research on information seeking and sharing via social sites to augment user enrichment. For example, it was claimed that content and technology gratifications were the two key factors that drive user satisfaction with social media communication [Liu et al. 2015], which was reflected in a study that experimented with Facebook groups focusing on discussion related to diabetes and found out that the user community aimed to construct the identity and recognition by information integration [Greene et al. 2011]. Different dimensions of users' motivation to use social media to share personal experiences and information were analyzed, which in turn influenced the social support between anonymous users [Oh and Syn 2015], along with the ability to cognitively process the broadcast information [Van Cauwenberge et al. 2014]. In a field study, Sin [2015] investigated the variation in problematic informational outcomes with the use of different social mediums between gender, whereas in another research study, Jansen et al. [2011] classified ecommerce information sharing behavior of the youth who used multiple social media platforms. Blanco et al. [2015] associated news broadcasts with other online news articles. In the context of production, flow, and consumption of information via social media communication within virtual communities, a significant homophily among the user categories was found in Twitter [Wu et al. 2011]. In another field study on social networks, it was claimed that weaker ties in the social graph played a more dominant role in the dissemination of novel information through social media platforms [Bakshy et al. 2012]. Regarding research on information sharing about media broadcasts, it was claimed that end user enrichment enhanced the social possibilities of broadcast events via information sharing with event-related user-generated content on social media [Alliez 2008]. All of these works focused on the user's information-sharing behavior supported by social networking platforms. Our research builds on this prior work by specifically introducing the concept of the social soundtrack as an information-sharing conversation medium.

There has also been research concerning second screen interactions on social media platforms from the perspective of end user engagement and generation of social media posts regarding TV shows. Prior research found that Twitter was increasingly used as a real-time audience communication channel for sharing TV experiences where the viewers were creating parallel narratives for events via second screen [Lochrie and Coulton 2012]. A modest interest was observed among users in using secondary screen to share information while viewing TV shows [Courtois and D'heer 2012]. In an experiment with users' engagement with second screens, users' second screen behaviors were examined concerning where and when people switched their attention between primary and second screens [Leroy et al. 2013]. Prior research also observed that sufficient social media is generated via texting on different social media sites using second screens [Lenhart 2012]. Basapur et al. [2012] report that there may be concerns of attention with the use of second screens during broadcast events. Scharl et al. [2016] examine social media posts concerning a seasonal show, automatically classifying sentiment relating to actors and events in the show. While conducting the social possibilities of TV affected by second screens, viewers' sentiments concerning the U.S. National Football League teams were analyzed by mining social media tweets to enable the viewers to better select the interesting programs [Zhao et al. 2011]. In other research related to generating online social interactions, the resulting buzz of specific American reality show–related tweets on the TV screen were investigated during the show [Benton and Hill 2012]. It exhibited that the specific tweets with new information resulted in more user engagement than the general tweets during airing of TV shows. In a separate research concerning users' engagement of seasonal TV shows via second screen, the predominant conversation patterns of TV show–related social media posts during live and after live broadcast of U.S. TV shows were examined; it was found that the different conversation patterns became predominant when the TV show was broadcast live compared to when it was not on the air [Mukherjee et al. 2014]. Also examining a seasonal TV show, Giglietto and Selva [2104] showed that the shows can affect the style of social media posts. Regarding viewers' conversations in groups about a TV show, it was found that viewers generated substantial social media content when the show was not being transmitted [Mukherjee and Jansen 2015a]. Examining the conversational patterns at the interplay of second screen, social soundtrack, and TV for different cultural biases, social media conversational patterns differed between U.S. and non-U.S. TV shows both in real-time transmission and after live broadcast [Mukherjee and Jansen 2015a]; however, none of this prior research measures the temporal interaction effects of social networks and second screens concerning IRL events, which is what we examine in this research.

As the prevalence of seasonal TV (i.e., a broadcast show scheduled over several weeks with new episodes released at intervals) has decreased, our research focus is on what we refer to as IRL broadcast media events. These broadcast media events are those IRL events that are anchored temporally and do not lend themselves to delayed viewing (i.e., recording and watching at a later time). These IRL events can generate substantial social media conversation [Lenhart 2012; Lindsay 2011; Oulasvirta et al. 2012]. Regarding research on natural disasters, Palen [2008] studied how social media is successfully used by a wide range of organizations for crisis and disaster management from the perspective of recovery capabilities. In a separate study, Sakaki et al. [2010] analyzed real-time Twitter interactions concerning earthquakes and proposed an earthquake reporting system. For sports-related events, the value of social media tools helped sports marketers and retailers to enhance the relationship marketing process [Williams and Chinn 2010]. Adidas used Twitter to become the most-talked-about brand in FIFA 2014 [Ruvolo 2014]. The digital mediatization of the 2008 Olympic Games was intensified in terms of amount and types of content posted on different social media platforms [Hutchins and Mikosza 2010]. Tang and Cooper [2012] evaluated the relationship between gender groups and the use of social media for the 2008 Olympics. Wang et al. [2012] analyzed the public sentiment for the 2012 U.S. presidential election; in a distinct research study, focused groups of users with similar biases were identified based on prior users' behavior on Twitter for the 2012 U.S. presidential election [Lin et al. 2013].

For this research, the specific IRL broadcast media event examined was Super Bowl XLIX. Prior research studies on the relationship among second screens, IRL broadcast events, and social media regarding IRL events is limited. Specifically, focus on prior Super Bowl research, the presence of Super Bowl 2012 was measured by tracking the number of comments posted (particularly on Twitter) compared to that in 2011 [Dumenco 2012]. Twitter was used as the social media platform to assess people's interest in car-related commercials aired during Super Bowl 2012; tweet patterns were analyzed to identify the relationship between tweets and nature of commercials [Lee et al. 2014]. Regarding the research of participation using second screens on the content analysis of TV shows, the second screen interaction on Twitter was studied to address the creation of consumer interest in brands televised during Super Bowl 2014 [Shin et al. 2015].

Although the aforementioned research speaks to the use of social networks to analyze viewer interactions concerning an event, prior research failed to investigate, in a systemic manner, the interplay among temporal phases of an IRL event, different social media platforms, and the multiple inherent categories within the social soundtrack via second screens, which we do in this research. In addition, prior research has mainly been limited to a single social media platform, whereas we investigate three social media platforms in this research.

As such, from prior works, there are several unanswered questions regarding second screen conversations concerning IRL events. How is social media technology used during the live broadcast of an IRL event? How does the media broadcast of IRL events influence social soundtracks? How does an IRL event–based social commentary in the social soundtrack influence interaction on different aspects of the event in phases? These are some of the questions that motivate our research on investigating the relationships between Super Bowl phases and Super Bowl categories of the social soundtrack on multiple social media platforms. Preliminary findings are reported in Mukherjee and Jansen [2015a, 2015c, 2016]. We significantly expand the research questions, methodology, results, and discussion that we present here.

3. RESEARCH QUESTIONS

The social environment influences and shapes individual human behavior [Ashford and LeCroy 2009]. Making broadcast media events that are more social influences human communication in a socially mediated way, affecting human thoughts and actions. Viewers of an IRL event use second screens to share messages on online social media platforms, which are the medium of conversation used to build social relationships; therefore, the social soundtrack can both influence and shape the social environment via the participants' information sharing.

Within the spectrums of U.S. broadcast media events shows, there are certain programs that draw a great deal of social media attention. Among these, we consider Super Bowl XLIX in our research, as it was the most-watched American TV program in history, at the time of the study, with an average audience of 114.4 million viewers [Schalter 2015]. Due to the high degree of viewership for the Super Bowl, companies (Budweiser, Nationwide, McDonalds, etc., for Super Bowl XLIX) sponsored expensive commercials televised during the event. Commercials, an integral aspect of the Super Bowl, have become their own cultural phenomenon alongside the game. A considerable number of people watch the event primarily to see and discuss the commercials. In addition to the game and ads, popular and iconic performers and musicians (e.g., Katy Perry, Lenny Kravitz, and Missy Elliot for Super Bowl XLIX) take part in the halftime show on game day.

For our research, we selected three social network platforms for social soundtrack data collection: Twitter, Instagram, and Tumblr. Twitter is one of the most popular microblogging sites. Most microblogging services share commonalities and are used for discussing brands [Jansen et al. 2009]. Instagram is a medium of communication where users perform capturing and online sharing of images and videos [Hu et al. 2014]. Tumblr is second largest microblogging service after Twitter. And it supports eight types of posts: images, videos, audios, text, answer, links, quotes, and chat [Chang et al. 2014].

There is considerable discussion in the social soundtrack on three aforementioned categories of game, commercials, and music, not only during but also before and after the Super Bowl. We term these temporal phases of the Super Bowl social soundtrack conversation as the *Pre* phase, *During* phase, and *Post* phase. The *Pre* phase highlights the audience's interaction and starts weeks ahead of the event day and continues until the event starts with the opening kickoff. The *During* phase is the period of the live broadcast of the event, in this case from kickoff to the final second of the game. The *Post* phase is the social soundtrack beginning the moment the event is over and extended to some point of time in the future, which can be defined as when the social soundtrack falls below some threshold.

In our research, we classify the second screen interactions into three broad Super Bowl–related second screen categories—commercials, music, and game—to identify the dependence of these categories among the *Pre*, *During*, and *Post* Super Bowl phases.

For clarity, we define our key constructs:

(1) *Second screen*: Computing device used for posting social media content to the social soundtrack
(2) *Social soundtrack*: Collection of social media posts from second screens concerning a particular event
(3) *IRL broadcast media event*: Happening anchored temporally and not lending itself for delayed viewing
(4) *Event category*: Classification of posts within the social soundtrack concerning an event subtopic.
(5) *Event phase*: Distinct period of an event for temporal classification of social soundtrack posts.

For this research, we believe the social soundtrack conversation regarding the specific Super Bowl categories changes in various phases. The social soundtrack conversation will also most likely change in specific phases for different categories. Thus, our premise is that there is a phase-category relationship in second screen conversations that exists for each of the three social media platforms. Based on this premise, we formulate our first research question to test the relationship among Super Bowl phases and categories for each of these three social media platforms.

RQ1. Is there a social soundtrack relationship with respect to the volume of posts among Super Bowl categories and Super Bowl phases based on the social media platform?

This research question informs retailers and marketers curious as to the dominance of the specific category in a specific phase during second screen communication on specific platforms. In a previous study based on a survey of Super Bowl XLIV viewers [Johnson and Lee 2011], the primary contributor to viewers' enjoyment was the competitiveness of the game itself with the specific teams competing. This indicates significantly more enjoyment based on the level of fans' engagement toward a specific team. The next largest category was the Super Bowl commercials, which were rated higher than the Super Bowl's musical entertainment (pregame show, National Anthem, halftime entertainment, etc.). The ad agencies engage to buy slots and build up the ads days before the game; they practice follow-ups afterward, as prices rise for the leftover slots as the game gets closer [Farhi 2014]. On the other hand, the NFL uses the halftime show as the revenue stream to contribute significantly to the Super Bowl profit [Florio 2014]. Therefore, the Super Bowl categories have temporal aspects before, during, and after the IRL event. To examine the phase-category relationships, we define the following hypotheses.

Hypotheses: There exists a relationship with respect to the volume of posts among Super Bowl categories and Super Bowl phases in second screen conversations on Twitter (Hypothesis 01), on Instagram (Hypothesis 02), and on Tumblr (Hypothesis 03).

The first research question does not identify the change in second screen interactions of categories among phases. It also does not determine the change in interactions in all phases among categories. This leads us to formulate our second and third research questions, which are characterized by the interplay of specific categories and three phases.

RQ2. Does the volume of second screen conversation with respect to Super Bowl categories in the social soundtrack significantly differ among Super Bowl phases?

RQ3. Does the volume of second screen conversation with respect to Super Bowl phases in the social soundtrack significantly differ among Super Bowl categories?

The second and third research questions highlight multiple perspectives. The social soundtrack conversations related to the categories via social networks enlighten the commercial opportunities [Zhang et al. 2011] at the intersection of the social networks, the broadcast media event, and second screens. Communication via second screens identifies social media's adaptation as the driver of interaction from the perspective of the viewing audience while the event is (not) broadcast live. We examine our second research question by forming three research hypotheses.

Hypotheses: There is a significant difference in the volume of second screen conversations in the social soundtrack related to Super Bowl commercials (Hypothesis 04), music (Hypothesis 05), and game (Hypothesis 06) among the Super Bowl phases.

Hypotheses 04, 05, and 06 are tested with the absolute volumes of categorical conversations in continuous scale among Super Bowl phases. Here, absolute volume in a continuous scale means that the volume of conversation is converted as a ratio between the volumes of social media interaction at an instant to the best of highest values of volume among all records among all Super Bowl categories. We are also curious to test the hypotheses with respect to the relative volumes of conversations of a specific category in a specific phase and are interested to find the dominant phase with respect to relative volumes across three conversation categories. We believe that the interphase relative volumes of conversation for a specific category (i.e., relative volumes of posts for a particular category over three different phases) may yield a different scenario compared to that of the absolute continuous scale volumes of postings of a specific category over three phases. We further formulate three hypotheses for research question 2 by taking the relative volumes of posts into account.

Hypotheses: There is a significant difference in the relative volume of second screen conversations in the social soundtrack related to Super Bowl commercials (Hypothesis 07), music (Hypothesis 08), and game (Hypothesis 09) among the Super Bowl phases.

Each of the six aforementioned hypotheses addresses commercials, music, and game categories separately among the *Pre*, *During*, and *Post* phases.

Testing with intraphase relative volumes of posts for the categories is synonymous to testing with the absolute volumes of categories, as the intraphase relative volume for

Table I. Volume of Collected Super Bowl XLIX Social Media Data by Social Media Platforms

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

a particular category represents what percentages of total volume of conversation in a time frame belongs to that category in a specific phase. The total volume of conversation in a period is the summation of posts corresponding to each of these three categories at that time.

Thus, research question 3 begets the following three hypotheses.

Hypotheses: There is a significant difference in the volume of second screen conversations in the social soundtrack in Pre (Hypothesis 10), During (Hypothesis 11), and Post (Hypothesis 12) Super Bowl phases among Super Bowl categories.

Hypotheses 10, 11, and 12 are tested with the absolute volumes of phase-based conversations on a continuous scale among categories. Here, absolute volume on a continuous scale is the ratio between volumes of social media interaction at an instant to the highest value of volume among all records in a particular phase. The hypotheses related to research question 3 address the significance of *Pre*, *During*, and *Post* phases separately for commercials, music, and game categories in the social soundtrack.

4. DATA COLLECTION AND RESEARCH DESIGN

Super Bowl XLIX took place on Sunday, February 1, 2015, at the University of Phoenix Stadium in Arizona. Kickoff time was 6:30 p.m. Eastern. NBC broadcasted the event. At the time of the study, Super Bowl XLIX was considered the most-watched program in American TV history [Patra 2015]. The average number of viewers was 114.5 million, reaching 118 million during the halftime show [Wikipedia 2015b].

We collected data related to Super Bowl XLIX from January 10, 2015, until of February 24, 2015, as shown in Table I, although other data collection methods have been used in prior research [Fleury et al. 2012]. Three social media platforms were used as data collection sites. To collect data, we embedded the respective APIs and tokens for Twitter, Instagram, and Tumblr in corresponding scripts with search queries. There was a list of queries that includes *superbowlxlix*, *superbowl49*, *superbowlcommercial*, *superbowlAd*, *halftimeshow*, *superbowlhalftime*, *sb49*, and *football*. The aim of forming this list of queries was to collect data for this research using each term as a search query on all three social media platforms. The query list was formed with these terms as they occurred most frequently as tags (#superbowlcommercial, #superbowlxilx, #halftimeshow, #superbowl49, etc.) in a sample dataset for all social media platforms collected against the seed query named *superbowl*. The sample data was collected for 48 hours (i.e., from 01/06/2015-16:00:00 to 01/08/2015-16:00:00) to identify the potential search queries; the sample data was not included in the dataset used in this analysis. We did not, ourselves, perform any stemming or other expansion of the query set. Instead, we leverage the internal searching algorithms of the various platforms.

4.1. Data Collection in Super Bowl Phases

The data collection period for Super Bowl XLIX is divided into three temporal phases (i.e., *Pre*, *During*, and *Post*) to evaluate phase-category (in)dependence. Table II shows the date and time of each phase.

We further display the distribution of the posts collected during three phases on three social media platforms in Tables III and IV. Table III shows the data collected during each phase, whereas Table IV shows the mean per hour posting during each phase. From Table III, it is noticed that although the volume of posts for the *Pre* and *Post*

Table II. Start and End Dates and Time for Super Bowl Phases

Super Bowl Phase	Start Date and Time	End Date andTime
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
Post	2/1/2015-22:30:01	2/24/2015-00:00:00

Table III. Volume of Collected Super Bowl XLIX Social Media Data in *Pre*, *During*, and *Post* phases on Twitter, Instagram, and Tumblr Social Media Platforms

	***Pre* Phase**	***During* Phase**	***Post* Phase**
Twitter	1,753,458	35,525	1,323,806
Instagram	452,761	16,459	342,042
Tumblr	24,695	6,544	20,330

Table IV. Hourly Mean Volume of Collected Super Bowl XLIX Social Media Data in *Pre*, *During*, and Post Phases on Twitter, Instagram, and Tumblr Social Media Platforms

	***Pre* Phase**	***During* Phase**	***Post* Phase**
Twitter	3,211.46	8,881.25	2,500.76
Instagram	829.23	4,114.75	630.86
Tumblr	45.23	16.36	38.39

phases are higher than that of the *During* phase, the rate of second screen interaction for the *Pre* and *Post* phases is lower than that of the *During* phase (see Table IV). Based on the findings in Tables III and IV, there is an obvious platform differences among the three, most notably with Tumblr, both in volume (lower) and in mean volume (lower in the *During* phase).

As we considered Twitter, Instagram, and Tumblr, we further explored the data types posted on Instagram and Tumblr. Tables V and VI display different types of posts supported by Tumblr and Instagram, respectively, and the number of postings collected. Twitter does not categorize tweets as different subcategories. From Table V, it is observed that among all three phases, there are three major types of postings on Tumblr. Blogs containing images hold the top position, followed by texts and videos. Audio has the least count in the *During* phase, whereas for the *Pre* and *Post* phases, Answer is the least. From Table VI, on Instagram, we have only two types of media posts. We noticed that people post images considerably more than videos.

4.2. Super Bowl Interaction Categories

Once we collect the data from all three social networks, we then classify the collected data into the three categories (commercials, music, and game) of second screen interaction for each social media platform. The categories were identified by means of the keywords collected from relevant Web sites. The keywords are in lowercase letters and are extracted from Web sites regarding commercials [Anonymous 2015; Ad Age Staff 2015], music [Wikipedia 2015a, 2015b], and game [Schalter 2015].

The list of Super Bowl commercial keywords contains the ad titles (e.g., *mercedes*, *coca cola*, *wix*, etc.), titles of the themes/videos for the ads (real strength, like a girl, etc.), the popular name of the brands (*coke*, *burrito*, etc.), hashtags associated with the spots (#realstrength, #likeagirl, #itsthateasy, etc.), and the first and last names of actors participating in Super Bowl commercial videos (*william*, *dafoe*, *braylon*, *o neil*, *o-neil*, *jeff*, *bridges*, etc.). We extracted 47 brands from relevant Web sites [Anonymous 2015; Ad Age Staff 2015] for our research.

The list of Super Bowl music keywords contains the first name and last name of the performers of the halftime and the pregame shows (*lenny*, *kravitz*, *katy*, *perry*, etc.),

Table V. Volume of Type of Posts in *Pre*, *During*, and *Post* Phases on Tumblr

	***Pre* Phase**			***During* Phase**		***Post* Phase**		
	Vol.	Percentage (%)	With Respect to *During* Phase (%)	Vol.	Percentage (%)	Vol.	Percentage (%)	With Respect to *During* Phase (%)
Answer	15	0.06	–0.09	10	0.15	17	0.08	–0.07
Audio	112	0.45	0.42	2	0.03	53	0.26	0.23
Chat	32	0.13	–0.33	30	0.46	47	0.23	–0.23
Link	526	2.13	1.79	22	0.34	334	1.64	1.30
Image	18,112	73.34	17.38	3,662	55.96	14,027	69.00	13.04
Quote	74	0.30	–0.37	44	0.67	79	0.39	–0.28
Text	3,975	16.10	–20.97	2,426	37.07	4,262	20.96	–16.11
Video	1,849	7.49	2.17	348	5.32	1,511	7.43	2.11
	24,695	100.00		65,444	100.00	20,330	100.00	

Table VI. Volume of Type of Posts in *Pre*, *During*, and *Post* Phases on Instagram

	***Pre* Phase**			***During* Phase**		***Post* Phase**		
	Vol.	Percentage (%)	With Respect to *During* Phase (%)	Vol.	Percentage (%)	Vol.	Percentage (%)	With Respect to *During* Phase (%)
Image	424,384	93.73	2.30	15,049	91.43	313,644	91.70	0.27
Video	28,377	6.27	–2.30	1,410	8.57	28,398	8.30	–0.27
	452,761	100.00%		16,459	100.00%	342,042	100.00%	

terms that describe the halftime show (*shark*, *palm*, *beach*, *flames*, etc.), and the songs (*teenage dream*, *california girls*, etc.).

The list of keywords related to the Super Bowl game contains the first name and last name of the players, coaches, umpires, referees, commentators (*brady*, *julian*, *edelman*, etc.), the field positions (*rusher*, *quarter back*, *quarter-back*, *red zone*, etc.), teams (*patriot*, *seahawks*, *hawks*, etc.), and other key terms related to game (*punt*, *fumble*, *tackle*, *intercept*, *goal*, etc.).

We assign the posts on social media platforms in commercials, in music, or in game categories, depending on the presence of terms from the respective keywords lists. These keywords are cross checked with the presence of the terms either in the body of the text or in the form of hashtags on Twitter and in the tag lists against the search results for Instagram and Tumblr. The terms are used as search queries for data collection on all three social networking platforms.

We do not assign the posts to any category that has terms from more than one keyword category list. For Twitter and Tumblr, we check the presence of the terms in tweets and blogs, whereas for Instagram, the terms are checked in the caption of the posts. We have 190,410 Twitter postings, 70,305 Instagram postings, and 9,705 Tumblr postings that belong to more than one category. We did not incorporate these mixed category postings in this research, as we consider Super Bowl categories as mutually exclusive. Apart from that, there are 99,523 tweets and 1,000 Tumblr posts not included in the analysis that do not belong to any category, such as soccer-related tweets, as *football* is used as the search query for data collection. In Asian, European, and African countries, *football* is synonymous to soccer, unlike in the United States and Canada.

| @jimmyfalon Yes ! I remember several years ago #Doritos #superbowl competition there ! I voted at that time|

| RT @PHXRCK5: Me and chambersXtina just shot our first superbowl commercial #firstofmany|

| Doritos Superbowlcommercial voting time! Here's my vote: https://t.co/I5pFF1HzeX |

Fig. 1. Snapshot of example postings for commercials, music, and game postings on Twitter.

| Tony with Ronald McDonalds !! #superbowl #mcdonalds #baby|

| One down, three to go until we meet our expectations. #finishthe fight #nfl #superbowl |

| Best Superbowlcommercial ever. #Budweiser #Beer #Frogs |

Fig. 2. Snapshot of example postings for commercials, music, and game postings on Instagram.

| <p>Robot Vs. Anna Kendrick - </br>Newcastle Superbowl Ad Storyboard</p> |

| <p>Instead of superbowl XLIX, can they just televise forty-nine superb Owls?</p> |

| <p>Katy Perry stans waiting for February. </p> |

Fig. 3. Snapshot of example postings for commercials, music, and game postings on Tumblr.

Figures 1 through 3 display example snapshots of commercials, music, and game category postings on Twitter, Instagram, and Tumblr, respectively.

We constructed 3 × 3 (phase × category) contingency tables from the distribution of the categories for second screen conversations on Twitter, Instagram, and Tumblr, respectively, as shown in Table VII.

After data collection, we segregate the count of posts collected for all three social media platforms and for all three Super Bowl categories into 5-minute intervals. We further segregate the categorical time-count data as *Pre*, *During*, and *Post* phases by annotating the time shown in Table II. Thus, each social soundtrack has phase-commentary and category time counts (5 minutes) that are used as the units of analysis in testing the research hypotheses corresponding to research questions 1 through 3 pertaining to the phase-category relationship.

5. METHODOLOGY

We use SPSS to evaluate our hypotheses for all three research questions. For the first research question, we perform chi-square tests to determine the phase-category relationship. For examining the second and third research questions, we use one-way ANOVA. Before performing one-way ANOVA on the absolute volume count data, we needed to convert it into a continuous scale. Thus, we express the continuous scale absolute volume as the ratio between the value at time t and the best of the highest counts recorded in three phases (category), as shown in Equation (1). In this

Table VII. 3 × 3 Contingency Tables for Twitter, Instagram, and Tumblr of Phase and Category

Super Bowl Phase	**Twitter**			
	Category			
	Commercials (c%; r%)	Music (c%; r%)	Game (c%; r%)	Total (c%; r%)
Pre	350,259 (57.0; 22.0)	506,035 (57.5; 31.8)	737,011 (55.5; 46.3)	1,593,305 (56.4; 100)
During	10,525 (1.7; 33.3)	12,029 (1.4; 35.8)	11,057 (0.8; 32.9)	33,611 (1.2; 100)
Post	253,745 (41.3; 21.2)	362,113 (41.1; 30.3)	580,082 (43.7; 48.5)	1,195,940 (42.4; 100)
Total	614,529 (100; 21.8)	880,177 (100; 31.2)	1,328,150 (100; 47.0)	2,822,856 (100; 100)
Super Bowl Phase	**Instagram**			
	Category			
	Commercials (c%; r%)	Music (c%; r%)	Game (c%; r%)	Total (c%; r%)
Pre	92,864 (55.6; 22.4%)	136,431 (54.2; 32.9)	185,784 (57.6; 44.8)	415,079 (56.0; 100)
During	2,683 (1.6; 18.3%)	5,748 (2.3; 39.2)	6,249 (1.9; 42.6)	14,680 (2.0; 100)
Post	71,464 (42.8; 23.0%)	109,458 (43.5; 35.2)	130,276 (40.4; 41.9)	311,198 (42.0; 100)
Total	167,011 (100; 22.5%)	251,637 (100; 34.0)	322,309 (100; 43.5)	740,957 (100; 100)
Super Bowl Phase	**Tumblr**			
	Category			
	Commercials (c%; r%)	Music (c%; r%)	Game (c%; r%)	Total (c%; r%)
Pre	6,934 (48.6; 34.0)	7,560 (51.2; 37.0)	5,914 (50.0; 29.0)	20,408 (49.9; 100)
During	2,594 (18.2; 41.1)	1,834 (12.4; 29.0)	1,889 (16.0; 29.9)	6,317 (15.5; 100)
Post	4,746 (33.2; 33.6)	5,370 (36.4; 38.0)	4,023 (34.0; 28.5)	14,139 (34.6; 100)
Total	14,274 (100; 34.9)	14,764 (100; 36.1)	11,826 (100; 28.9)	40,864 (100; 100)

equation, j represents the phase (category) and t represents an instance of the 5-minute time window. The continuous scale of count data satisfies the normality condition. T_i denotes the range of time windows for each phase (category). For a specific phase, T_i's for categories are same; however, for a specific category, T_i's for phases are different[1].

$$scaled\_count_t^j = \frac{volume_t^j}{MAX\{max\{volume_{Tk}^1\}, max\{volume_{Tl}^2\}, \ldots..max\{volume_{Tr}^j\}\}} \tag{1}$$

To compute relative count data, we put absolute volume in both the numerator and the denominator of Equation (2). In this equation, i represents the phase and j represents the category.

$$rel\_count_j^i = \frac{volume_j^i + 1}{\sum_j volume_j^i + 3} \text{ at time } t, \tag{2}$$

The denominator includes a constant (i.e., 3) to avoid the zero division if at a particular time frame for a social network; the volumes for all three categories for a specific phase become zero. As there are three categories, we add 1 to the volume of each category (i.e., numerator) that sums to 3 in the denominator.[2]

The data concerning scaled volume and relative volume maintain the normality condition. Therefore, we apply the Games-Howell (GH) test as the post hoc analysis to identify the dominance of specific interaction category in specific phase in the phase-category space. We use the GH test as the data violates the homogeneity of variance

[1]The range of 5-minute time intervals in the *During* phase is shorter than that in the *Pre* and *Post* phases.
[2]There are 5-minute time windows in Tumblr where the volumes for all three categories are recorded as zero in a specific phase.

(significance of Levene's statistic <0.05), but the data does follow the equality of means assumption (significance of Welch's statistic <0.05).

For the first research question, we perform the chi-square test using SPSS on 3×3 phase-category contingency tables (see Table VII), where each cell $C^k{}_{i,j}$ gives the observed frequency of second screen interaction in the Super Bowl phase i for interaction category j on social network platform k [Mukherjee and Jansen 2015a].

In SPSS, we run two separate ANOVA tests to evaluate the second and third research questions. The critical value of the $F^{ANOVA}{}_{(2,\ >120)}$ is 2.996 at the 95% confidence interval ($\alpha = 0.05$). For research question 2, the second screen interactions in 5-minute time intervals for each category over the three phases are used as the unit of analysis or independent variable, and the denominator of Equation (1) is the best in the set of highest counts recorded in all three phases. For research question 3, the second screen interactions in 5-minute time intervals for each phase over three categories are used as the unit of analysis or as the independent variable, and the denominator of Equation (1) is the largest of the highest counts recorded for all three categories. The ANOVA test identifies that the mean of the tweet counts in 5-minute time intervals of at least one phase (category) is significantly different from the others for each category (phase).

6. RESULTS

6.1. Research Question 1

Chi-square tests were carried out to test three hypotheses associated with the first research question. We have 3×3 contingency tables for Twitter, Instagram, and Tumblr in Table VII. We have $\chi^2{}_{\text{critical}} = 9.49$ with df $= 4$ at $\alpha = 0.05$.

Hypotheses: There exists a relationship between Super Bowl categories and Super Bowl phases in second screen conversations on Twitter (Hypothesis 01), on Instagram (Hypothesis 02), and on Tumblr (Hypothesis 03).

From the 3×3 contingency table shown in Table VII for Twitter, we carry out our chi-square test where $\chi 2(4, 0.05) = 4{,}501.75$ and the p-value is $<<0.05$. For Twitter, there exists a relationship between phases and categories. Hypothesis 01 is fully supported.

We perform the chi-square test on the 3×3 contingency table for Instagram shown in Table VII. The $\chi 2(4, 0.05) = 891.36$, and the p-value is $<<0.05$. The result supports Hypothesis 02 and shows the existence of phase-category relationships for Instagram.

The chi-square test on the 3×3 contingency table for Tumblr (see Table VII) supports Hypothesis 03 as the test results $\chi 2_{(4,\ 0.05)} = 190.25$ with a p-value of $<<0.05$. Thus, there exists a dependency between phases and categories on Tumblr.

To identify the dependence between a specific interaction category and specific Super Bowl phases, we examine the second and third research questions. Identifying the dependence of categories of conversation on phases of an IRL event will facilitate the retailers, broadcasters, and music companies to focus on the conversation of a specific category in a specific phase to increase the sales of brands, promote the popularity of the broadcast network, and formulate the strategies of launching the music videos of particular artists.

6.2. Research Question 2

We performed one-way ANOVA tests to evaluate three research hypotheses related to research question 2. The volume of social soundtrack on a particular category is in continuous scale formed using Equation (1) to test Hypotheses 04 through 06.

Hypotheses: There is a significant difference in the volume of second screen conversation in the social soundtrack related to Super Bowl commercials (Hypothesis 04), music (Hypothesis 05), and game (Hypothesis 06) among the Super Bowl phases.

Table VIII. ANOVA Statistics with Respect to Continuous Scale Absolute Volume for Twitter, Instagram, and Tumblr on Super Bowl Commercials, Super Bowl Music, and Super Bowl Game Categories

Super Bowl Commercials Category		
Social Media Platform	$\mathbf{F^{ANOVA}_{(2,\ 12859)}}$	***p*-Value**
Twitter	69.74	0.00
Instagram	72.78	0.00
Tumblr	97.79	0.00
Super Bowl Music Category		
Twitter	70.49	0.00
Instagram	63.58	0.00
Tumblr	92.50	0.00
Super Bowl Game Category		
Social Media Platform	$\mathbf{F^{ANOVA}_{(2,\ 12859)}}$	***p*-Value**
Twitter	74.73	0.00
Instagram	63.89	0.00
Tumblr	109.88	0.00

We evaluate Hypothesis 04 on Twitter, Instagram, and Tumblr. The top portion of Table VIII displays the F-statistic with the *p*-values. There is a significant difference in commercial-related social conversation among Super Bowl phases for all social media platforms.

We test Hypothesis 05 on Twitter, Instagram, and Tumblr. The middle portion of Table VIII displays the F-statistic with the *p*-values. It is seen that there is a significant difference in music-related social conversation among Super Bowl phases for all social media platforms.

We test Hypothesis 06 on Twitter, Instagram, and Tumblr. The bottom portion of Table VIII displays the F-statistic with the *p*-values. It is seen that there is a significant difference in game social conversation among phases for all social media platforms.

We define the phase(s) as the predominant phase(s) if the mean(s) of that phase(s) is(are) significantly higher than that of the remaining phase(s) compared among the categories. To test the predominant phase(s) among the categories, we perform the GH test.

For Hypothesis 04, the *During* phase emerges as the predominant phase for second screen interaction in the commercials category (see the top portion of Table IX).

For Hypothesis 05, again the *During* phase is predominant in the music category (see the middle portion of Table IX) on all social media platforms.

For Hypothesis 06, the *During* phase becomes predominant relative to the *Pre* and *Post* phases for Twitter in the game category (see the bottom portion of Table IX).

Figure 4 depicts the hourly mean of postings on all three social media platforms for all three categories over all three phases of Super Bowl XLIX.

Hypotheses 04 through 06 are tested with the continuous scale absolute volumes of categorical conversations among phases finding that the *During* phase becomes predominant for all three categories across three social media platforms. It is obvious that the *During* phase will be dominant, as the means of conversations in the *During* phase are substantially higher than the *Pre* and *Post* phases, as displayed in Figure 4.

The ANOVA test of Hypotheses 07 through 09 gives the following results displayed in Table X. These hypotheses are evaluated using relative volumes computed using Equation (2).

The top portion of Table X displays the F-statistic with the *p*-values. It is seen that there is a significant difference in the relative volume of posts concerning commercials among phases for all social media platforms. Hypothesis 07 is fully supported.

Table IX. Dominant Phases and T-Statistic for Other Phases with Emerging Phases with Respect to Continuous Scale Absolute Volume for All Super Bowl Categories

Super Bowl Commercials Category			
Social Media Platform	**Dominant Phase**	**T-Values with Other Phases**	
Twitter	*During*	*Pre*: 12.55*	*Post*: 23.57*
Instagram	*During*	*Pre*: 17.79*	*Post*: 20.73*
Tumblr	*During*	*Pre*: 30.63*	*Post*: 32.19*
Super Bowl Music Category			
Social Media Platform	**Dominant Phase**	**T-Values with Other Phases**	
Twitter	*During*	*Pre*: 16.70*	*Post*: 25.24*
Instagram	*During*	*Pre*: 11.37*	*Post*: 13.16*
Tumblr	*During*	*Pre*: 36.71*	*Post*: 38.25*
Super Bowl Game Category			
Social Media Platform	**Dominant Phase**	**T-Values with Other Phases**	
Twitter	*During*	*Pre*: 16.11*	*Post*: 21.07*
Instagram	*During*	*Pre*: 19.71*	*Post*: 23.34*
Tumblr	*During*	*Pre*: 45.95*	*Post*: 46.96*

*Denotes significance.

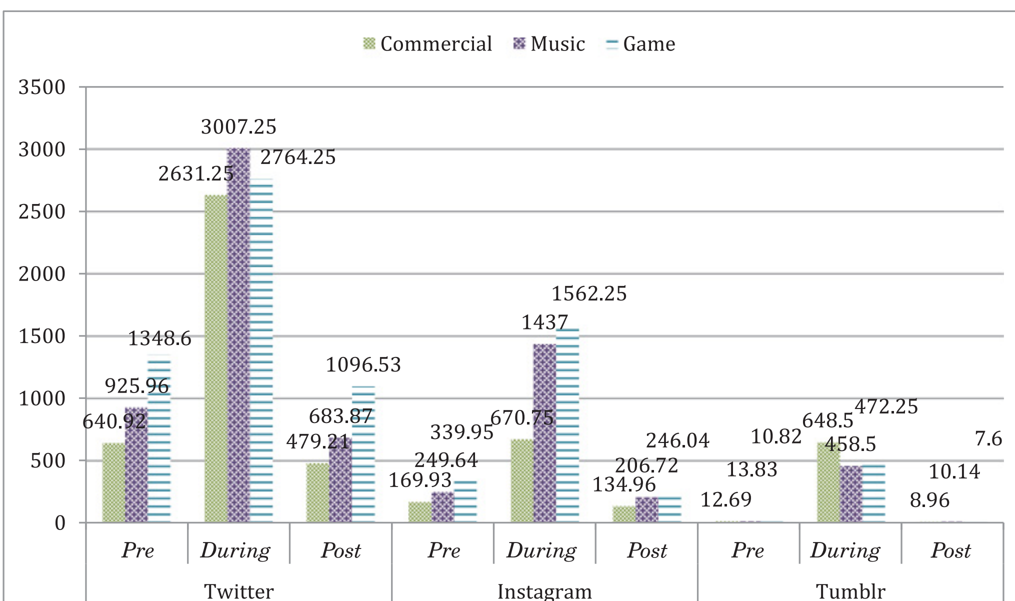

Fig. 4. Hourly mean of Super Bowl commercials, music, and game interactions during the *Pre*, *During*, and *Post* phases for all social media platforms.

The middle portion of Table X displays the F-statistic with the *p*-values. There is a significant difference in the relative volumes of music related social conversation among phases for all social media platforms. Hypothesis 08 is fully supported.

The bottom portion of Table X displays the F-statistic with the *p*-values. There is a significant difference in game social conversation among phases for all social media platforms. Hypothesis 09 is fully supported.

To test the predominant phase(s) among the categories with respect to the relative volumes, we perform the GH test.

Table X. ANOVA Statistics with Respect to Relative Volumes for Twitter, Instagram, and Tumblr on Super Bowl Commercials, Super Bowl Music, and Super Bowl Game Categories

Super Bowl Commercials Category		
Social Media Platform	$F^{ANOVA}_{(2, 12859)}$	***p*-Value**
Twitter	129.58	0.00
Instagram	28.27	0.00
Tumblr	8.61	0.00
Super Bowl Music Category		
Social Media Platform	$F^{ANOVA}_{(2, 12859)}$	***p*-Value**
Twitter	154.54	0.00
Instagram	81.87	0.00
Tumblr	5.60	0.00
Super Bowl Game Category		
Social Media Platform	$F^{ANOVA}_{(2, 12859)}$	***p*-Value**
Twitter	381.369	0.00
Instagram	128.681	0.00
Tumblr	26.59	0.00

Table XI. Dominant Phases and T-Statistic for Other Phases with Emerging Phases with Respect to the Relative Volume for All Super Bowl Categories

Super Bowl Commercials Category			
Social Media Platform	**Dominant Phase**	**T-Values with Other Phases**	
Twitter	*During*	*Pre*: 15.32*	*Post*: 17.73*
Instagram	*Post*	*Pre*: 6.44*	*During*: 8.54*
Tumblr	*Pre* and *Post* (mean of Pre is higher)	*During*: 4.82*	*Post*: 1.78 *p*-value: 0.176
Super Bowl Music Category			
Social Media Platform	**Dominant Phase**	**T-Values with Other Phases**	
Twitter	*During*	*Pre*: 2.90*	*Post*: 4.80*
Instagram	*During*	*Pre*: 4.31*	*Post*: 2.92*
Tumblr	*Pre* and *During* (mean of *Pre* is higher)	*During*: 0.337 *p*-value: 0.939	*Post*: 3.36*
Super Bowl Game Category			
Social Media Platform	**Dominant Phase**	**T-Values with Other Phases**	
Twitter	Post	*Pre*: 24.79*	*During*: 13.30*
Instagram	*Pre* and *During* (mean of *Pre* is higher)	*During*: 1.85 *p*-value: 0.154	*Post*: 15.95*
Tumblr	*During*	*Pre*: 3.25*	*Post*: 2.74*

*Denotes significance.

For Hypothesis 07, the *During* phase emerges as the predominant phase for the relative volume of second screen interaction in commercials for Twitter, whereas it is the *Post* phase that appears as the predominant one for Instagram. Both *Pre* and *Post* phases are predominant for Tumblr (see the top portion of Table XI).

For Hypothesis 08, again, the *During* phase is predominant with respect to the relative volume of posts in music categories on Twitter and Instagram social media platforms; however, for Tumblr, it is both the *Pre* and *During* phases that pop up as being predominant (see the middle portion of Table XI).

For Hypothesis 09, the *Post* phase becomes predominant with respect to the relative volume of posts in comparison to the *Pre* and *During* phases for Twitter in the game category (see the bottom portion of Table XI). Interestingly, although *Pre* and *During* mark their presence as predominant, there is no significant difference between the *Pre* and *During* phases for the game category on Instagram. For Tumblr, the *During* phase is predominant for the relative volume of second screen conversations in the game category.

The relative volume of game-related conversation in the *During* phase is less than that in the *Post* phase for Twitter, unlike the relative volumes of conversation for commercials and music for Twitter. For Instagram, the *Post* phase is predominant for the commercials category, unlike music, where the *During* phase is strong. For Tumblr, although the *During* phase is predominant in game category, the *Pre* phase leads the other two categories. Thus, we observe an interesting mixed response for identifying predominant phases in a category-based social soundtrack.

We believe that although the absolute volume of second screen conversations related to a particular category in the *During* phase is much higher than that in *Pre* and *Post* phases, the relative volumes for that category in the *During* phase may be less, as the absolute volumes of conversations in the other two remaining categories in the *During* phase are considerably higher than that in *Pre* and *Post* phases. If there are three categories, say X, Y, and Z, the relative volume of second screen conversations related to category X at time t_1 is the ratio between the count of category X–related discussion and the summation of counts of second screen conversations on category X, category Y and category Z (see Equation (2)) at t_1. For example, the relative volume of the game category is the ratio between game-related conversations to the total volume of posts over different times in the *During* phase. This ratio for *Pre* and *Post* phases on Twitter is greater than that in the *During* phase, as game-related discussions on Twitter are much higher than those for commercials and music in the *Pre* and *Post* phases compared to that in the *During* phase. The result implies that the relative volumes can also be an important metric of observation besides the absolute volume from the perspective of retailers, broadcasters, and entertainment industries, as a measurement of relative volumes yields different results for category-specific interphase conversations.

6.3. Research Question 3

For research question 3, we stick to the continuously scaled values of absolute volume, as it tests the difference in social conversation over three categories in a specific phase. Here the testing of the hypotheses corresponding to research question 3 is contained within a specific phase.

For research question 3, we evaluate the difference in second screen interaction among categories in each phase. Here, the second screen interactions in 5-minute time intervals of each phase among three categories are used as the unit of analysis. A separate ANOVA test identifies that means of the tweet counts in a 5-minute time interval of at least one category are significantly different from the others for each phase. The volume of social soundtrack conversations on a particular phase are in a continuous scale formed using Equation (1) to test Hypothesis 10, Hypothesis 11, and Hypothesis 12.

Hypotheses: There is a significant difference in the volume of second screen conversations in the social soundtrack in Pre (Hypothesis 10), During (Hypothesis 11), and Post (Hypothesis 12) Super Bowl phases among Super Bowl categories.

The top portion of Table XII displays the F-statistic with the p-values for each of the social media platforms. There is a significant difference in second screen conversations in the *Pre* phase among the categories for all social media platforms. Hypothesis 10 is fully supported.

The middle portion of Table XII displays the F-statistic with the p-values for each of the social media platforms. There is a significant difference in second screen

Table XII. ANOVA Statistics with Respect to Relative Volume for Twitter, Instagram, and Tumblr in Super Bowl Phases

***Pre* Super Bowl Phase**		
Social Media Platform	**$F^{ANOVA}_{(2, 19665)}$**	***p*-Value**
Twitter	20,684.88	0.00
Instagram	9,184.81	0.00
Tumblr	270.90	0.00
***During* Super Bowl Phase**		
Social Media Platform	**$F^{ANOVA}_{(2, 144)}$**	***p*-Value**
Twitter	4.56	0.01
Instagram	90.53	0.00
Tumblr	66.35	0.00
***Post* Super Bowl Phase**		
Social Media Platform	**$F^{ANOVA}_{(2, 18768)}$**	***p*-Value**
Twitter	12,141.22	0.00
Instagram	5,040.39	0.00
Tumblr	126.55	0.00

Table XIII. Emerging Categories and T-Statistic for Other Categories with Emerging Categories with Respect to Continuous Scale Volume for All Super Bowl Phases

***Pre* Super Bowl Phase**			
Social Soundtrack	**Dominant Category**	**T-Values with Other Categories**	
Twitter	Game	Commercials: 205.74*	Music: 125.10*
Instagram	Game	Commercials: 135.77*	Music: 70.00*
Tumblr	Music	Commercials: 18.50*	Game: 21.92*
***During* Super Bowl Phase**			
Social Soundtrack	**Dominant Category**	**T-Values with Other Categories**	
Twitter	Game and music (music has higher mean)	Commercials: 3.10*	Game: 0.72 *p*-value = 0.76
Instagram	Game and music (game has higher mean)	Commercials: 13.55*	Music: 1.34 *p*-value = 0.38
Tumblr	Commercials	Music: 10.33*	Game: 10.56*
***Post* Super Bowl Phase**			
Social Soundtrack	**Dominant Category**	**T-Values with Other Categories**	
Twitter	Game	Commercials: 155.17*	Music: 106.84*
Instagram	Game	Commercials: 100.40*	Music: 36.37*
Tumblr	Commercials and music (mean of music is higher)	Commercials: 1.89 *p*-value = 0.14	Game: 12.61*

*Denotes significance.

conversations in the *During* Super Bowl phase among the categories for Twitter, Instagram, and Tumblr. Hypothesis 11 is fully supported.

The bottom portion of Table XII displays the F-statistic with the *p*-values for each of the social media platforms. There is a significant difference in second screen conversations in the *P*ost phase among categories for all social media platforms. Hypothesis 12 is fully supported.

We call the category(ies) an *emerging category(ies)* if the mean(s) of the category(ies) is(are) significantly higher than that of the remaining one(s) compared over the phases. To test the emerging category(ies) among the phases, the GH test is performed. Table XIII presents the combined results of post hoc analysis for Hypotheses 10 through 12.

For Hypothesis 10, the second screen interaction related to the game category is dominant on Instagram and Twitter, and music is the dominant category on Tumblr in the *Pre* phase (see the top portion of Table XIII). For Hypothesis 11, game and music become predominant on Twitter in the *During* phase, although the music category has a higher mean of second screen interaction. On Instagram and Tumblr, game and commercials are the dominant categories, respectively (see the middle portion of Table XIII). The GH test for Hypothesis 12 identifies game as the dominant category on Twitter and Instagram in the *Post* phase. On Tumblr, postings related to both music and commercials become dominant, as no significant difference is found between these two categories (see the middle portion of Table XIII). From the perspective of the relative volume of conversations, the game category is predominant in the majority of phases for the majority of social networks, unlike commercials, which are predominant from a continuous scale absolute volume perspective.

In the *Pre* and *Post* phases, the game-related discussions have dominance over the other two categories on Twitter and Instagram. On Tumblr, it is either music- or commercials-related conversations that become stronger than the game for all three phases. Reactions to commercial and music videos can be better described in blogs relative to game-related activities, which are momentary and therefore can be posted predominantly as tweets and captions.

A variation of this result of research question 3 was observed in Mukherjee and Jansen [2016], where the comparison was performed on count data. In the present study, the count data was transformed into continuous scale, as ANOVA should be performed on continuous scale data.

We refrained from testing the significance of emerging categories in a specific phase from a relative volume perspective, as testing with intraphase relative volumes of posts for the categories is synonymous to testing with the continuous scale of absolute volumes of categories in that phase.

7. DISCUSSION AND IMPLICATIONS

7.1. Discussion of Results

In this research, we investigated three research questions pertaining to second screen interactions highlighting the use of three social networks in sharing information in the social soundtrack about Super Bowl XLIX in three phases (*Pre*, *During*, and *Post*) of the IRL media event broadcast. Three Super Bowl categories (commercials, music, and game) were formed for *Pre*, *During*, and *Post* phases. The first research question addressed the (in)dependence among the phase and categories. The second research question was concerned with the change in the rate of social interaction via second screens across the three phases for each of three categories. The third research question addressed the change in peoples' interest among phases for the categories.

The results of research question 1 established the existence of a phase-category relationship, as the results clearly show. Research question 2 was based on absolute volume converted to a continuous scale with respect to the highest record and the relative volume of social soundtrack conversations, respectively, where we found that the *During* phase remained dominant relative to *Pre* and *Post* phase counterparts for all categories across all three social media platforms. For research question 3, the relative volume of second screen interactions concerning music during the live broadcast media event of the Super Bowl (i.e., *During* phase) eclipsed that in the *Pre* and *Post* phases for the music category on Twitter and Instagram.

However, for commercials, we get a mixed response, where *During* and *Post* phases were predominant on Twitter and Instagram, respectively. Both the *Pre* and *Post* phases dominated the *During* phase on posts in the commercials category on Tumblr.

Interestingly, for Tumblr, the second screen interaction for the game category was significantly high in the *During* phase, but for Twitter, the discussion in the *Pre* and *Post* phases outperformed the *During* phase.

We further explored interest in the categories in each phase in terms of second screen interaction on different social media platforms. From an absolute volume of conversation with continuous proportion perspective, it was observed that people indulged in discussion on the game before, during, and after the broadcast media event via Twitter and Instagram. For Tumblr, the interactions related to commercials and music surpassed the game-related buzz.

7.2. Implications

Concerning the practical implication of the findings, certainly the various social media platforms have favored phases and categories of interaction. Social communication via second screens among viewers concerning the game category dominated relative to the other categories on Instagram in all three phases of the social soundtrack and was also paramount on Twitter in the *Pre* and *Post* phases. These social media platforms lend themselves to momentary communications, whereas Tumblr apparently does not.

With the focus on the game category in the social soundtrack, brands may hire those players as the prospective ambassadors of their products or service [Mathre 2014], leveraging Instagram and Twitter. People generally idolize sports stars and the musical artists. Thus, the logo of the brands that sponsor them will have a great impact when shared on the social soundtrack [Gianatasio 2015a]. This may eventually increase product sales and generate profit.

In the *During* phase, the rate of second screen interaction related to commercials and music rose significantly on Twitter (see Figure 4). For Tumblr, the brands remained the focus of the second screen communication in the *During* phase (see Figure 4). With these insights, retailers can advertise their brands or services by targeting the viewers engaged on these social media platforms as potential consumers during key phases. The real-time sentiment analysis of the evolving stream of social conversation via the social soundtrack [Guerra et al. 2014] eventually helps the retailers or entertainment industries launch a social-based recommender system framework [Ma et al. 2011] benefited by the phase-wise information extracted from different social media platforms. Thus, technology has temporal influences on social soundtracks for media broadcast IRL events.

Interestingly, the absolute volume of the social soundtrack for the music category was higher than the other two categories during weeks before the kickoff started (see the top portion of Table XIII). The music and entertainment industries can strategically launch new releases by mining the social soundtrack mediums concerning the popularity of the songs as the artists perform in the halftime show (see the middle portion of Table XI) or in pregame sessions (see the Tumblr row in the top portion of Table XIII). This marketing analysis can provide potential insight into potential sales and revenue [Gianatasio 2015b]. For example, during Super Bowl L, the halftime performer Beyonce used the event to strategically announce her new tour and the actual halftime performance as a social message concerning race relations in the United States.

The growth of social interaction via second screen during a live broadcast media event increases the possibility of direct communication between brands and consumers. Integrating broadcast media events' social soundtracks via social networks shrinks the virtual distance between brands and consumers, thus highlighting a rise in potential brand recall, boosting advertising campaigns, and enhancing sale possibilities via word-of-mouth advertising [Jansen et al. 2009]. The stronger message association due to the presence the second screen interaction generates higher purchase intent among the consumers of the brands [Schivinski and Dabrowski 2014].

8. STRENGTHS AND LIMITATIONS

As in all studies, there are limitations to this research. For instance, the first limitation is that we garnered 3 million tweets even though there were 28 million tweets reported during the Super Bowl telecast, so this sampling raises the issue of possible bias in our sample. However, assuming that the APIs are randomly sampled, we do not consider this a major concern, although increased data may strengthen our findings. Yet the substantial amount of data used for this research provides important insights. As a second limitation, there may exist spam messages or automatically generated messages that can be shared/reposted/retweeted. This may affect also our results. Our present study did not filter out such spam or bots, which we will focus on in future work.

In terms of strengths, our research is one of the first research projects examining IRL events that use a large number of social media data from multiple platforms within the same period. Our research used a large quantity of data from multiple social media platforms collected at the same time, which is rarely done. The research findings present important insights in identifying the temporal significance of shift among second screen–based social media conversations on IRL categories and phases. Our analysis of the category and phase relationships from several angles show statistically significant relationships. We also introduced and clearly defined the constructs, which can be the basis for future research.

9. CONCLUSION

In this work, we analyzed three research questions regarding second screen interactions to determine the dependence between the three phases with three categories. The three research questions were examined from the perspective of human information processing in terms of the volume and pace of comments posted as acts of information sharing. We believe that our research contributes to understanding viewer behavior and interaction via social soundtracks while watching a mass media broadcast of an IRL event in an emerging avenue of social soundtrack research [Scharl et al. 2016]. Analysts and researchers can benefit from this work by understanding how and when to run a multisite analysis to measure the impact of an IRL event. In future work, we will study how different elements in the social soundtrack conversation concerning categories (commercials, music, game, etc.) change in different phases for the IRL event in terms of volume and content aspects, such as sentiment and formality. However, as our focus here surrounds information content, we could also expand the research to include the social networking and interactions occurring within conversations in the social soundtrack, including how the information is diffused throughout the social network. We further explore the relative effect of time and that of different subcategories of commercials on the relationship between social soundtrack postings on each of the platforms and Web searches.

REFERENCES

G. Abdulla, B. Liu, and E. Fox. 1998. Searching the World-Wide Web: Implications from studying different user behavior. In *Proceedings of the World Conference of the World Wide Web, Internet, and Intranet*, 1–8.

Ad Age Staff. 2015. Super Bowl XLIX Ad Chart: Who Bought Commercials in Super Bowl 2015. *Ad Age*. Retrieved January 12, 2017, from http://adage.com/article/special-report-super-bowl/super-bowl-xlix-ad-chart-buying-big-game-commercials/295841/.

Damien Alliez. 2008. Adapt TV paradigms to UGC by importing social networks. In *Proceedings of the 6th European Conference on Changing Television Environments (EuroITV'08)*. 1–2.

Anonymous. 2015. 2015 Super Bowl commercials, news related to the 2015 Super Bowl . . . *About the Game and the More Important Bit, the Commercials*.

Jose Ashford and Craig LeCroy. 2009. *Human Behavior in the Social Environment: A Multidimensional Perspective*. Cengage Learning, Belmont, CA.

Eytan Bakshy, Itamar Rosenn, Cameron Marlow, and Lada Adamic. 2012. The role of social networks in information diffusion. In *Proceedings of the 21st International Conference on World Wide Web.* ACM, New York, NY, 519–528.

Santosh Basapur, Hiren Mandalia, Shirley Chaysinh, Young Lee, Narayanan Venkitaraman, and Crysta Metcalf. 2012. FANFEEDS: Evaluation of socially generated information feed on second screen as a TV show companion. In *Proceedings of the 10th European Conference on Interactive TV and Video*. ACM, New York, NY, 87–96.

Adrian Benton and Shawndra Hill. 2012. The spoiler effect?: Designing social TV content that promotes ongoing WOM. In *Proceedings of the Conference on Information Systems and Technology (INFORMS'12).*

Roi Blanco, Gianmarco De Francisci Morales, and Fabrizio Silvestri. 2015. IntoNews: Online news retrieval using closed captions. *Information Processing and Management* 51, 148–162.

Anna Van Cauwenberge, Gabi Schaap, and Rob Van Roy. 2014. TV no longer commands our full attention: Effects of second-screen viewing and task relevance on cognitive load and learning from news. *Computers in Human Behavior* 38, 100–109.

Yi Chang, Lei Tang, Yoshiyuki Inagaki, and Yan Liu. 2014. What is Tumblr: A statistical overview and comparison. *ACM SIGKDD Explorations Newsletter* 16, 21–29.

Cédric Courtois and Evelien D'heer. 2012. Second screen applications and tablet users: Constellation, awareness, experience, and interest. In *Proceedings of the 10th European Conference on Interactive TV and Video.* ACM, New York, NY, 153–156.

Simon Dumenco. 2012. Five amazing facts about social media and the Super Bowl. *Ad Age*. Retrieved January 12, 2017, from http://adage.com/article/special-report-super-bowl/amazing-facts-social-media-super-bowl/232545/.

Paul Farhi. 2014. The rules of the Super Bowl advertising game. *Washington Post* Available at http://www.washingtonpost.com.

Alexandre Fleury, Jakob Schou Pedersen, Mai Baunstrup, and Lars Bo Larsen. 2012. Interactive TV: Interaction and control in second-screen TV consumption. In *Proceedings of the 10th European Conference on Interactive TV and Video (EuroITV'12).* 104–107.

Mike Florio. 2014. NFL wants Super Bowl halftime performers to pay for the privilege. *Pro Football Talk*. Retrieved January 12, 2017, from http://profootballtalk.nbcsports.com/2014/08/19/nfl-wants-super-bowl-halftime-performers-to-pay-for-the-privilege/.

David Gianatasio. 2015a. Pepsi's music chief makes the Super Bowl sing: On the brand's ties with artists like Katy Perry. *Adweek*. Retrieved January 12, 2017, from http://www.adweek.com/news/advertising-branding/pepsis-music-chief-makes-super-bowl-sing-162515.

David Gianatasio. 2015b. Why the Super Bowl halftime show has become the biggest ad of all: Katy perry, brands poised to win big. *Adweek*. Retrieved January 12, 2017, from http://www.adweek.com/news/television/why-super-bowl-halftime-show-has-become-biggest-ad-all-162528.

Fabio Giglietto and Donatella Selva. 2104. Second screen and participation: A content analysis on a full season dataset of tweets. *Journal of Communication* 64, 260–277.

Jeremy A. Greene, Niteesh K. Choudhry, Elaine Kilabuk, and William H. Shrank. 2011. Online social networking by patients with diabetes: A qualitative evaluation of communication with facebook. *Journal of General Internal Medicine* 26, 287–292.

Pedro Calais Guerra, Wagner Meira Jr., and Claire Cardie. 2014. Sentiment analysis on evolving social streams: How self-report imbalances can help. In *Proceedings of the 7th ACM International Conference on Web Search and Data Mining (WSDM'14).* ACM, New York, NY, 443–452.

Yuheng Hu, Lydia Manikonda, and Subbarao Kambhampati. 2014. What we instagram: A first analysis of Instagram photo content and user types. In *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM'14).* 1–4.

Brett Hutchins and Janine Mikosza. 2010. The Web 2.0 olympics athlete blogging, social networking and policy contradictions at the 2008 Beijing games. *Convergence: The International Journal of Research into New Media Technologies* 16, 279–297.

Bernard J. Jansen, Kate Sobel, and Geoff Cook. 2011. Classifying ecommerce information sharing behaviour by youths on social networking sites. *Journal of Information Science* 37, 120–136.

Bernard J. Jansen, Mimi Zhang, Kate Sobel, and Abdur Chowdury. 2009. Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology* 60, 2169–2188.

James E. Johnson and Donghun Lee. 2011. Super Bowl commercial and game consumption for the college demographic. *Sport Journal.* Retrieved January 12, 2017, from http://thesportjournal.org/article/super-bowl-commercial-and-game-consumption-for-the-college-demographic/.

Hyeoncheol Lee, Yanggon Kim Kim, Kwangmi K. O. Kim, and Youngsub Han. 2014. Sports and social media: Twitter usage patterns during the 2013 Super Bowl broadcast. In *Proceedings of the International Conference on Communication, Media, Technology, and Design*. 250–259.

Amanda Lenhart. 2012. Teens, smartphones and texting. In *Pew Internet and American Life Project* Pew Research, 1–2.

Julien Leroy, François Rocca, Matei Mancas, and Bernard Gosselin. 2013. Second screen interaction: An approach to infer TV watcher's interest using 3D head pose estimation. In *Proceedings of the 22nd International Conference on World Wide Web (WWW'13)*. 465–468.

Yu-Ru Lin, Drew Margolin, Brian Keegan, and David Lazer. 2013. Voices of victory: A computational focus group framework for tracking opinion shift in real time. In *Proceedings of the 22nd International Conference on World Wide Web (WWW'13)*. 737–748.

Bruce R. Lindsay. 2011. Social media and disasters: Current uses, future options, and policy considerations. In *CRS Report for Congress.* Congressional Research Service.

Ivy L. B. Liu, Christy M. K. Cheung, and Matthew K. O. Lee. 2015. User satisfaction with microblogging: Information dissemination versus social networking. *Journal of the Association for Information Science and Technology* 67, 56–70.

Mark Lochrie and Paul Coulton. 2012. Sharing the viewing experience through second screens. In *Proceedings of the 10th European Conference on Interactive TV and Video.* ACM, New York, NY, 199–202.

Hao Ma, Dengyong Zhou, Chao Liu, Michael R. Lyu, and Irwin King. 2011. Recommender systems with social regularization. In *Proceedings of the 4th ACM International Conference on Web Search and Data Mining (WSDM'11)*. ACM, New York, NY, 287–296.

Ryan Mathre. 2014. Seattle Seahawk and Super Bowl champion Derrick Coleman becomes Starkey Hearing Technologies Hearing Ambassador. *BusinessWire*. Retrieved January 12, 2017, from http://www.businesswire.com/news/home/20140326006082/en/Seattle-Seahawk-Super-Bowl-Champion-Derrick-Coleman.

Partha Mukherjee and Bernard J. Jansen. 2014. Social TV and the social soundtrack: Significance of second screen interaction during television viewing. In *Social Computing, Behavioral-Cultural Modeling, and Prediction*, J. Salerno, S. J. Yang, D. Nau, and S. K. Chai, (Eds.). Springer, 317–324.

Partha Mukherjee and Bernard J. Jansen. 2015a. Analyzing second screen based social soundtrack of TV viewers from diverse cultural settings. In *Social Computing, Behavioral-Cultural Modeling, and Prediction*, N. Agarwal, K. Xu, and N. Osgood, (Eds.). Springer, 375–380.

Partha Mukherjee and Bernard J. Jansen. 2015b. Evaluating pattern for group interactions using second screens. In *Proceedings of the 2015 International Conference on Computing, Networking, and Communications (ICNC'15)*. 433–437.

Partha Mukherjee and Bernard J. Jansen. 2015c. Analyzing the social soundtrack from second screens before, during, and after real-life events. In *Proceedings of the 2015 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT'15).* 1–6

Partha Mukherjee and Bernard J. Jansen. 2016. Second screen interaction analysis for IRL events: Phase-category investigation of the Super Bowl 2015 social soundtrack. In *Proceedings of the 7th International Conference on Information and Communication Systems (ICICS'16).* 13–19.

Partha Mukherjee, Jian-Syuan Wong, and Bernard J. Jansen. 2014. Patterns of social media conversations using second screens. In *Proceedings of the 2014 BigData / SocialCom / CyberSecurity Conference.*

Sanghee Oh and Sue Yeon Syn. 2015. Motivations for sharing information and social support in social media: A comparative analysis of Facebook, Twitter, Delicious, YouTube, and Flickr. *Journal of the Association for Information Science and Technology* 66, 2045–2060.

Antti Oulasvirta, Tye Rattenbury, Lingyi Ma, and Eeva Raita. 2012. Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing* 16, 105–114.

Leysia Palen. 2008. Online social media in crisis events. *Educause Quarterly* 31, 76–78.

Kevin Patra. 2015. Super Bowl XLIX is most-watched show in U.S. history. *NFL*. Retrieved January 12, 2017, from http://www.nfl.com/news/story/0ap3000000467823/article/super-bowl-xlix-is-mostwatched-show-in-us-history.

Julie Ruvolo. 2014. Embedded with Adidas' social media team at the World Cup in Rio: Striving to be the most talked-about brand at the tournament. *Ad Age*. Retrieved January 12, 2017, from http://adage.com/article/global-news/embedded-adidas-social-media-team-world-cup/294016/.

Takeshi Sakaki, Makoto Okazaki, and Yutaka Matsuo. 2010. Earthquake shakes Twitter users: Real-time event detection by social sensors. In *Proceedings of the 19th International Conference on World Wide Web (WWW'10).* ACM, New York, NY, 851–860.

T. Y. Schalter. 2015. Super Bowl XLIX: Power ranking the top 25 players in this year's game. *Bleacher report*. Retrieved January 12, 2017, from http://bleacherreport.com/articles/2343013-super-bowl-xlix-power-ranking-the-top-25-players-in-this-years-game.

Arno Scharl, Alexander Ubmann-Haidvogel, Alistair Jones, Daniel Fischl, Ruslan Kamolov, Albert Weichselbraun, and Walter Rafelsberger. 2016. Analyzing the public discourse on works of fiction—detection and visualization of emotion in online coverage about HBO's game of thrones. *Information Processing and Management* 52, 129–138.

Bruno Schivinski and Dariusz Dabrowski. 2014. The effect of social media communication on consumer perceptions of brands. *Journal of Marketing Communications* 22, 189–214.

Hyeonjeong Shin, Changhyun Byun, and Hyeoncheol Lee. 2015. The influence of social media: Twitter usage pattern during the 2014 Super Bowl game. *International Journal of Multimedia and Ubiquitous Engineering* 10, 109–118.

Sei-Ching Joanna Sin. 2015. Social media and problematic everyday life information-seeking outcomes: Differences across use frequency, gender, and problem-solving styles. *Journal of the Association for Information Science and Technology* 67, 1793–1807.

Tang Tang and Roger Cooper. 2012. Gender, sports, and new media: Predictors of viewing during the 2008 Beijing olympics. *Journal of Broadcasting and Electronic Media* 56, 75–91.

Hao Wang, Dogan Can, Abe Kazemzadeh, François Bar, and Shrikanth Narayanan. 2012. A system for real-time Twitter sentiment analysis of 2012 US presidential election cycle. In *Proceedings of the ACL 2012 System Demonstrations.* 115–120.

Wikipedia. 2015a. List of Super Bowl Halftime Shows. Retrieved January 12, 2017, from https://en.wikipedia.org/wiki/List_of_Super_Bowl_halftime_shows.

Wikipedia. 2015b. Super Bowl XLIX Halftime Show. Retrieved January 12, 2017, from https://en.wikipedia.org/wiki/Super_Bowl_XLIX_halftime_show.

Jo Williams and Susan J. Chinn. 2010. Meeting relationship-marketing goals through social media: A conceptual model for sport marketers. *International Journal of Sport Communication* 3, 422–437.

Shaomei Wu, Jake M. Hofman, Winter A. Mason, and Duncan J. Watts. 2011. Who says what to whom on Twitter. In *Proceedings of the 20th International Conference on World Wide Web (WWW'11)* ACM, New York, NY, 705–714.

Mimi Zhang, Bernard J. Jansen, and Abdur Chowdhury. 2011. Business engagement on Twitter: A path analysis. *Electronic Markets* 21, 161–175.

Siqi Zhao, Lin Zhong, Jehan Wickramasuriya, and Venu Vasudevan. 2011. Analyzing Twitter for social TV: Sentiment extraction for sports. In *Proceedings of the 2nd International Workshop on Future of Television (FutureTV'11)*. 11–18.

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