Repository Istituzionale dei Prodotti della Ricerca del Politecnico di Bari

The managerial relevance of Social TV: a theoretical and empirical examination

(Article begins on next page)

14 July 2024

Department of Mechanics, Mathematics and Management
MECHANICAL AND MANAGEMENT ENGINEERING
Ph.D. Program
SSD: ING-IND/35−MANAGEMENT ENGINEERING

Final Dissertation

The managerial relevance of Social TV: a theoretical and empirical examination

by
Angela Fortunato

Referees:

Prof.ssa Dangelico Rosa

Prof. Lerro Antonio

Supervisors:

Prof. Gorgoglione Michele

Ing. Licciardi Carlo *(Telecom Italia)*

Ing. Martini Giovanni *(Telecom Italia)*

Coordinator of Ph.D Program:

Prof. Demelio Giuseppe

XXIX cycle, 2014-2016

Table of contents

INTRODUCTION

The term "social television" or "social TV" refers to "a variety of experimental systems that claim to support social experiences for television viewers and to the research into such experiences" (Harboe, 2012). In recent years, this idea of connecting specifically non-colocated TV viewers via telecommunication technologies has recently received considerable attention from both industry and research (Shirazi et al., 2011). Notably, by using smartphones and tablets, namely "second screen" devices (Doughty, Rowland, & Lawson, 2012; Hess et al., 2011), viewers who do not share the same living room can interact during the viewing experience particularly through the social network websites, such as Facebook and Twitter (Giglietto & Selva, 2014). They can express their own thoughts related to what they are watching (Doughty, Lawson & Rowland, 2011), thus enriching TV contents through real-time backchannel conversations. On the other hand, TV broadcasters and producers are also adopting several strategies to include or enhance social TV practices within a TV program's context in order to create engagement around TV shows and consequently increase their popularity. These strategies can consist in displaying Twitter elements on the TV screen as well as developing applications useful to interact with the TV program, to interact with other viewers or to have access to additional contents. The conversations published on social media around TV shows are able to produce a huge number of data, public available, which can be analyzed in order to obtain useful insights.

The main goal of this PhD thesis is to provide an analysis of the social TV phenomenon from a managerial viewpoint, supported by an empirical analysis focused on a specific TV show's case, i.e., "The Voice of Italy". Particularly, the empirical analysis is focused on a popular Italian talent show characterized by a high interest on social media and it demonstrates how the huge number of data generated around television can be used to produce valuable information for TV broadcasters and producers. Indeed, by considering

long-term data and different specific kind of viewers' interactions on social network sites, such as Twitter, they can extract interesting insights to understand how to design the TV program, specifically its contents as well as social strategies useful to encourage viewers to interact online.

The present research is structured in three main phases. In the first stage, I perform a systematic review of the literature, in order to collect all the research studies focused on the social TV phenomenon, thus building an overview of all aspects that have been already analyzed. Consequently, a summary of the main gaps and future research directions is provided, in the attempt to further stimulate the academic debate on the topic. The review organizes and presents literature findings, with related gaps, by distinguishing the two main aspects concerning the social TV. The first is represented by the technological development, since the technology had a key role within the diffusion's process of this phenomenon. On the other hand, the analysis of viewers' behaviors is relevant both for technology and social strategies development, as well as to understand the impact of social TV experiences across different contexts.

Three main gaps emerge. First, considering the technological aspects, more applications and systems need to be developed in order to obtain more general guidelines, which are useful to develop more effective applications and consequently to offer a better experience to viewers. Second, the applications' design needs to obtain more feedback also by general studies, i.e., studies not focused on specific applications and functionalities' design, but on different TV contexts. Third, it remains unexplored the value of the amount of data generated around TV shows, therefore it is useful to show how the huge number of data generated while watching TV can be used to offer insights to TV producers. These gaps are in turn used to identify the research questions to be investigated in the second and third phases of the research. The objective of the second phase, indeed, is to provide a first empirical

analysis of data concerning a specific TV show, in order to demonstrate that the social TV phenomenon can be positioned within the big data issues. Indeed, the huge number of interactions on online social networks allows TV producers to collect data and obtain relevant insights to effectively design the TV shows. Finally, in the third phase, data concerning the same TV show are deeply analyzed by considering the different kinds of interactions occurring on Twitter. Specifically, I show that, in order to obtain valuable insights, it is useful to consider the different kinds of interactions, since specific TV contents and social strategies differently affect the different kinds of viewers' interactions.

The three phases generated three distinct chapters that are reported in this dissertation. The first chapter (entitled "Social Television: a literature review and research directions") provides an overview of the extant literature concerning the social TV phenomenon. Particularly, it presents the social TV context in terms of definitions, trends and industry's evolution and, by following the methodology developed by Tranfield, Denyer & Smart (2003), provides a systematic review of the wide collection of papers belonging to several research areas, from computer science to marketing. Indeed, the social TV research is not defined within a specific scientific area, therefore it needs a deeply exploration of the topics across the different areas concerning the social TV phenomenon. The overview considered also the so-called "grey literature": social TV is a recent topic, therefore important sources of information has been presented as conference proceedings, dissertations and theses (Adams, Smart, & Huff, 2016). Findings are grouped according to two categories of analysis: "technologies" and "viewers' behaviors". The first one considers all the aspects related to the development of social TV applications, systems, as well as specific functionalities and services and finally to the integration and the proposition of guidelines. The second one includes several works focused on the exploration of behaviors, reactions, preferences of viewers within a specific TV context, e.g. a specific TV program or TV program's genre,

since design guidelines can derive from both specific applications' studies and extensive studies concerning TV usage and viewers' behavior (Chorianopoulos, 2008). Results show that the most part of previous work in the social TV research has been focused on the technological aspects: authors found that TV viewers who used the applications had more fun and felt a greater sense of connectedness towards the TV program and the other viewers, thus enriching the social experience around live TV content. Concerning the exploration of viewers' behavior, few authors focused on specific TV programs: they found behavioral differences between different TV contexts, such as genres of television shows as well as live and non-live transmissions. Other authors deeply explored the viewers' motivations and specific factors or perceptions influencing the motivations of interacting while watching TV. Previous works has also tried to explore the response in terms of viewers' behavior towards the social TV initiatives or strategies, which are able to increase the interest of viewers in social media activities while watching television, thus significantly enhancing also the viewer's engagement in the television program, which has been measured by neural indicators. The literature review highlights the need of further research concerning the social TV phenomenon. Despite the larger number of applications already developed and tested, it emerges the need of further general research, specifically focusing on specific program genres. It would be relevant also to systematically analyze the factors influencing the viewers' behavior on social media while watching TV. Finally, it remains unexplored the value that social TV represents for TV producers and broadcasters, despite the huge number of data generated around TV shows.

In the second chapter (entitled "Leveraging big data for sustaining innovation in the Social TV context"), the social TV phenomenon is positioned within the wider context of big data. Specifically, the chapter is focused on the key role of social media, as relevant kinds of external sources, to facilitate innovation for firms. They represent one of the main

sources of big data generating a large amount of knowledge about customers' preferences and reactions. Therefore, they can provide interesting insights for organizations in different industries. However, as emerges from the literature review of both social TV and big data, firms are increasingly interested in exploring how to use them, but it is not clear how to extract new insights, thus adding valuable knowledge, since they require the use of specific techniques. Particularly, scholarly attention has examined the use of social media in some limited contexts and few works explored how the social media data can be useful for TV stakeholders to analyze different aspects related to the TV consumption, as well as to the effects of specific TV contents, in order to improve TV show's quality (Marasanapalle et al., 2010). In order to achieve valuable insights concerning the TV show, I analyze the generation of social media traffic, defined as the amount of the viewers' interactions around a specific topic and considered as an indicator of success. Notably, I classify the TV show's contents in order to analyze their impacts on social media and consequently evaluate their potential of increasing or decreasing the Twitter traffic. In addition, I consider also the social media elements, particularly specific Twitter elements displayed on the TV screen (i.e., official hashtag and other different ones) in order to obtain valuable knowledge concerning all the different elements of the TV show that can be used to increase the social media traffic through a better design of the TV show. Findings highlight that considering the trends and behaviors within the whole TV show allows broadcasters and producers to understand how to better design the TV show's contents as well as the social media elements in order to reach their scope, e.g., increasing the Twitter traffic. Indeed, in order to design the next season of the TV show, producers should dedicate a wider space within the TV show to specific TV contents, such as the performances and the web room, since they increase the social media traffic. Finally, in comparison with some previous works, I not only focus on the TV show's contents, but also on the use of social media elements, particularly Twitter elements, e.g.,

the official hashtag and other different ones, which need to be combined in order to increase the social media traffic.

In the third chapter (entitled "Social television: leading online viewer engagement"), I study the connections between all the variables shown as relevant from prior research in the social TV domain (i.e., social strategies and TV contents, including commercial breaks) with the three kinds of online activities. Indeed, viewers can interact through different ways on Twitter: they can post tweets, thus generating original tweets; they can share existing tweets, thus generating the so-called retweets; finally, they can reply to existing tweets, thus generating a reply. Even though several studies highlighted the existence of relevant differences between these different types of online engagement (Boyd et al., 2010; Chen, 2011; Hill and Benton, 2012; Kim et al., 2015; Sousa et al., 2010; Suh et al., 2010; Wohn and Na, 2011), all the previous studies have examined the viewers' online engagement looking at only one single type of activity without distinguishing between the effects of posting, replying and sharing tweets. I adopt the same methodology proposed in the previous chapter, i.e., the hierarchical regressions approach, to analyze the relationship between variables. Results show that the relationship between TV contents, social strategies and online engagement is different according to different kind of online activity. Indeed, viewers decrease their posting behavior while increase their sharing behavior during commercial breaks. Second, viewers increase or decrease their posting behavior, while they do not modify their sharing behavior depending on the specific TV contents. Third, certain kinds of social strategies have a positive effect on the number of original tweets, while they do not affect retweets and replies. TV producers should take into account that, in order to encourage viewers' interactions on social network sites, a TV program's design should consider the different types of online activities, since the whole number of interactions, generating around a TV show, is the result of the different kinds of online activities.

CHAPTER 1. SOCIAL TELEVISION: A LITERATURE REVIEW AND RESEARCH DIRECTIONS

1. Introduction

Although the television has always been a social medium, the term "social television" or "social TV" has attracted considerable attention only in recent years (Shirazi et al., 2011), since it refers to the whole set of new technologies offering non-colocated TV viewers a social experience around television contents. Indeed, the mobile technology, particularly the so-called "second screen" devices, played a significant role in the shift from traditional television to social television: the use of smartphones and tablets radically changed the social aspects around the TV consumption in terms of modality and impact. A huge number of viewers can interact real time, during the viewing experience, through the social network websites, such as Facebook and Twitter. They are able to express their thoughts, reactions, preferences as well as respond to other viewers' comments. On the other hand, TV producers are increasingly adopting social strategies in order to encourage the viewers' participation on social networks, thus creating a set of backchannel conversations that enriches the TV show. Concerning the USA TV season 2015-2016, Nielsen (2016) stated that nearly a billion tweets, i.e., Twitter messages, has been sent in 2015, particularly during sports events, political debates and TV series. Several examples can be considered by both industry and research studies around the world. They are "The Super Bowl", "The Oscars", "The Walking Dead", "The Voice", "L'Isola dei Famosi", "Mob City" as many other TV shows. These examples show how this trend generates millions of tweets and how TV producers test several strategies to include or enhance social interactions within a TV program's context. On the other hand, the social TV practices are also related to the interaction between viewers

and the TV shows. Indeed, some producers developed also social strategies as well as social TV applications related to the TV programs, in order to increase the viewers' enjoyment and participation through several kinds of activities related to the program. For instance, through this kind of applications viewers can vote, respond to quizzes, show preferences and reactions towards specific contestants, as well as access to many additional contents related to the program. All these activities can lead to an increase of interest towards the TV shows, thus enhancing the viewers' enjoyment during the viewing experience. All the conversations generated around TV programs produce a huge number of public data within social media, which can be downloaded, structured and analyzed in order to obtain useful insights for both viewers and TV producers.

Although the scientific research is trying to investigate several aspects concerning the social TV context, the fact that the social TV research is not defined within a specific scientific area highlights the need of a deeply exploration of the topics across several areas concerning the social TV phenomenon. Indeed, the variety of the scientific areas makes difficult to obtain an overview of the phenomenon and consequently identify the key aspects and the research gaps and further directions. Therefore, following the methodology developed by Tranfield, Denyer & Smart (2003), I performed a systematic review of the wide collection of papers belonging to the several research areas, from computer science to marketing. Particularly, I had to include also the so-called "grey literature", since social TV is a recent topic, therefore important sources of information has been presented as conference proceedings, dissertations and theses (Adams, Smart, & Huff, 2016). I grouped and discussed literature findings according to two categories of analysis: "technologies" and "viewers' behaviors". The first one considers all the aspects related to the development of social TV applications, systems, as well as specific functionalities and services and finally to the integration and the proposition of guidelines. The second one includes several works

focused on the exploration of behaviors, reactions, preferences of viewers within a specific TV context, e.g. a specific TV program or TV program's genre, since design guidelines can derive from both specific applications' studies and extensive studies concerning TV usage and viewers' behavior (Chorianopoulos, 2008). Findings show that the most part of previous work in the social TV research has been focused on the technological aspects, particularly concerning the applications' design and evaluation. Authors found that TV viewers who used the applications had more fun and felt a greater sense of connectedness towards the TV program and the other viewers, thus enriching the social experience around live TV content. By evaluating specific functionalities and services, authors found that text is used more often than voice communication, but also that rich modes of communication have the potential to interrupt content viewing (Metcalf et al., 2008). However, they stated that a social TV system has to provide viewers with a variety of opportunities: for instance, it should include communication functionalities on different levels of engagement, i.e., quick responses versus free-form communication, or also provide different functionalities for interacting and communicating synchronously as well as asynchronously. Concerning the viewers' behaviors exploration, few authors (e.g., Schirra, Sun & Bentley, 2014; Doughty, Lawson & Rowland, 2011) focused on specific TV programs, which are characterized by a large amount of conversations on social network sites, and found behavioral differences between different TV contexts, such as different TV shows' genres as well as live and non-live transmissions. Other authors deeply explored the viewers' motivations and specific factors or perceptions influencing the motivations of interacting while watching TV. Moreover, it has been found that social interactions can influence also the real life decisions, e.g., in the political elections' context. Finally, both active and passive behaviors are influenced by personal engagement with the content, but they are influenced in different ways. Previous works has also tried to explore the response in terms of viewers' behavior towards the social TV initiatives or strategies, e.g., displaying tweets while TV show is on air, which

encourages viewers in taking actions related to television viewing, as well as engaging with the TV show's brand sponsors. Consequently, these strategies are able to increase the interest of viewers in social media activities while watching television, thus significantly enhancing also the viewer engagement in the television program, which has been measured by neural indicators. Despite these advantages, few authors have also found that like normal coviewing, social TV viewing can lead also to increase the viewers' distraction.

The literature review highlighted the need of further research concerning the social TV phenomenon. Several aspects have not yet been deeply explored. From the technological viewpoint, despite the larger number of applications already developed and tested, it emerges the need of further general research, specifically focusing on a specific program genre. To this aim, the study of viewers' behavior, without considering a specific application's design, needs to be enhanced also to improve the design of both applications and social strategies. It would be relevant also to systematically analyze the factors influencing the viewers' behavior on social media while watching TV. Finally, it is not clear the value that social TV represents for TV producers and broadcasters, despite the huge number of data generated around TV shows.

2. The social TV context

In recent years, the idea of connecting non-colocated TV viewers via telecommunication technologies, which refers to social TV, has recently received considerable attention (Shirazi et al., 2011) from both industry and research. Notably, the term "social television," or "social TV," over the last years has been defined within a specific context: as reported by Harboe (2012), it refers to "a variety of experimental systems that claim to support social experiences for television viewers and to the research into such experiences". Indeed, the presence of mobile technology used in conjunction with television played a significant role in the shift

from traditional television to social TV. However, television has always been a social medium: traditionally viewers discussed about TV contents the day after the viewing or they talked to each other also during the viewing within their living room. Nevertheless, during the last years, the social aspect around the TV consumption has changed in terms of modality and impact (Mukherjee & Jansen, 2014; Doughty, Lawson & Rowland, 2011). Indeed, by using smartphones and tablets, namely "second screen" devices (Doughty, Rowland, & Lawson, 2012; Hess et al., 2011), viewers interact with each other before, during and after the viewing experience, as in the past, but the interactions occur also and especially between viewers who do not share the same living room, the same television device, named "main screen". Particularly, the most important revolution is represented by the extent of real-time interactions: indeed, they occur no more between the few viewers sharing the living room; on the contrary, they occur between a huge number of viewers interacting through the social network websites, such as Facebook and Twitter (Giglietto & Selva, 2014). Therefore, TV shows are increasingly enriched by real-time backchannel conversations, since viewers use social media to broadcast their own thoughts, sentiments, opinions and emotions related to what they are watching (Doughty, Lawson & Rowland, 2011). In this context, TV broadcasters and producers are trying to understand how to use this trend to reach their aims, which are traditionally related to the increase of the TV program's popularity and consequently to the increase of its viewership.

The adoption of social TV practices from the side of viewers, as well as broadcasters and producers, has been characterized by several examples. In a report concerning the TV season 2015-2016, Nielsen (2016) stated that nearly a billion tweets, i.e., Twitter messages, has been sent in the U.S. in 2015. Sports events, such as "The Super Bowl", count the larger number of tweets related to the program: indeed, 3.7 millions of tweets have included the Super Bowl's hashtag, i.e., #SB50, a word that identifies all the tweets related to the Super

Bowl's topics. A relevant number of Twitter interactions occurs during special TV programs, such as "The Oscars", but also during political debates and TV series, e.g., "The Walking Dead" is one of the most discussed on Twitter with an average of 435,000 tweets. On the other hand, TV producers have tested several strategies to include or enhance social TV practices within a TV program's context. Indeed, Social TV is also considered a new interactive television service (Shin, 2013), since it allows viewers to interact also with the TV show, e.g., by voting or respond to TV show's questions and other similar interactive activities. For instance, concerning "The Walking Dead", at the bottom of the screen certain hashtags are displayed, so that Twitter users that are watching the TV show can be encouraged in posting tweets while watching the episodes. This kind of social strategy creates engagement and conversation between the show and its viewers as well as between viewers and it leads also the hashtag to become popular, since many Twitter users post the hashtag within their tweets. "The Voice" is another interesting example, since both hashtags and specific users' tweets are displayed, while the TV show is on air: the engagement generated by these different social strategies has been subject matter of the research concerning the social TV phenomenon (see, for instance, Hill and Benton, 2012). Other producers also developed social TV applications related to the TV programs, in order to increase the viewers' enjoyment and interaction through several kinds of activities related to the program, e.g., voting, expressing preferences, showing reactions to specific events occurring during the TV show through the application. "L'Isola dei Famosi", a popular Italian reality show, developed a social TV application to allow viewers to access to a variety of quizzes, surveys and additional contents related to the program. The interaction between TV and social media is also often used to increase the interest towards a TV show before it is on air or to keep the interest alive also between episodes. For instance, "Mob City" a TNT series concerning Los Angeles mobsters in the 1940s, posted many tweets including short

videos, photographs or other elements to build fans on Twitter before its premiere in December 2013 (Newman, 2013).

While viewers increasingly interact before, during and after watching TV shows and producers study the best social strategies to attract viewers' attention and interactions on social networks' sites, a huge number of data become public available. Indeed, the conversations published on social media can be easily accessible, thus it is possible to download, structure and analyze data deriving from social media, in order to obtain useful insights.

In this context, the scientific research is trying to investigate the several aspects concerning social TV, which cover a large variety of research areas, such as computer science, psychology and marketing. Therefore, since the social TV research is not defined within a specific scientific area, this paper aims at deeply exploring the topics belonging to the several areas concerning the social TV phenomenon.

3. Methodology

In order to explore the topics concerning the social TV phenomenon within the different scientific areas, I have reviewed the wide collection of papers belonging to social TV, from computer science to marketing. To this aim, I adopted the methodology developed by Tranfield, Denyer & Smart (2003) and already adopted within several research domains (see, for instance, Ardito, Messeni Petruzzelli, & Albino, 2015; Crossan & Apaydin, 2010; Meier, 2011; Zott et al., 2011; Carpenter et al., 2012; Keupp et al., 2012; Phelps et al., 2012).

As suggested by Ardito, Messeni Petruzzelli, & Albino (2015), I followed a number of steps:

1.   Since the social TV is a concept concerns both TV as a media and the social aspects related to the TV consumption, I selected an initial list of 12 keywords, divided into two categories (see Table 1). Specifically, category "TV" considers keywords related to the concept of TV, as a medium that allows viewers to enjoy multimedia contents. Instead, category "social" includes words referring to the new social aspects of TV consumption.

Table 1. List of keywords by category.

Category "social"	Category "TV"
social media	Interactive TV
Social network*	Multiscreen
Microblogging	Coviewing
Twitter	Viewers' engagement
Online behavior*	
Online interaction*	
Online engagement	
Multitasking	

2.   The search labels from category "TV" were combined with the word "social", while those belonging to the category "social" were combined with the word "TV" or "television" in the attempt to collect all the articles that have linked TV to its new social aspects. Thus, this procedure produced 12 concrete search strings: some examples are represented by ['social media' and 'TV'], ['interactive TV' and 'social'], ['multiscreen' and 'social'].

3.   Although in previous works (e.g., Crossan & Apaydin, 2010; Zott et al., 2011; Keupp et al., 2012; James et al., 2013) the systematic review was limited to peer-reviewed journal articles, I have considered also books, book chapters, and conference proceedings. Indeed,

16

since the social TV research is a recent topic, most of the ongoing research has been presented within conferences, which tried to collect definitions and summaries and all the current knowledge concerning the phenomenon. As stated by Adams, Smart, & Huff (2016), the systematic reviews concerning new fields of inquiry have to include the so-called "grey literature", i.e., anything that has not been published in a traditional format as conference proceedings, dissertations and theses, since it can provide an important source of information.

4.   Google Scholar was the main database for the literature search for journals' papers as well as proceedings papers and books. The search strings described in the previous stage were used to search for the title, abstract, and author-provided keywords as well as articles' contents.

5.   Then, I further selected the relevant papers. First, papers have been identified through the analysis of titles, in order to evaluate the correspondence with social TV topics. Then, they have been selected through the analysis of abstracts and finally the analysis of the specific contents, when the abstracts did not provide a clear description concerning the aim of the articles, adopting two main inclusion criteria (see Table 2). This process of analysis has led to a list of 46 manuscripts. As reported in Fig. 1, the most part of the papers has been published in 2008 and 2011, however starting from 2011 the number of papers concerning the social TV phenomenon is again increasing.

Table 2. Inclusion criteria.

Criteria	**Reason for inclusion**
Theoretical papers	These articles are included because they provide the basis for summarizing and integrating empirical evidence.
Quantitative and qualitative empirical studies	These articles are included because they provide extant empirical evidence.
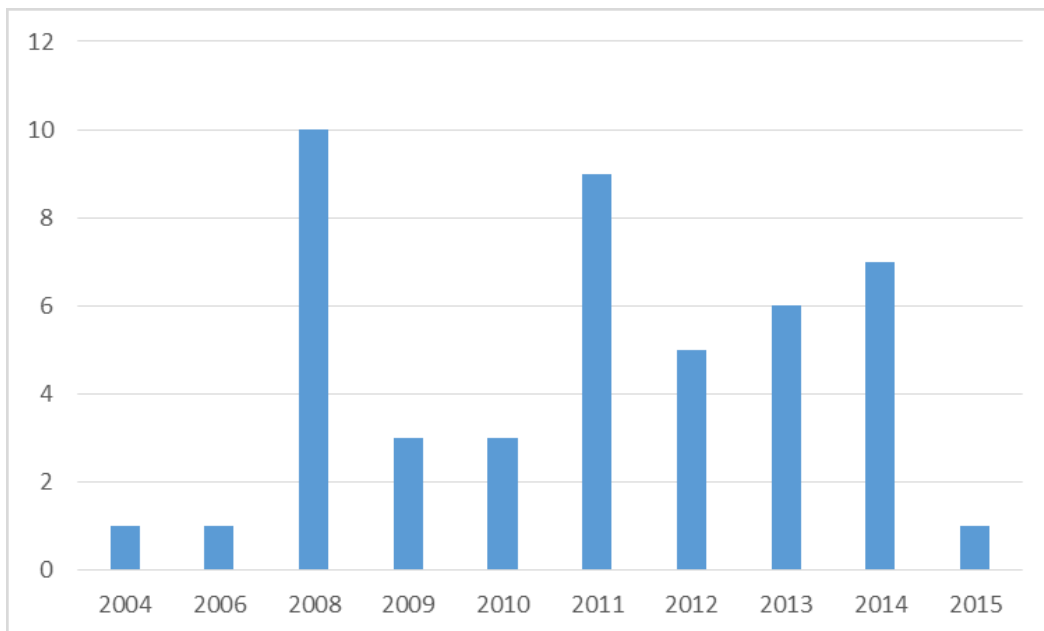
Figure 1. Retrieved papers categorized by year of publication.

Notably, these years have been identified as specific phases of the social TV market's evolution. Fig. 2 shows the timeline of the social TV market, from its early days to 2012, expressed by the number of the applications for second screen devices developed and spread for commercialization. The timeline shows that 2008 can be considered within the period of the early days of social TV market's development. Particularly, the development of

applications for second screen devices is at its early stages. On the other hand, the 2011 is included between the multiplication and consolidation periods; therefore, the increase of the scientific research concerning the social TV phenomenon reflects the interest towards the market's growth.

Figure 2. The evolution of social TV market (Fuchs, 2012).

Finally, the most part of selected papers (63%) is represented by articles presented at conferences. One of the most important conferences concerning the social TV topics is the European Interactive TV Conference, which, after the 2013 edition, has become the International Conference on Interactive Experiences for Television and Online Video.
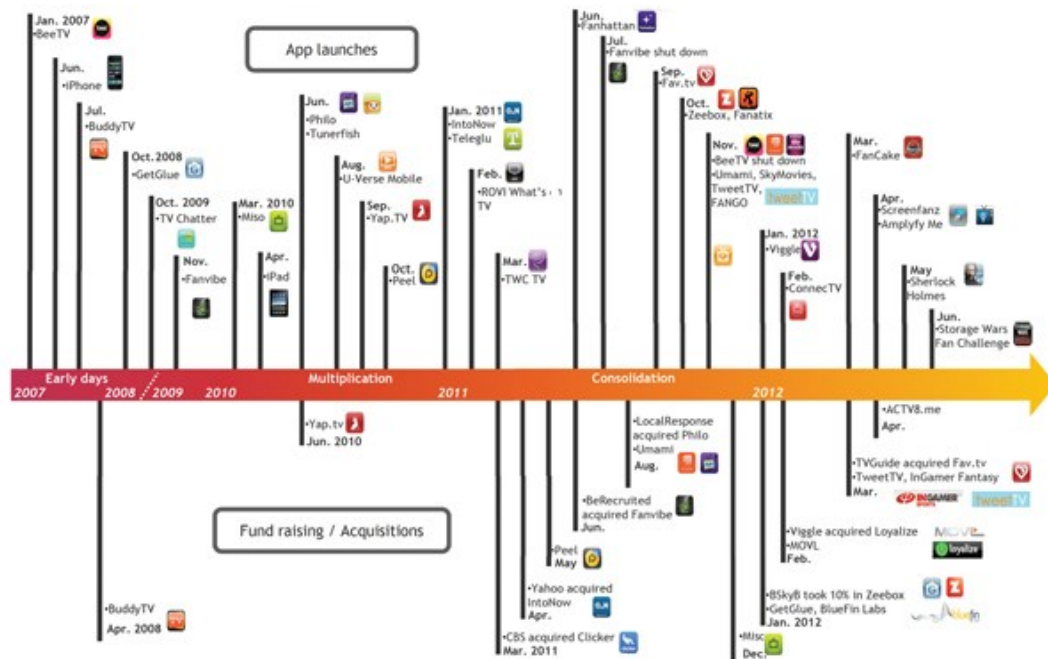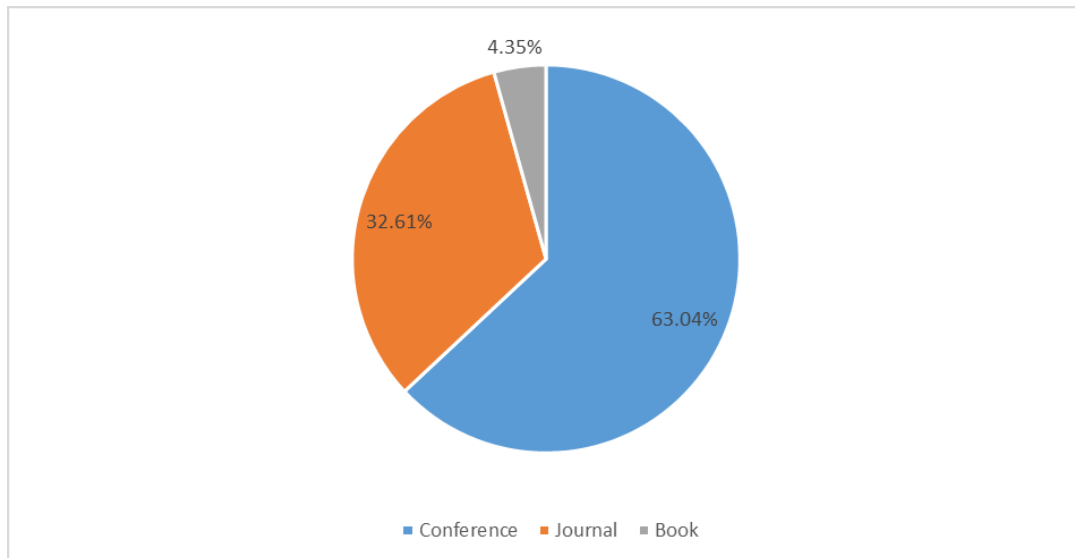
Figure 3. Retrieved papers categorized by type of publication.

4. Literature findings

After the literature review previously described, I grouped and discussed literature findings according to two categories of analysis: "technologies" and "viewers' behaviors". Notably, I grouped all the works related to the technology's development and evaluation under the category "technologies", which considers all the aspects related to the applications' design and development, specific functionalities and services' development and finally integration and proposition of guidelines. On the other hand, I identified also several works focused on the "viewers' behaviors": authors tried to explore behaviors, reactions, preferences of viewers related to a specific application's design or to the general social TV usage within a specific TV context, e.g. a specific TV program or TV genre. I chose these two categories, since in this kind of contexts some authors develop and evaluate the applications, while others try to explore psychological and social behaviors within the technological context (Carroll, 1997). Thus, it is also important to transfer the insights deriving from the behavior's examination to the design of applications (Spiekermann and Corina, 2000): design guidelines can derive from both specific applications' studies and

extensive studies concerning TV usage and viewers' behavior (Chorianopoulos, 2008). As a result, the selected papers belong to different areas, such as computer science, communication science, psychology and marketing.

4.1 Technologies

The most part of previous work in the social TV research has been focused on the applications' design and evaluation. The main task of social TV systems consists in providing TV viewers with technical support for colocated and geographically distributed TV watching and social interaction (Gross, Fetter, & Paul-Stueve, 2008). Indeed, most works described the implementation of prototypes that allow the combination between TV and internet, particularly the integration of the social media interactions within the TV context (Coppens, Trappeniers & Godon, 2004; Gurrin et al., 2010; Huron, Vuillemot, & Fekete, 2013; Shirazi et al., 2011). AmigoTV, developed by Coppens, Trappeniers & Godon (2004), represents an example of social TV applications. It is a prototype combining broadcast television with rich communication and community support, with the aim of leveraging a rich social experience around a specific TV show. Similarly, Huron, Vuillemot, & Fekete (2013) deployed Bubble-TV, which includes live visualization of TV viewers' tweets, as a persistent background for a French TV show, allowing its viewers to explore and comment the social activities that occur around the show.

Most of the developed prototypes have been tested through a field evaluation over a certain period and involved the participation of households or single users (Metcalf et al., 2008; Harboe et al., 2008; Tullio & Harboe, 2008; Huang et al., 2009; Basapur at al., 2012; Palviainen, Kuusinen & Väänänänen-Vainio-Mattila, 2013; Almeida et al., 2012). The test of social TV applications allowed researchers and developers to understand the preferences of users and consequently the value that social TV applications can offer to viewers.

21

Particularly, users appreciated the ability to see their friends' presence on the system, the ability to see or suggest the programs they were currently watching, and the ability to send short messages to one another (Metcalf et al., 2008). Particularly, the presence information offered by social TV applications also allowed participants to learn more about other viewers' TV viewing habits and preferences and promoted a sense of connectedness between them (Metcalf et al., 2008). Moreover, by adopting the focus groups methodology, Harboe et al. (2008) found that the social television experience they developed provided viewers value only under certain favorable conditions. These applications had a considerable impact on viewers' TV experience. Indeed, Shirazi et al. (2011), after conducted an uncontrolled user study during the soccer world cup 2010, found that TV viewers who used the app had more fun and felt more connected to other viewers. Furthermore, Basapur et al. (2012) found that their prototype allowed participants to feel more connected with their TV shows, thus having an enriched social experience around live TV content.

Within the "technologies" category, some papers have been focused on technological aspects and features, which take into account specific conditions of social TV usage (Wu et al., 2013; Jin et al., 2013; Hu et al., 2014; Lee, Seong Cho & Ryu, 2011). For instance, Wu et al. (2013) developed a social TV system including cloud services to offer mobile users a living-room experience, by allowing them to interact on social networks while watching the video. Similarly, Jin et al. (2013) adopted the cloud computing paradigm to encapsulate media services and provided users with attractive multi-screen and social features. Other papers focused also on the use of social TV for specific categories of users, who are characterized by different habits and needs and who can consider the social TV as a way to increase their social interactions in everyday life, i.e., elderly people (Sokoler & Svensson, 2008; Abreu et al., 2011). Moreover, some authors explored the social awareness issues related to audience interactivity within television show broadcasts (Mitchell et al., 2010;

Mantzari, Lekakos & Vrechopoulos, 2008). Specifically, Mitchell et al. (2010) introduced a mechanism for providing social awareness to individual users of an IPTV system. The goal consists in facilitating an intuitive and simple media selection mechanism when considering vast amounts of live TV channels and on-demand content. Finally, few works provided an overview of concepts and systems as well as studies belonging the social TV domain (see, for instance, Gross, Fetter & Paul-Stueve, 2008).

The focus on technological development is also underlined by the large number of papers that aims at integrating and evaluating specific functionalities and services (Coppens, Trappeniers & Godon, 2004). One of the most relevant topics related to the evaluation of specific functionalities concerns the use of text or voice communication (Tullio & Harboe, 2008; Huang et al., 2009; Geerts, 2006). Several authors explored the viewers' choices of communication modality, their topics of conversation and the sense of connectedness, by analyzing how and under which conditions viewers use these kinds of functionalities. Particularly, some authors found that text is used more often than voice communication (Tullio & Harboe, 2008; Huang et al., 2009) or they are used in combination (Tullio & Harboe, 2008). They also found that rich modes of communication, such as free-form text messages or voice communication, have the potential to interrupt content viewing (Metcalf et al., 2008). On the other hand, services related to the collection and analysis of data generated around the TV consumption have been studied. The main idea consists in extracting valuable messages and valuable user information from conversations in order to provide viewers with a deep social experience. In order to allow users to read microblogging messages related to the TV program they are currently watching, a social TV system needs to integrate a service able to select the TV program-related messages. To this aim, Dan, Feng, & Davison (2011) proposed an approach able to collect all microblogging messages related to a given TV program, i.e., to capture the association between the TV program and

the message. A further step is represented by the extraction of valuable information from conversations. For instance, Martins, Peleja & Magalhães (2012) developed new methods of measuring TV viewers' feedback and new multi-screen interaction paradigms. Particularly, they analyzed chat-messages in order to detect the mood of viewers towards a given show (i.e., positive vs negative) and used this kind of information to inform the viewer about the show popularity, by displaying this information on the screen. Moreover, Zhao, Wickramasuriya & Vasudevan (2011) extend their web service, which recognizes major events in the US National Football League (NFL), in order to extract TV watchers' sentimental reaction to major events in live broadcast sports games in real-time. This system aim at enabling TV watchers to better select interesting programs in real-time and to produce personalized program summaries.

Despite the development and evaluation of this variety of applications and services, Huron, Vuillemot & Fekete (2013) have highlighted that more research and different applications are needed to identify best practices and develop general guidelines. Concerning the need of general guidelines, Cesar & Geerts (2011) provided a structured overview concerning the social TV systems' development. Based on a survey of over thirty systems, they identified a number of key categories for differentiating social TV systems. Particularly, they categorized social TV applications based on the social purpose, i.e., content selection and recommendation, communication, community building, and status update, in order to identify also future developments. Moreover, Chorianopoulos & Lekakos (2008) identified two dimensions to design and evaluate social TV systems: the presence of the viewers, e.g., colocated viewing in groups or distance viewing, and the type of communication between viewers, e.g. synchronous communication that happens in real time and asynchronous communication that happens with a time lag. Ducheneaut et al. (2008) tried to propose guidelines as well as specific features based on a series of studies illustrating how people

interact with each other in front of a television set. On the other hand, Geerts and De Grooff (2009) collected twelve sociability heuristics to offer guidelines useful to design and evaluate social television systems and interactive television in general, as well as social television applications. For instance, they stated that a social TV system has to include communication functionalities on different levels of engagement, i.e., quick responses versus free-form communication, or also provide different functionalities both for synchronous and asynchronous interaction and communication.

However, Basapur et al. (2012) underlined that, despite the value the social TV applications offer to viewers, participants also described some concerns like distraction from TV show. Harboe et al. (2008) stated also that designing for the social dynamics at the beginnings, ends, and outside of conversations remains an open challenge. However, some interesting impacts have also been examined: Metcalf et al. (2008) observed and stated that seeing what programs friends are watching can be a motivation for viewers for changing their schedule of viewing based on what they saw others doing. These kinds of observations can highlight relevant advantages for TV operators, which aim at increasing the TV audience and popularity.

4.2 Viewers' behaviors

Despite the huge quantity of data generated through the social network sites, little research has been focused on the examination of viewers' behaviors not strictly related to a specific applications' design. However, some authors derived from the design evaluation general insights concerning the viewers' behavior.

They explored if the viewers' behaviors on social media are influenced by specific conditions. For instance, based on a user study of a social TV system, Geerts, D., Cesar, P. & Bulterman, D. (2008) examined how television genres can play a role in the use of social

interactive television systems. Particularly, they found that news, soap, quiz and sport are genres during which viewers talk most while watching, while film, news, documentaries and music programs are potentially popular genres during which viewers tend to less interact with each other. Dezfuli et al. (2011) also presented an explorative study concerning the role of interpersonal relationships on social interactions while watching TV and its link to video genres. They found that the desired relationship for social interactions depends both on strong relationship between viewers and on program genre. These results can have considerable impact on designing social interactive television systems to enhance social interactions between remote viewers. Finally, Hamaguchi et al. (2012) analyzed the results of experiments conducted on a large-scale social TV system, thus discussing the viewing behavior of users in social TV systems. Findings highlighted that there is a bias in the genres of programs that are viewed and that the satisfaction of viewers increases.

Few studies focused on the examination of viewers' behavior not linked to a specific application's design, but to a specific TV program. For instance, Doughty, Lawson & Rowland (2011) explored the viewers' behavior, considered as an aggregated trend, running some preliminary analysis of viewers' Twitter postings during the UK TV shows, The X Factor and Question Time. Based on their findings, they stated that posting Twitter messages is an indicator of viewers' engagement towards the TV shows and therefore this kind of activity increase with broadcast media. Moreover, using the third season of Downton Abbey as a case study, Schirra, Sun & Bentley (2014) explored motivations for live-tweeting around a TV show. Particularly, they analyzed Twitter conversations from the first to the last TV show's episode as well as 11 semi-structured interviews, and they found that the decision to post tweets depends on a variety of personal considerations, such as the desire to share the interest towards the TV show with a larger community. Furthermore, Doughty, Rowland, & Lawson (2012) also investigated the nature of television audiences, which

engage in social interactions while watching TV. They considered two different genres of television show, a celebrity oriented reality TV show and a panel discussion show. They found some similarities, such as a part of audience tightly connected and another part less connected and identified also the presence of 'celebrities' and well known people or organizations, such as media companies, which are characterized by a different behavior. As a conclusion, during the viewing viewers tend to form networks characterized by different traits and motivations to interact on social networks while TV shows are on air. Another interesting comparison already investigated concerns the live and non-live broadcast of TV programs. Particularly, Mukherjee & Jansen (2014) performed statistical tests on more than 418,000 tweets from second screens for three popular TV shows, thus identifying significant differences concerning the second screen usage between the two contexts: indeed, they found that the usage of second screen devices are characterized by different number of tweets. Therefore, live transmission of TV shows generates higher social interaction in comparison with non-live TV shows, thus measuring in particular a higher engagement of mobile users when the show is live. Finally, another basis for comparison has been found within the specific TV genre. Indeed, Giglietto & Selva (2014) presented a content analysis of the huge number of tweets posted during an entire season of a specific TV genre, i.e., talk shows. They considered the season's most engaging moments, thus observing a relationship between typology of broadcasted scenes, style of comments, and the modality of participation. This means that different TV contents can lead to different kinds of social interactions. Finally, Marasanapalle, et al. (2010) presented a case study focused on a popular TV show, which was aired for the first time in a season. By using text-mining techniques, they explored the main themes during the show, the elements within the show that drove popularity and the kind of viewers who were tweeting on the show. Therefore, they showed how to obtain certain kind of information by using available data.

Other works deeply investigated the motivations and some specific factors or perceptions influencing the motivations. Notably, Shin (2013) empirically investigated the influence of perceived sociability on the viewers' motivations and attitudes towards the social TV practices. The author developed a model to validate the relationship of perceived sociability to social presence, usability, and intention, thus demonstrating that the sociability has a key influence on viewers' social TV practices. Hwang & Lim (2015) examined viewers' motivation and feelings concerning the interaction with other viewers, while watching sports, focusing on the social TV experience during the 2012 London Olympic Games. By adopting the structural equation modeling, they found that information and excitement motives of social TV are positively related to social presence, while convenience and information motives positively predicted sports channel commitment. It has been observed also that social interactions around the TV programs are able also to influence decision within real life. Nee (2013) presented a research with the aim of identifying motivations and political outcomes of social TV usage and found that the frequent use of social media while watching TV can lead people to engage with a specific candidate on Facebook or Twitter and to be influenced by candidates' social media presence when making the voting decision. Finally, Pagani, M., and Mirabello (2011) found that the personal engagement with the content and social-interactive engagement (resulting from the perceived sense of community, intrinsic enjoyment, and participation experience) differentially influence both active and passive behavior.

Another interesting topic concerning the analysis of the viewers' behavior is related to the response of viewers towards the social TV initiatives. By examining Twitter users' behavior, Nagy & Midha (2014) found that if tweets are displaying while TV show is on air, viewers would take actions related to television viewing and they also engage with the TV show's brand sponsors. On the other hand, Pynta et al. (2014) measured the participants'

neural responses while they watched a live television broadcast and freely interact on social-media platforms, such as Twitter. The results indicated that engaging in social media activities while watching television can significantly enhance viewer engagement in the television program, measured by neural indicators.

All these advantages have been identified as relevant also by marketing and advertising research and industry. However, since social TV requires the attention of viewers towards a secondary screen, some authors have also explored relevant consequences of engaging in social TV activities on viewers' attention. Notably, through a controlled laboratory experiment, Bellman et al. (2014) found that like normal coviewing, social TV viewing distracts from ad-processing, reducing unaided recall and brand attitude favorability, compared to individual (solus) viewing. This finding has been confirmed also by previous studies concerning the use of social TV applications (Metcalf et al., 2008; Basapur et al., 2012).

5. Conclusion and research directions

The use of mobile technology combined with television viewing activities has received considerable attention in the recent years (Shirazi et al., 2011) and has been defined "social television", since it enhances the social practices concerning television programs. Technology had a key role in the shifting from traditional television to social TV: it allows the development of services and applications, thus providing viewers the functionalities to interact with other viewers around the TV show. Although TV has always been social, this trend has changed the modality and impact (Mukherjee & Jansen, 2014; Doughty, Lawson & Rowland, 2011) of social activities. One of the main changes concerns the real-time

interactions, which involve at the same time a huge number of viewers, specifically through the use of social network websites, such as Facebook and Twitter (Giglietto & Selva, 2014).

While the industry is rapidly evolving from both the viewers and producers sides, in the recent years a large variety of research area, such as computer science, psychology and marketing, has investigated several aspects concerning the social TV phenomenon. This paper collected and explored the topics belonging to the several areas concerning the social TV phenomenon, in order to build an overview of the current insights and knowledge around the social TV topics. Notably, I presented a systematic review based on the methodology developed by Tranfield, Denyer & Smart (2003) and included also the so-called "grey literature", which has been considered relevant by Adams, Smart, & Huff (2016) for investigating new fields of inquiry. The review allows us to derive two main categories of analysis: the technological aspects and the viewers' behaviors insights.

Due to the key role of technology (Gross, Fetter, & Paul-Stueve, 2008), I observed that most part of previous work in the social TV research has been focused on the applications' design and evaluation. Notably, previous research mainly described the implementation of prototypes that are able to combine TV and internet, in particular they generally focus on the integration of the social media interactions within the TV context (Coppens, Trappeniers & Godon, 2004; Gurrin et al., 2010; Huron, Vuillemot, & Fekete, 2013; Shirazi et al., 2011). Most of them have been tested through a field evaluation over a certain period and have been characterized by the involvement of whole households or single users (see for instance, Metcalf et al., 2008), in order to understand the preferences of users and consequently the value that social TV applications can offer to viewers. Indeed, they found that the television experience is enriched if combined with social TV systems, although this value has been verified only under certain favorable conditions: when using social TV systems, participants

perceive a greater sense of connectedness with other viewers as well as with the TV shows and have more fun.

Several works focused on developing, integrating and evaluating specific functionalities and services (Coppens, Trappeniers & Godon, 2004). For instance, functionalities and services can consist in integrating voice communication technologies (Tullio & Harboe, 2008; Huang et al., 2009; Geerts, 2006) to enhance the sense of connectedness, as well as services related to the collection and analysis of data generated around the TV consumption, in order to offer viewers relevant insights useful to evaluate and potentially choose TV programs.

Although some papers have provided overviews and proposed guidelines to design and evaluate social television systems and applications, more research and different applications are needed to identify best practices and develop general guidelines (Vuillemot & Fekete, 2013). Furthermore, it has also been underlined that, despite the value the social TV applications offer to viewers, participants also described some concerns like distraction from TV show.

Some authors derived from the design evaluation more generalizable insights concerning the viewers' behavior. For instance, they found that specific television genres, such as news, soap, quiz and sport, lead viewers to interact most while watching, while others lead to few interactions during the viewing.

In the attempt to explore the viewers' behavior without focusing on a specific application's design, few authors (Schirra, Sun & Bentley, 2014; Doughty, Lawson & Rowland, 2011; Doughty, Rowland & Lawson, 2012; Marasanapalle, et al. 2010) focused their analysis on specific TV programs, such as Downton Abbey, The X Factor, Question Time and other TV shows, which are characterized by a large amount of conversations on social network sites. They found behavioral differences between: genres of television show;

celebrities' and well known people or organizations and other users; live and non-live transmissions; different typologies of broadcasted scenes; different themes within the TV show. Other authors deeply explored the viewers' motivations as well as specific factors or perceptions influencing the motivations. Notably, they found that: perceived sociability influences the viewers' motivations and attitudes towards the social TV practices; information and excitement motives of social TV are positively related to social presence, while convenience and information motives positively predicted sports channel commitment. Notably, social interactions can have influence also on real life decisions: for instance, as stated by Nee (2013), in the context of political elections, using social media while watching TV can help people to interact with a specific candidate on social network sites, thus be influenced when making the voting decision. Finally, both active and passive behaviors are influenced by personal engagement with the content, but they are influenced in different ways.

Previous works has also tried to explore the response in terms of viewers' behavior towards the social TV initiatives or strategies. When producers displays tweets while TV show is on air, viewers are encouraging in taking actions related to television viewing, as well as engaging with the TV show's brand sponsors. In general, this kind of stimuli are able to increase the engagement of viewers in social media activities while viewing television, thus significantly enhancing also the viewer engagement in the television program, which has been measured by neural indicators. Despite these advantages, few authors have also found that like normal coviewing, social TV viewing can lead also to increase the viewers' distraction.

The literature review highlighted the need of further research concerning the social TV phenomenon. Several aspects have not yet been deeply explored. From the technological viewpoint, despite the larger number of applications already developed and tested, thus

generating some guidelines, it emerges the need of further general research. It would be useful to define more general guidelines, since the variety of applications and relative tests is not able to offer complete observations to research and industry. On the other hand, since the use of social TV systems and applications is very heterogeneous in terms of users, contexts and TV programs, it should need a focus on a specific program genre in order to develop appropriate development's guidelines. On the contrary, the attempts proposed until now focused on developing a comprehensive design, fitting all contexts and TV programs.

To this aim, the examination of viewers' behavior, without considering a specific design, needs to be enhanced. Indeed, the design of applications has to respond to viewers' needs and the comparison of viewers' behavior between different contexts can be useful to understand their habits. It would be relevant also to systematically analyze the factors influencing the viewers' behavior on social media while watching TV. Since social TV can be considered a cross research topic, it needs the convergence of the contributions of the different research area in order to identify factors of influence, motivations and then predict behaviors.

Finally, the literature review underlined also a key question from a managerial viewpoint, which is the identification of the value not only for viewers, which highlighted also the distraction issues, but also for the other stakeholders. They are the TV producers, broadcasters and advertisers, which need to understand how the huge number of data generated through the social TV practices can be extracted and analyzed to reach managerial aims.

CHAPTER 2. LEVERAGING BIG DATA FOR SUSTAINING INNOVATION IN THE SOCIAL TV CONTEXT

1. Introduction

The relevance of the "open innovation" approach within the innovation process has been highlighted by both research and industrial domains (Chesbrough & Appleyard, 2007). The access to external sources has become very frequent for several type of firms, in order to achieve and sustain innovation. Previous research focused on the conditions that make firms able to accept the access to external knowledge (Hussinger & Wastyn, 2011), as well as the influence of several factors on the innovative performance. Moreover, concerning the innovative performance other aspects have been also investigated. Indeed, some works analyzed the interaction between different environmental contexts and the adoption of distinct open search strategies, thus demonstrating the relevant role of the environmental dynamism to define the firms' open search strategy (Cruz-González, López-Sáez, Navas-López, & Delgado-Verde, 2015). Others studied the factors influencing the search strategies' effectiveness and the relationship between appropriability strategy and the openness of external search (Laursen & Salter, 2014). Finally, few studies compared the ways to effectively manage innovation at the market-level, especially in terms of benefits and costs of innovation governance mechanisms (Felin & Zenger, 2014).

One of the most current interesting aspects concerning the open innovation, i.e., access to external sources, is represented by the diffusion of social media, which decreased the communication costs and are thus facilitating the open innovation adoption in several domains (Chesbrough & Appleyard, 2007). Particularly, social media changed the relationship between organizations and their stakeholders, specifically their customers,

which are able to interact online and as one of the main sources of big data generate a large amount of knowledge about customers' preferences and reactions. Indeed, big data can provide interesting insights for organizations, which are increasingly interested in exploring how to use them: they are able to allow traffic patterns' analyses as well as the predictive likelihood of an event (George, Haas & Pentland, 2014). However, one of the challenges concerning the big data consists in understanding how to extract new insights, thus adding valuable knowledge, since they require the use of specific techniques. Despite the increasing interest towards big data, few works have been focused on the big data, particularly social media data, as external sources to acquire customers' knowledge and, consequently, to improve products and services (Thomke & von Hippel, 2002; Zanjani, Rouzbehani, & Dabbagh, 2008). As reported by Chua & Banerjee (2013), this knowledge can be useful to improve the quality of existing products or services or to develop new ones. Particularly, scholarly attention has examined the use of social media in some limited contexts and few works explored how the social media data can be useful for TV stakeholders to analyze different aspects related to the TV consumption, as well as to the effects of specific TV contents, in order to improve TV show's quality (Marasanapalle et al., 2010). Indeed, the diffusion of the use of smartphones and tablets while watching TV has led to a new concept of TV, named social TV, which is characterized by the generation of real time viewers' interactions on social networks. Therefore, the role of social media within the innovation process can be observed also in the social TV domain, where social media data perform a crucial role in providing knowledge. Indeed, as viewers interact during and around the TV shows, broadcasters and other stakeholders can have access to a large amount of data published online, particularly on Facebook and Twitter, useful to analyze different aspects related to the TV consumption. I focused on the use of big data, particularly social media data, as external source of knowledge for innovation, particularly to improve the quality of a TV show, by analyzing the viewers' reactions on social media, i.e., the generation of social

35

media traffic defined as the amount of the viewers' interactions around a specific topic. Notably, in order to achieve valuable insights concerning the TV show, I classified the TV show's contents in order to analyze their impacts on social media and consequently evaluate their potential of increasing or decreasing the Twitter traffic, considered as an indicator of success. In this analysis, I considered also the social media elements, particularly specific Twitter elements displayed on the TV screen (i.e., official hashtag and other different ones) in order to obtain valuable knowledge concerning all the different elements of the TV show that can be used to increase the social media traffic through a better design of the TV show.

The paper is structured as follows. In the next section, I described the existing literature concerning the open innovation and the use of big data as external sources of knowledge in the specific domain of social TV. Then, I depicted the methodology adopted to analyze data concerning a specific TV show: I described the research setting and the collected data, the variables and the methodological approach to analyze data. Finally, I showed and discussed the results obtain from this analysis, by highlighting the theoretical and managerial contributions as well as limitations and further directions for future research.

2. Theory

2.1 The rise of Open Innovation

"Open innovation", one of the most important topics in recent management literature, represents the dominant approach to drive the innovation process (Cassiman & Valentini, 2016). Indeed, many firms have increasingly access to a wide range of external sources of knowledge, e.g., suppliers, customers and competitors, with the aim of achieving and sustaining innovation (Laursen & Salter, 2006; Chesbrough & Appleyard, 2007). However, there are specific conditions that lead firms to access to external sources, while some kinds

of sources, e.g., when knowledge is acquired from competitors, lead firms to an internal resistance against the external knowledge's acquisition (Hussinger & Wastyn, 2011).

Previous works have explored several aspects concerning the open innovation adoption. Berchicci (2013) investigated the role of the R&D system configuration; specifically, he confirmed the relevance of external sources, but he also studied the influence that the tradeoff between internal and external R&D processes exerts on an innovative performance. According to the author, firms characterized by a relatively low external R&D could obtain a greater innovative performance, by increasing the percentage of their external R&D. However, in order to take advantage from the external R&D, they have to consider also their own technological knowledge and R&D capabilities, which perform a relevant moderating role in the innovation process. Furthermore, Cassiman & Valentini (2016) tested the complementarity between acquiring external knowledge and selling knowledge and posited that engaging in acquiring external knowledge increases also the return from selling knowledge in terms of R&D productivity; thus, the effect of the first is not independent from the second and vice versa. Notably, they suggested that the reinforcing effect between acquiring and selling knowledge may exist not at the firm level, but at the industry-level. Cruz-González et al. (2015) provided insights about the complexity of external knowledge search by organizations. They investigated the effect of openness on overall firm performance, by studying how distinct open search strategies interact with different environmental contexts. Their results suggested that managers have to take into account the environmental dynamism, since it represents a relevant factor to define the firms' open search strategy. On the other hand, Laursen & Salter (2006) studied the factors influencing the external search strategies' effectiveness. Specifically, they investigated the differences in terms of external search strategies among firms and their influence on the ability to achieve innovative performance. They found that firms who adopt open search strategies,

especially who search both widely and deeply tend to be more innovative, although there is a point where additional search becomes unproductive. Following this line of enquiry, Laursen & Salter (2014) explored also the paradox of openness, i.e., the relationship between appropriability strategy and the openness of external search. They showed that appropriability can be a limitation for openness, since at high levels of appropriability the levels of openness decrease. Other works focused on comparative studies useful to identify the ways to effectively manage open innovation across governance forms and markets (Felin & Zenger, 2014; Garavelli, Messeni Petruzzelli, Natalicchio, & Vanhaverbeke, 2013). Particularly, Felin & Zenger (2014) examined benefits and costs of several forms for governing innovation by evaluating their access to (a) different communication channels for knowledge sharing, (b) different types of incentives, and (c) different types of property rights. Therefore, they identified in which circumstances it is better to adopt specific forms of governance and the related reasons: for instance, accessing users and user communities is a governance form characterized by the advantage to access a huge amount of information, that otherwise would remain hidden, useful to solve simple and decomposable problems.

2.2 Open Innovation, Big Data and Social TV

All the studies discussed in the previous section underlined the relevance of the access to external knowledge for firms, by investigating factors and conditions that can support or limit the decision to acquire knowledge from external sources. However, the decline of communication costs is facilitating open invention and coordination, thus making the open innovation adoption possible for more industries around the world (Chesbrough & Appleyard, 2007). Indeed, the social media, i.e., the online services that support online social interactions among users (Dutta, 2010), are able to allow multi-way communication between organizations and their stakeholders by decreasing costs and then increasing efficiency in

comparison with the traditional communication channels (Gallaugher & Ransbotham, 2010). They can also facilitate the knowledge sharing, which, in turn, may lead to interesting advantages concerning the innovation process of different kinds of organizations (Pan, 2012; Soto-Acosta, Perez-Gonzalez, & Popa, 2014; Palacios-Marqués, Merigo, & Soto-Acosta, 2015; Sigala & Chalkiti, 2014). Social media are particularly able to enhance the communication between organizations and their customers (Chua, 2011), which have been defined by Laursen & Salter (2006) as one of the most important sources of external knowledge, after suppliers. Many organizations are increasingly trying to make the use of social media valuable for several aims (Levy, 2009). As one of the main sources of big data, social media are able to generate a large-volume data that can be useful to produce valuable insight for firms (McKinsey Global Institute, 2011). As stated by George, Haas & Pentland (2014), big data are attracting attention because of the size of dataset, but above all because of the insights that the large-volume data can provide. Indeed, organizations are increasingly interested in exploring how to use big data, since they allow to predict individual action, consumer choice, search behavior, provide traffic patterns' analyses or the predictive likelihood of an event (George, Haas & Pentland, 2014). However, they require the use of powerful computational techniques to reveal trends and patterns and extract new insights, which can generally complement more static analysis and adding valuable knowledge from collective experiences, sometimes also real time.

Particularly, concerning the social media data, one of the most interesting way to use them is to collect data related to the interactions occurring online, in order to provide a large amount of knowledge about customers over time in order to understand their preferences and reactions (Chua, 2011; Magnier-Watanabe, Yoshida, & Watanabe, 2010). This knowledge can be incorporated for innovation (Thomke & von Hippel, 2002) of existing products or services, by improving their quality, or in terms of new products and services'

development (Zanjani, Rouzbehani, & Dabbagh, 2008). Indeed, Palacios-Marqués et al. (2015) studied the effect of online social media on firm performance and found a significant positive relationship between social media and innovative capacity, which, in turn, leads to a better firm performance. Chua & Banerjee (2013) analyzed the use of social media in Starbucks by combining a qualitative case study and a qualitative research technique that draws data from computer-mediated communication channels. Specifically, Starbucks, based on a traditional business model, acquires knowledge from customers in order to identify customers' expectations, behaviors and preferences by monitoring their conversations and the sentiment on the ground. By using social media, the company transforms its customers in active contributors of innovation by allowing them to contribute to the creation and evaluation of new ideas.

The bond between social media and traditional business has also characterized the TV industry (Carrascosa, Gonzalez, Cuevas, & Azcorra, 2013), by shaping new media consumption's habits and opening new possibility of data exploitation. Notably, the diffusion of the use of smartphones and tablets during the television program's viewing has changed also the relationship between TV broadcasters and viewers. Indeed, people watching TV are also writing messages pertaining to their opinions on social media, such as Twitter, one of the most popular social network site for TV show. This trend refers to the social TV phenomenon, i.e., the increasing use of a variety of systems that support social interactions for television viewers (Harboe, 2009). This kind of viewers' activities leads to the production of a large amount of data, which consist in Twitter or Facebook messages posted by viewers expressing their opinions, emotions or preferences about the TV show they are watching. The amount of the viewers' interactions represents also the traffic generated by the TV show or specific TV content (Marasanapalle, Vignesh, Srinivasan, & Saha, 2010). Particularly, on Twitter the traffic around a specific TV show is aggregated

using an official hashtag, a word referred to a specific topic that is preceded by a hash. When the traffic around the show reaches high levels in the Twitter community, it becomes one of the hottest emerging topics, which is considered a big success (Carrascosa et al., 2013). A considerable traffic has the potential to attract the interest of other viewers that are watching another TV show and lead them to switch the channel real time or to decide to start to watch the show the next episode. Moreover, it can also attract the interest of other mass media, thus increasing the media impact of the TV show and consequently the interest of advertisers towards the TV show.

The relevance of the social media in TV industry has also shaped the role of companies that focused predominantly on providing social media insights (Proulx & Shepatin, 2012). Social media data are, indeed, useful for broadcasters, producers and other stakeholders to analyze different aspects related to the TV consumption in general, as well as to the specific TV contents' popularity. For instance, some works developed methods to exploit the large amount of Twitter messages in order to obtain better TV viewing rates, by combining traditional audience data with social media data (Wakamiya, Lee, & Sumiya, 2011). Furthermore, Jacobson (2013) analyzed the influence that the viewers' interactions on Facebook concerning "The Rachel Maddow Show" have on the topics subsequently covered by the TV program. The author, indeed, found a positive correlation between topics discussed on Facebook and the ones subsequently broadcasted on TV, thus highlighting the use of social media to define the media agendas. On the other hand, few works focused on specific TV programs' contents. Nakazawa, Erdmann, Hoashi, & Ono, 2012) developed a new method to collect and analyze social media data related to a TV program on Twitter to automatically extract significant scenes within the program. On the other hand, Marasanapalle et al. (2010) have explored the value of Twitter as an important source to collect real-time reactions to certain live events, particularly for the television media. They

demonstrated that collecting information concerning the viewers' reactions on social media can help broadcasters and producers identify the contents and elements of the TV show that became popular as well aspects that could be improved in the next episode. Consequently, they can be able to better design the next TV show's episode of a weekly or daily show.

Positioned in the Social TV context, this paper is focused on the use of big data for open innovation: it concerns the use of social media data as external source of knowledge for innovation in TV industry, specifically in the social TV context. Particularly, I studied how to improve the quality of a TV show through the achievement of valuable insights extracted from social media data generated by viewers while watching TV. Scholarly attention has examined the use of social media in online business and offline companies (e.g. Chua, 2011; Levy, 2009). However, the extent to which the use of social media can be considered as an external source of knowledge for organizations belonging to the Social TV domain has not been adequately explored until now. First, previous works did not consider all TV show's contents, but they analyzed the impact of few topics that emerge from the viewers' social interactions around the TV show. On the contrary, I adopted a methodology based on the classification of the TV show's contents in order to analyze their impacts on social networks and consequently evaluate if they have the potential to increase or decrease the Twitter traffic, which is an indicator of success. Second, I proposed a long-term analysis, therefore all the episodes have been considered in order to obtain relevant feedbacks concerning the whole season that can be useful to design the next one. Another element of novelty is represented by the social media elements. Indeed, I did not consider only the TV show's contents, as done in previous works; I analyzed also the effects of the social media elements displayed on the TV screen, particularly the Twitter elements, such as the official hashtag and other different hashtags, which are used to lead viewers to interact on Twitter, in order to increase the Twitter traffic.

42

3. Methodology

3.1 Research Setting

In order to explore the use of big data for innovation in the social TV context, particularly to improve the TV show's quality, I used social media data coming from the second edition of the Italian TV show "The Voice of Italy", that is a singing talent show based on the format of the American show "The Voice". The show had one episode a week of around 180 minutes and lasted 14 weeks. It has been characterized by intensive interactions between contestants, coaches and viewers during different types of episodes. During the so-called "blind auditions", coaches had to evaluate and choose contestants in order to form a team. After this first part of the show, contestants had to perform and coaches and viewers evaluated them by voting. Moreover, viewers interacted on social media sites, specifically Twitter, during the show including in the Twitter messages' text the TV show's official hashtag, i.e., #tvoi. The official hashtag is used to aggregate all the viewers' interactions within the same Twitter topic (Doughty, Rowland & Lawson, 2012), thus it is easier for viewers to find other viewers and follow the conversation's flow. In order to lead the viewers' interactions on Twitter, the broadcaster displayed different Twitter elements on the screen during the show, e.g., generally the official hashtag, but also other different kinds of hashtags referred to the teams and the specific contestants.

3.2 Data and Variables

The TV show's official hashtag works as a filter for both viewers and TV show's stakeholders. Indeed, by using #tvoi as a filter, I collected approximately 550,000 viewers' interactions over Twitter, named tweets, via third party. I structured all tweets in a database with the respective time-stamp, useful to associate each tweet with a specific minute during

the show. As a result, I measured the viewers' interactions as the total number of tweets per minute including the TV show's official hashtag. Second, I structured in the dataset the types of TV content that viewers were watching minute by minute for the duration of show, including also the minutes and length of the commercial breaks. Third, I collected the type of Twitter elements that the broadcaster displayed on the screen minute by minute. Both TV contents and Twitter elements data have been collected by watching all TV program's episodes (available in streaming on the TV show's official website), reporting and classifying them as explained in Table 3. Fourth, I gathered the number of viewers who were tuned on the show's channel also minute-by-minute (viewership) via third party who allowed us the access to the Italian viewership database. I considered the viewership, since some researchers have observed that the Twitter traffic is mainly produced by TV viewers, which usually discuss their favorite shows through online social networks (Baym, 2000; Krämer, Winter, Benninghoff, & Gallus, 2015; Ross, 2008), thus underlying the existing relationship between viewership and social media traffic. Table 3 reports the list of collected variables listing their type, values and description.

Finally, each observation includes information concerning tweets, TV contents, Twitter elements and viewership, since I have the total number of tweets, the TV content and the Twitter element displayed on the screen for each minute of the TV show. In conclusion, I collected 2,400 observations corresponding to the number of minutes of show broadcasted during the 14 weeks.

In Fig. 4, as an example, I show the trend of the viewers' interactions, i.e., the total number of tweets, during the first episode of the show. I observed that some peaks, those marked by red circles, correspond to the performance of contestants; on the other hand, the viewers' interactions reach some of the lowest points during the minutes dedicated to the commercial breaks, marked through a green line. This first observation seems to suggest that some kinds

44

of TV content are able to produce a higher effect on viewers' interactions in comparison with other contents.
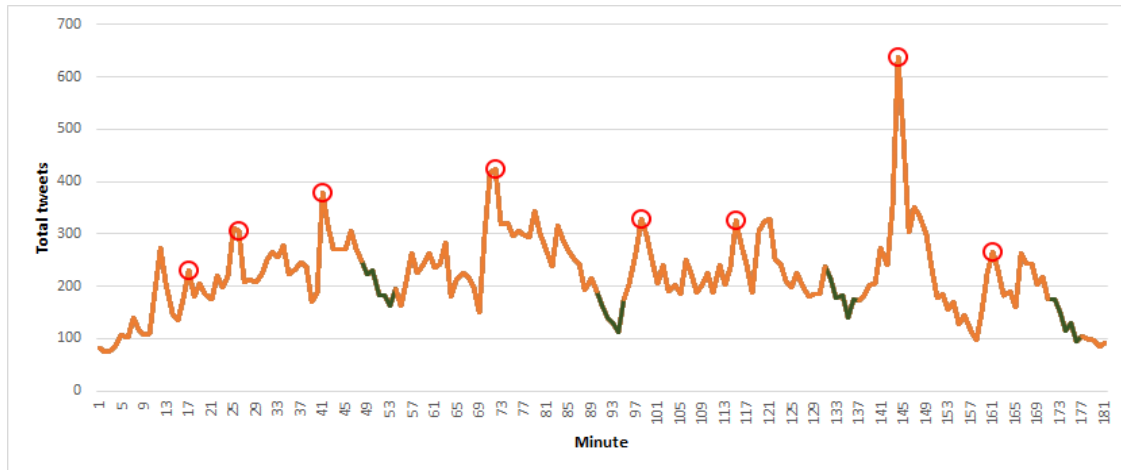
Figure 4. Viewers' interactions over time during the first episode.

By simply compare the trend within the first episode and some specific TV contents, such as performances and commercial breaks, it seems that there is a correspondence between what is happening on the screen and the traffic generated by viewers. This observation can be considered as a first confirmation that it is possible to identify TV show's contents, which increase the Twitter traffic by analyzing social media data. However, there are peaks that do not correspond to performances, therefore it also underlines the need to analyze the whole dataset in order to analytically find which kinds of contents increase or decrease the Twitter traffic.

Table 3. List of variables.

Name	Type	Values	Description
Time – Minute	Continuous	1-225	# of minute within the episode
Time – Episode	Continuous	1-14	# of episode within the season
Viewership	Continuous	0.6-5.2 (million)	# of viewers watching the show
TV Content	Dummy	Show	General contents
		Perf	Performance
		Coach	Coaches' comments
		Choice	Contestant's choice
		Steal	Steal of eliminated contestant
		Webroom	Web Room
		Break	Commercial break
Twitter elements	Dummy	None	No Twitter elements
		Hashtag	Official Hashtag
		Name	Contestant name's hashtag
		H+N	Hashtag and Name's hashtags
		Team	Team's hashtag
		H+T	Hashtag and team's hashtags
		T+Vote	Team's hashtags and Vote
		N+T+V	Hashtag's, Name's hashtags and Vote
		H+T+V	Hashtag's, Team's hashtags and Vote
Total tweets	Continuous	16-4172	# of total tweets

3.3 Analysis

Since the aim consists of using social media data to obtain valuable insights in order to improve the show quality, I analyzed the whole season, i.e., all episodes of the show, and analyzed the effects of all contents and Twitter elements displayed on the screen on the viewers' social interactions.

In order to do so, I built linear regression models by measuring the dependent variable, i.e., the total number of tweet, with a time delay of one minute with respect to the measurement of independent variables, since there is a lag in time between what viewers visualize on TV screen and their online activity (Nielsen Neuro, 2015). The independent variables are TV contents and Twitter elements. TV Content is defined as a nominal variable that describes what type of contents viewers are watching on the TV screen. Viewers can watch a contestant's performance (Perf), as well as the coaches' comment about the performance (Coach). Contestants can be eliminated or chosen (Choice) and further an eliminated contestant can be reintegrated (Steal). During the show, the Twitter activity is depicted showing numbers and tweets' texts (Webroom) and the show is periodically interrupted when TV commercials are broadcasted (Break). There are also less specific contents during the show (Show). Twitter element is represented by a nominal variable describing what message the broadcaster delivered to viewers on the first screen. Broadcaster can display the official hashtag of the TV show (Hashtag), the contestant name's hashtag (Name) and also the team's hashtag (Team). Sometimes these kinds of hashtags are combined displaying both the official and name's hashtags (H+N), as well as official and team's hashtags (H+T). In other cases, hashtags are displayed at the same time of an invitation to vote a contestant, combining the team's hashtag (T+Vote), the team and contestant's hashtag (N+T+V), and the team and official hashtags (H+T+V). Finally, sometimes no Twitter elements are displayed on the screen (None). Since the Web room

consists in showing also tweets' text, it could be considered a hybrid form between TV content and Twitter element. Finally, as control variables I considered viewership, measured as the number of viewers synchronized in each minute on the TV channel, and two measures of time trends, the minute in each episode and the number of episode, since I observe the aggregate phenomenon of viewers' interactions (Hill & Benton, 2012; Kim, Kim, Keegan, Kim, Kim, & Oh, 2015).

We adopted the hierarchical linear regressions approach (Baron & Kenny, 1986; Frazier, Tix, & Barron 2004). First, I built a linear regression model considering only the control variables as independent variables in order to check their significance (Model 1). Then I added one independent variable at time in order to check the significance of the partial models (Model 2 and Model 3). The independent variable were the TV content and Twitter element. Then, I built the complete model, which included both control variables and all the independent variables (Model 4).

4. Results

In this section, I show the results obtained from the analyses. As discussed in previous section, first I built linear regression models considering only the control variables, i.e. viewership, episode and minute. Table 4 reports the results of this model, i.e., model 1, which is useful to check the significance of control variables among the different models.

As expected, I found that viewership has a positive and significant effect on viewers' interactions, thus confirming that the more viewers watching the TV show the more online activity on Twitter (Baym, 2000; Krämer et al., 2015; Ross, 2008). I also found that the number of the episode has also a positive and significant effect on viewers' online activity, thus confirming an increasing trend in viewers' interactions during the show's season (Hill

48

& Benton, 2012; Kim et al., 2015). Finally, I did not find any statistically significant effect of the minute of the episode, thus demonstrating that there are not increasing nor decreasing trends during each episode.

After controlling the effects of the control variables on dependent variables, I also built the partial models (model 2 and model 3) before the complete model, i.e., model 4, which finally includes both control variables and all the independent variables. Table 4 shows also the results of all the models, both the partial and the complete ones.

The results of all these models confirm the effects of the control variables, i.e. the positive effect of viewership and episode on the viewers' interactions. In addition, the results show that both TV contents and Twitter elements have different effects on viewers' online activity. In particular, I found that the commercial breaks do not generate a significant reduction of the number of viewers' interactions, despite the observation in Fig. 4. This result means that looking at one episode of the TV show is not sufficient to understand which contents lead to a higher or lower traffic. I also found that some contents, specifically live performance and web room, generate a significant increase of viewers' interactions, while some other contents, i.e., steal, generate a significant reduction of the viewers' online activity. Similarly, I found that some Twitter elements generate a positive and significant effect on the number of total tweets: especially more specific Twitter elements, such as Team hashtag and Name hashtag, generate a positive effects on viewers' interactions when they are displayed during the invitation to vote. The official hashtag and the other kinds of hashtag alone do not produce any interesting effects on the viewers' interactions.

Table 4. Coefficients of hierarchical regressions approach.

	Model 1	Model 2	Model 3	Model 4
Constant	-185.979 (17.857)***	-184.25 (18.713)***	-175.148 (18.072)***	-172.318 (18.884)***
Minute	0.039 (0.068)	0.028 (0.068)	0.033 (.068)	0.022 (0.068)
Episode	13.659 (0.947)***	13.165 (0.987)***	13.081 (1.008)***	12.412 (1.055)***
Viewership	9.953E-5 (0.000)***	90.964E-5 (0.000)***	9.693E-5 (0.000)***	9.742E-5 (0.000)***
Break		1.133 (12.461)		0.503 (12.461)
Show		*omitted*		*omitted*
Perf		17.112 (9.603)(*)		19.334 (10.013)(*)
Coach		-8.424 (10.715)		-13.360 (10.858)
Choice		8.018 (15.997)		9.562 (16.176)
Steal		-116.327 (46.595)*		-114.816 (46.358)*
WebRoom		124.672 (45.165)**		125.926 (44.947)**
None			*omitted*	*omitted*
Hashtag			-4.075 (13.846)	-11.315 (14.282)
Name			23.570 (17.050)	21.723 (17.278)
H+N			89.139 (122.166)	72.496 (122.012)
Team			-70.998 (20.508)**	-78.894 (20.745)***
H+T			-101.109 (77.308)	-117.905 (77.477)
T+Vote			25.970 (15.035)(*)	27.605 (15.256)(*)
N+T+V			78.298 (23.536)**	71.884 (23.767)**
H+T+V			11.637 (46.690)	18.262 (46.736)
R^2	0.282	0.536	0.536	0.546
Adj. R^2	0.281	0.288	0.288	0.298

Notes: *Stat. sign. ***p<0.001; **p<0.01; *p<0.05; (*)p<0.1*

50

5. Discussion and Conclusions

Previous literature on innovation has shown the relevance of the "open innovation" approach to drive the innovation process in several kinds of firms. Indeed, the access to external sources has become a very interesting topic for both research and industry. Most of recent research have explored many aspects concerning the open innovation adoption, but little research has been focused on the value of big data for innovation, particularly the use of social media data as external sources to acquire customers' knowledge and, consequently, to improve products and services. Specifically, few works explored how the social media data can be useful for TV stakeholders to analyze different aspects to improve TV show's quality in the social TV context, an industry characterized by the wide generation of social media data due to the diffusion of smartphones and tablets. I demonstrated that the social media data referred to the viewers' interactions can be useful to identify the TV contents and Twitter elements, which drive the social media traffic. I collected approximately 550,000 tweets related to the Italian TV show "The Voice of Italy" through the TV show's official hashtag, as well as the types of TV contents and the types of Twitter elements displayed minute by minute on the screen. Finally, I applied the hierarchical linear regressions approach on 2,400 observations in order to extract valuable insights concerning the effects of the TV show on social media traffic.

First, I observed that generally the amount of viewers' interactions increases episode by episode during the whole season, which can be considered as an indicator of success: as the show evolves within the season, the viewers increase their conversations around it, thus meaning that their interest increases. However, this trend is not confirmed within the episode.

Concerning the show's contents and elements, I found that some TV contents and Twitter elements have positive effects on the viewers' social interactions. Specifically, viewers

increase their social interactions when a performance is on air and when the Twitter interactions around the show are depicted showing numbers and tweets' texts during the web room. Consequently, in order to reach a considerable traffic and then to attract the interest of other viewers that are watching another TV show, broadcasters or producers may decide to dedicate more time to performances and also to the web room or to similar contents. On the other hand, they could decide to eliminate the steal from the selection process, since it reduces significantly the viewers' online activity. Concerning the Twitter elements, results show the positive effects of specific hashtags if combined with the invitation to vote. Therefore, the hashtag alone does not generate any effect on the viewers' online activity, thus it seems useless to show frequently all the hashtags, if the aim consists in encouraging the viewers' interactions. As shown, the big data can be deployed to make decision for innovation in social TV context. Indeed, analyzing social media data provides useful insights concerning how to improve the TV show, specifically which kinds of contents and Twitter elements can be helpful to reach a higher social media traffic.

5.1 Theoretical contributions

Previous works in open innovation have explored several topics concerning the open innovation adoption (Cassiman & Valentini, 2016; Laursen & Salter, 2006; Laursen & Salter, 2014; Chesbrough & Appleyard, 2007; Hussinger & Wastyn, 2011; Berchicci, 2013; Cruz-González et al., 2015; Garavelli et al., 2013; Felin & Zenger, 2014). Despite the increasing interest towards the value of big data and the relevant role of social media for organizations, little research has been focused on the use of big data, particularly social media data, as external sources of open innovation for several kinds of industries. Big data are, indeed, able to provide valuable insights for organizations (George, Haas & Pentland, 2014), but organizations need to understand how they can be analyzed to obtain valuable

knowledge for innovation. Therefore, I explored the use of big data, particularly social media, for innovation, specifically to improve the quality of an existing product. Notably, I demonstrated that analyzing a whole dataset of social media data, i.e., the social interactions on Twitter, can provide interesting insights concerning the impact of the product on social media.

I have chosen the TV industry, since the increasing use of smartphones and tablets while watching TV is able to produce real time a large amount of public data around the TV shows, allowing broadcasters and producers to have access to rich and relevant knowledge. The rise of the social TV, i.e., the trend of interacting on social networks while watching TV, and the huge amount of knowledge available within the social interactions around TV shows explains the interest on the use of big data for innovation in the social TV context. Indeed, social media data are assuming a crucial role to understand audience and consequently improve the TV show's quality.

This paper is focused on exploring the use of big data for open innovation, one of the most relevant topic in the recent management literature, in the social TV context. Notably, its contribution consists in showing the value of social media data to make decisions for innovation concerning a TV show, in order to increase the Twitter traffic around it and consequently its popularity, by analyzing the effects of the TV show's contents on social media, such as Twitter. I have considered all the episodes in order to obtain a reliable evaluation of the effects and therefore valuable insights to better design the next season. For instance, in order to design the next season of the TV show, producers should dedicate a wider space within the TV show to the performances and the web room, since they increase the social media traffic. Finally, in comparison with some previous works, I not only focused on the TV show's contents, but also on the use of social media elements, particularly Twitter

elements, e.g., the official hashtag and other different ones, which need to be combined in order to increase the social media traffic.

To the best of my knowledge, this is the first attempt to use the big data, particularly the social media data, to adopt innovation in social TV context. This kind of study is radically new in social sciences, especially in management research. Specifically, it meets the need to understand how social media data can be considered as new sources of value, by categorizing data, assessing their quality, and identifying their impact (George, Haas & Pentland, 2014). One of the main point is represented by the choice of methodological approach. George, Haas & Pentland (2014) stated that the large size of big data generally does not allow considering reliable the typical statistical approach, which establishes the significance of results through the p-values. However, they observed that stepwise regression methods may be appropriate approaches. Therefore, the approach I used to analyze the effects of TV show's contents and Twitter elements on Twitter traffic can be considered as a first effort to explore the value of social media data in social TV, but I aim at identifying also other useful techniques in order to further analyze big data in this context.

5.2 Managerial contributions

Big data have the potential to provide powerful and actionable insights for different kind of scopes. Although this value is well known in some industries and for some kinds of products and services, it is not clear in other sectors. Particularly, the whole datasets that firms are able to gather from social media are not so easy to manage in an effective way, although they offer a huge value as an external and low-cost source. In the context of social TV, the real time availability of social media data leads to mainly focus on short-term insights. However, considering the trends and behaviors within the whole TV show allows broadcasters and producers to understand how to better design the TV show's contents as

well as the social media elements in order to reach their scope, e.g., increasing the Twitter traffic. Particularly, this study shows that some TV show's contents and Twitter elements are able to positively affect the Twitter traffic: the performances and the web room increase the viewers' social interactions as well as some combinations of Twitter elements. These insights can help managers to make decisions concerning the TV show's design and to improve its quality.

The study I proposed highlights two main aspects. The first one is related to the difference between short-term and long-term observations. If the broadcaster or the producer observes the reaction to a specific content in terms of the viewers' social interactions, he/she can infer that the type of content can lead to a specific viewers' social media response. However, the response may depend on other factors: the specific character or the specific moment, so that the reactions could not be generalized to other similar contents. On the contrary, by analyzing the whole season and categorizing the TV contents, it could be possible to generalize the effects: on average, the performance produces a positive reaction without depending on factors related to the specific moments. A second aspect is related to the use of Twitter elements during the TV shows. Broadcasters are often displaying several kind of social media elements, since they expect that a frequent reminder of social media interactions can lead to an increase of social media traffic. However, it is unknown the effect of the variety of social media elements displayed on the screen. Analyzing the effects of the social media elements displayed on the screen can be useful to better design the integration of these elements within the TV contents. Furthermore, the result concerning the effects of the web room shows that the integration of the social media elements, e.g., by disclosing tweets' text, Twitter traffic, trending topic, within a specific space during the TV show can lead to better results than displaying frequently hashtags on the screen.

5.3 Limitations and further research

These results are characterized by some limitations that may of course open the doors to future research. First, I considered the number of total tweets as the measure of viewers' interactions around the TV shows. However, there are different types of activities that viewers can choose to join conversations, such as posting tweets, sharing tweets and replies to existing tweets. Therefore, as next step, I will consider the different types of viewers' activities in order to compare results across them and extend the current insights concerning the effects on social media traffic, since results can change according to the type of tweets used as measure of viewers' interactions. Second, results do not provide an explanation of the effects of TV show's elements. A semantic analysis of tweets could be useful to better understand which are the topics and the sentiment of viewers' conversations and provide an explanation of the positive effects of some TV contents or Twitter elements on the viewers' online activity. Finally, results have to be analyzed after defining a scope. I posited that the aim consists in increasing the conversations around the TV show, but broadcasters and producers can be also interested in reducing the viewers' social interactions in specific moments of the TV show, since the online activity can steal attention from the TV content. As next steps, it would be interesting to analyze the results of this kind of study focusing on different scopes of broadcasters and producers, as well as other stakeholders, such as advertisers.

CHAPTER 3. SOCIAL TELEVISION: LEADING ONLINE VIEWER ENGAGEMENT

1. Introduction

As of the early days, TV broadcasters have encouraged viewers to interact and talk about TV shows to increase the audience's interest around them, thus gaining viewers and their engagement towards the shows' contents. Today viewers interact real time on social networks, chat about TV shows and share online messages during the viewing experience, due to the rise of the "Social TV" (Proulx & Shepatin, 2012). This phenomenon refers to the increasing use of a variety of systems that support social experiences for television viewers (Harboe, 2009), thus allowing several online activities and then generating the so-called "online viewer engagement" (OE) (Hill & Benton, 2012; Lim et al., 2015), that is the amount of viewers' interactions occurring online. In this new context, in order to increase the OE, TV broadcasters have developed several kind of strategies, such as showing Twitter elements on the TV screen during the show. In fact, viewers exposed to this kind of strategies, namely "Social TV strategies" (Hill & Benton, 2012), are supposed to post more comments on the social networks.

Social TV has raised the interest of the scientific community, which has studied some aspects of this phenomenon. Several scholars have reviewed the strategies that broadcasters use during TV shows (Bruns & Burgess, 2011; Chen, 2011; Harrington et al., 2012; Hill & Benton, 2012; Proulx & Shepatin, 2012). In particular, it was found that showing some kinds of Twitter elements on the screen may increase the online viewer engagement (Hill & Benton, 2012). It was also shown that several other variables can play an important role in driving OE. In particular, the TV show's viewership (i.e., number of viewers watching the

TV show) (Baym, 2000; Ross, 2008) specific time trends during the shows (Hill & Benton, 2012; Kim et al., 2015) and TV contents (Buschow et al., 2014; Giglietto & Selva, 2014; Kim et al., 2015; Wohn & Na, 2011) can drive the online viewer engagement. Among different TV contents, it has been demonstrated that the commercial breaks can have specific effects on the viewers' activity (Giglietto & Selva 2014; Moriarty & Everett, 1994; Tse & Lee, 2001; Wohn & Na, 2011; Hill & Benton, 2013). For instance, Wohn & Na (2011) observed that people post more emotional tweets, i.e., tweets including emotional verbs (i.e., hate, love) or with emoticons, and less informational tweets, i.e., tweets describing the program's content, during the commercial breaks, while Hill & Benton (2013) observed more original tweets generated during the episode than during the commercial breaks. Most of the aforementioned works were focused on studying the online engagement generated through Twitter, one of the most important Social TV tool. In particular, the online engagement was studied distinguishing between three different kinds of activity, i.e., posting, sharing and replying to Twitter's messages (Boyd et al., 2010; Chen, 2011; Hill & Benton, 2012; Kim et al., 2015; Sousa et al., 2010; Suh et al., 2010; Wohn & Na, 2011).

However, research has only scratched the surface of the phenomenon so far. In fact, prior research has studied the influence of one single type of variable on OE at a time, while the influence of relevant variables, such as the viewership or the time trends, was not controlled. Moreover, all the previous studies have examined the viewers' online engagement looking at only one single type of activity without distinguishing between the effects of posting, replying and sharing comments. Building a more complex model is important for a better understanding of the real effects of the Social TV phenomenon. I aim at filling this gap. In particular, I study the connections between all the variables shown as relevant from prior research in the Social TV domain (i.e., Social TV strategies and TV contents, including commercial breaks) with the three kinds of online activity (i.e., posting, sharing and replying

activities). I also control the influence of viewership and time trends on the online engagement. I explore the research issue using data coming from the 2014 edition of "The Voice of Italy", a popular Italian TV show and applying the hierarchical linear regressions approach.

In the paper, I show the following main results. First, users decrease their posting behavior while increase their sharing behavior during commercial breaks. Second, users increase or decrease their posting behavior while they do not modify their sharing behavior depending on the specific TV contents. Third, certain kinds of Social TV strategies have a positive effect on the number of original tweets, while they do not affect retweets and replies. I can claim these findings, because I controlled the effects of viewership and time trends. I confirmed the influence of viewership on the online engagement and the existence of time trends. Particularly, I found that the online engagement increases episode by episode, showing a positive long run trend, while original tweets decrease minute by minute during the episode.

2. Prior work

Research has shown that television is a facilitator of social interactions, bringing people together and giving them a broad variety of topics to discuss (Morrison & Krugman, 2001; Newcomb, 1994; Tichi, 1991). Moreover, it affects viewers (Shrum, 1999) in terms of shaping, reinforcing or changing their reactions (Holbert & Tchernev, 2012). This depends on factors such as the type of contents or messages shown on screen (Potter, 2012; Shrum, 1999). In recent years, the television domain has been interested by the phenomenon of "Social TV", which refers to the variety of systems that support social practices associated with TV viewing (Harboe, 2009). Social networks have thus gained a relevant role, since they allow viewers to share online their real-time viewing experiences (Cesar & Geerts,

2011), generating the online interactions about the TV program, namely the online viewer engagement (OE) (Hill & Benton, 2012; Lim et al., 2015).

Research has studied several aspects of Social TV that I review below. Some researchers have observed the social practices of TV viewers, which usually discuss their favorite shows through online social networks (Baym, 2000; Krämer et al., 2015; Ross, 2008). This strong relationship between audience and online communities underlines the existing relationship between viewership and online engagement. Other authors have studied viewers' motivations and the ways they interact on social network sites while watching TV. They found that the viewers reveal different motivations to interact while watching TV shows (Doughty et al., 2012; Krämer et al., 2015; Schirra et al., 2014), such as communicating with others, gathering information, being entertained or exploiting the closeness to celebrity to increase their own popularity. The existence of different motivations leads to different frequencies of usage of Social TV applications (Krämer et al., 2015). As a consequence, the viewers' online engagement results in a complex process driven by multiple factors such as program-related variables as well as individuals' trait (Guo & Chan-Olmsted, 2015). A few studies have analyzed how viewers' messages are related to what viewers are watching. They have found that specific patterns of communications activities (Buschow et al., 2014; Giglietto & Selva, 2014; Kim et al., 2015; Wohn & Na, 2011) are related to different TV programs and TV contents (Buschow et al., 2014; Wohn & Na, 2011). Notably, it has been largely demonstrated that commercial breaks have to be considered particular TV contents, because of their specific effects on viewers' activity (Giglietto & Selva, 2014; Moriarty & Everett, 1994; Tse & Lee, 2001; Wohn & Na, 2011). Finally, previous works have highlighted the existence of time trends within the episode or the season of a TV program (Hill & Benton, 2012; Kim et al., 2015).

As Twitter has become the most common social network in the context of Social TV (Wilson, 2015), researchers have analyzed the way topics were grouped by Twitter hashtags (Bruns & Burgess, 2011) and the different types of activity when using Twitter: posting original tweets (posting a message); replies (replying to an existing message); retweets (sharing an existing message) (Boyd et al., 2010; Chen, 2011; Hill & Benton, 2012; Kim et al., 2015; Sousa et al., 2010; Suh et al., 2010; Wohn & Na, 2011).

Several scholars have reviewed the strategies that broadcasters use during TV shows, the so-called "Social TV strategies" (Hill & Benton, 2012). They may consist in adopting program's official hashtags (Bruns & Burgess, 2011; Deller, 2011; Harrington et al., 2012; Proulx & Shepatin, 2012), or displaying on the first screen social media elements such as viewers' tweets (Harrington et al., 2012; Hill & Benton, 2012; Proulx & Shepatin, 2012), or leveraging the use of second screen applications, i.e., mobile applications dedicated to the program, to deliver several types of trigger (Basapur et al., 2011; Buschow et al., 2014; Lochrie & Coulton, 2012; Proulx & Shepatin, 2012). Social TV strategies aim at attracting people's interest towards a show (Proulx & Shepatin, 2012) and increasing the viewers' involvement (Torrez-Riley, 2011). They are used to prompt real-time viewers to interact online with the TV programs and to share online messages (Harboe, 2009; Harboe et al., 2008; Hill & Benton, 2012). Only few studies have analyzed the effects of the Social TV strategies on viewers' activities. For instance, Hill & Benton (2012) analyzed the effects of different social strategies displayed on the first screen in the American show "The Voice". The authors found that showing a show-related tweet on the screen increases the number of retweets, while showing a hashtag on the screen increases the viewers' online engagement during commercial breaks. Another study (Fortunato et al., 2015) showed that in certain circumstances, online engagement can be predicted by the show contents rather than by the use of Social TV strategies and that the overall number of tweets is highly correlated to the

number of viewers. Finally, Holmes et al. (2012) examined viewers' visual attention while interacting with synchronized second-screen applications and found that the presence of the second screen dramatically decrease the attention towards TV contents. All these studies have shed much light on several aspects of the Social TV phenomenon. However, this initial body of literature shows some gaps. First, prior works have studied the influence of one single type of variable on OE at a time, particularly Social TV strategies or TV contents. Therefore, the effects of these variables have not been compared to each other. Second, it is necessary to control the influence of exogenous variables, particularly viewership and time trends, when studying the effect of Social TV strategies and TV contents on OE. Third, research has focused on only one single type of online viewers' activity. In fact, it has not extensively studied and compared the different online activities, i.e. posting, replying and sharing comments.

Building and testing a more complex model of viewers' online activity would be important, because it would clarify the drivers of online engagement and, in turn, the source of business value related to Social TV strategies. This research represents a step in the attempt of filling these gaps. I propose a model of TV viewers' online engagement, studying the effect of all the relevant variables and controlling the influence of viewership and time trends. I studied the relationships among these variables by analyzing the three kinds of online activity on Twitter, i.e., posting original tweets, retweets and replies respectively.

3. Methodology

Since the aim is to investigate the drivers of the OE and, in particular, the relationships between OE and the Social TV strategies, I propose a model containing OE, TV contents and Social TV strategies. OE is modeled by three kinds of online activity, i.e. posting original

tweets, sharing tweets (retweets) and replying to tweets (replies). The model also check the effects of two control variables, i.e., viewership and time trends.

We used data coming from the second edition of the Italian TV show "The Voice of Italy", that is a singing talent show based on the format of the American show "The Voice". In the show contestants, coaches and viewers interact. Contestants have to be chosen from one coach to form a team during the so-called blind auditions. After that, they perform and coaches and TV viewers evaluate them by voting. The show had one episode a week of around 180 minutes and lasted 14 weeks. The TV broadcaster delivers different Social TV strategies to viewers during this show (discussed below and shown in Table 5).

Viewers interacted on Twitter during the show using the official TV show hashtag. I collected approximately 550,000 viewers' interactions over Twitter (i.e., tweets) including the official TV show hashtag via third party. I structured all tweets in a database with the respective time-stamp and label (distinguishing between original tweets, retweets and replies). I used the time-stamp to associate each tweet with a minute during the show. Second, I structured in the dataset the type of content that viewers were watching minute by minute for the duration of show, including in the dataset the minutes and length of the commercial breaks. Third, I collected the type of Social TV strategies that the broadcaster was delivering on the main screen minute by minute. Both TV contents and Social TV strategies data have been collected by watching all TV program's episodes (available in streaming on the program's official website), reporting and classifying them as explained below. Fourth, I gathered the number of viewers who were tuned on the show's channel also minute by minute (viewership) via third party who allowed us the access to the Italian viewership database.

Table 5. List of variables.

Name	Type	Values	Description
Time – Minute	Continuous	1-225	# of minute within the episode
Time – Episode	Continuous	1-14	# of episode within the season
Viewership	Continuous	0.6-5.2 (million)	# of viewers watching the show
TV Content	Dummy	Show	General contents
		Perf	Performance
		Coach	Coaches' comments
		Choice	Contestant's choice
		Steal	Steal of eliminated contestant
		Webroom	Web Room
		Break	Commercial break
Social TV strategy	Dummy	None	No Twitter elements
		Hashtag	Official Hashtag
		Name	Contestant name's hashtag
		H+N	Hashtag and Name's hashtag
		Team	Team's hashtag
		H+T	Hashtag and team's hashtag
		T+Vote	Team's hashtag and Vote
		N+T+V	Team's, Name's hashtags and Vote
		H+T+V	Hashtag, Team's hashtag and Vote
Total tweets (TT)	Continuous	16-4172	# of total tweets
Original tweets (OT)	Continuous	6-783	# of original tweets
Retweets (RT)	Continuous	6-3849	# of retweets
Replies (RP)	Continuous	0-138	# of replies

Each observation includes information on tweets, TV contents, Social TV strategies and viewership.

Table 5 reports the list of collected variables listing their type, values and description. According to prior research (Hill & Benton, 2012; Lim at al., 2015), I measured OE as the total number of tweets including the TV show's official hashtag (TT). Then, in order to define the other three OE metrics, I classified these tweets as follows: original tweets (OT), measured by the number of tweets posted by viewers; retweets (RT), measured by the number of retweets, i.e., the share of existing tweets; replies (RP), measured by the number of replies to existing tweets. Therefore, I have the total number of tweets (TT), the number of original tweets (OT), the number of retweets (RT), the number of replies (RP), the number of TV viewers (viewership), the TV content shown on the screen and the social TV strategies used for each minute of the TV show. In conclusion, I collected 2,400 observations corresponding to the number of minutes of show broadcasted during the 14 weeks.

According to prior research (Hill & Benton, 2012), I built the linear regression models by measuring the dependent variables (OE metrics) with a time delay of one minute with respect to the measurement of independent variables, since there is a lag in time between what viewers visualize on TV screen and their online activity (Nielsen Neuro, 2015). The independent variables are the TV contents and Social TV strategies.

TV Content is defined as a nominal variable that describes what type of contents viewers are watching on the TV screen. Viewers can watch a contestant's performance (Perf), as well as the coaches' comment about the performance (Coach). Contestants can be eliminated or chosen (Choice) and further an eliminated contestant can be reintegrated (Steal). During the show, the Twitter engagement is depicted showing numbers and tweets' texts (Webroom) and the show is periodically interrupted when TV commercials are broadcasted (Break). There are also less specific contents during the show (Show). Social TV strategy is

65

represented by a nominal variable describing what message the broadcaster delivered to viewers on the first screen. Broadcaster can display the official hashtag of the TV show (Hashtag), the contestant name's hashtag (Name) and also the team's hashtag (Team). Sometimes these kinds of hashtags are combined displaying both the official and name's hashtags (H+N), as well as official and team's hashtags (H+T). In other cases, hashtags are displayed at the same time of an invitation to vote a contestant, combining the team's hashtag (T+Vote), the team and contestant's hashtag (N+T+V), and the team and official hashtags (H+T+V). Sometimes no Twitter elements are displayed on the screen (None). Since the Web room consists in showing also tweets' text, it could be considered a hybrid form between TV content and Social TV Strategy. Finally, as control variables I considered viewership, measured as the number of viewers synchronized in each minute on the TV channel, and two measures of time trends, the minute in each episode and the number of episode. Indeed, since I observed the aggregate phenomenon of online engagement, a change in the number of viewers may affect the overall number of tweets (Baym, 2000; Ross, 2008; Krämer et al., 2015), as well as a variation in OE may be caused by time trends (Hill & Benton, 2012). I included these measures to test the existence of a relationship between independent variables and dependent variables by excluding the effect of the control variables, but also to identify possible online engagement's trends in time.

I explored the research issue through hierarchical linear regressions (Baron & Kenny, 1986; Frazier et al., 2004). First of all, I built a linear regression model considering only the control variables as independent variables in order to check their significance. Then I added one independent variable at time in order to check the significance of the partial models. The independent variable were the TV contents and Social TV strategies. Then, I built the complete model, which included both control variables and all the independent variables. I

repeated this process as many time as the number of dependent variables, i.e. total tweets (TT), original tweets (OT), retweets (RT) and replies (RP).

4. Results

In this section, I show the results obtained from the analyses. As discussed in previous section, first of all I built linear regression models considering only the control variables, i.e. viewership, episode and minute. Table 6 reports the results of these models, exploring the relationship between control variables and dependent variables. In particular, each column of Table 6 is referred to a linear regression built with a specific dependent variable (TT, OT, RT and RP namely).

Table 6. Coefficients of hierarchical regression models, control variables.

	Total tweets (TT)	Original tweets (OT)	Retweets (RT)	Replies (RP)
Constant	-185.979	-66.869	-119.11	-2.703
	(17.857)***	(7.614)***	(13.647)***	(0.587)***
Episode	13.659	4.588	9.071	0.398
	(0.947)***	(0.404)***	(0.723)***	(0.031)***
Minute	0.039	-0.057	0.096	-0.001E-06
	(0.068)	(0.029)*	(0.052)	(0.002)
Viewership	9.953E-5	5.436E-05	4.518E-05	1.626
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
R^2	0.282	0.325	0.165	0.148
Adj. R^2	0.281	0.325	0.164	0.147

Notes: *Stat. sign. ***p<0.001; **p<0.01; *p<0.05; (*)p<0.1*

As expected, I found that viewership has a positive and significant effect on all the OE metrics, thus confirming that the more viewers watching the TV show the more online activity on Twitter.

Table 7. Coefficients of hierarchical regression models, complete model.

	Total tweets (TT)	Original tweets (OT)	Retweets (RT)	Replies (RP)
Constant	-172.318 (18.884)***	-40.771 (7.763)***	-131.546 (14.477)***	-3.005 (0.623)***
Minute	0.022(0.068)	-0.073 (0.028)*	0.095 (0.052)	-0.001 (0.002)
Episode	12.412(1.055)***	3.789 (0.434)***	8.624 (0.809)***	0.359 (0.035)***
Viewership	9.742E-5(0.000)***	4687E-05 (0.000)***	5.055E-05 (0.000)***	1.733E-06 (0.000)***
Break	0.503 (12.461)	-29.103 (5.122)***	29.606 (9.553)**	1.44 (0.411)***
Show	*omitted*	*omitted*	*omitted*	*omitted*
Perf	19.334(10.013)(*)	22.612 (4.116)***	-3.279 (7.677)	0.476 (0.33)
Coach	-13.360(10.858)	-8.956 (4.464)(*)	-4.404 (8.324)	0.128 (0.358)
Choice	9.562(16.176)	14.717 (6.649)(*)	-5.155 (12.401)	1.019 (0.534)
Steal	-114.816(46.358)*	-60.481 (19.057)**	-54.334 (35.54)	-2.479 (1.529)
WebRoom	125.926(44.947)**	41.293 (18.477)(*)	84.632 (34.458)(*)	3.564 (1.483)(*)
None	*omitted*	*omitted*	*omitted*	*omitted*
Hashtag	-11.315(14.282)	-0.002 (5.871)	-11.314 (10.949)	-0.486 (0.471)
Name	21.723(17.278)	19.293 (7.103)*	2.43 (13.246)	-0.332 (0.57)
H+N	72.496(122.012)	-2.851 (50.157)	75.347 (93.539)	-0.03 (4.025)
Team	-78.894(20.745)***	-24.223 (8.528)**	-54.671 (15.904)***	-2.188 (0.684)***
H+T	-117.905(77.477)	-54.774 (31.849)	-63.131 (59.397)	-2.723 (2.556)
T+Vote	27.605(15.256)(*)	29.747 (6.271)***	-2.142 (11.696)	0.738 (0.503)
N+T+V	71.884(23.767)**	81.394 (9.77)***	-9.51 (18.221)	0.905 (0.784)
H+T+V	18.262(46.736)	26.742 (19.212)	-8.48 (35.83)	1.068 (1.542)
R2	0.546	0.387	0.178	0.162
Adj. R2	0.298	0.382	0.172	0.156

Notes: *Stat. sign. ***p<0.001; **p<0.01; *p<0.05; (*)p<0.1*

68

I also found that the number of the episode has also a positive and significant effect on all the OE metrics, thus confirming an increasing trend in OE through the show's season. Finally, I did not find any statistically significant effect of the minute of the episode on the OE metrics, thus demonstrating that there are not increasing nor decreasing trends in OE during each episode.

After controlling the effects of the control variables on the dependent variables, I also built the partial models before the complete model including both control variables and all the independent variables. Table 7 shows the results of the complete model, while Tables A1 and A2 in appendix show the results of the partial models. As in previous case, each column of Table 7 is referred to a linear regression model built with a specific dependent variable (TT, OT, RT and RP namely). The results shown in Table 7 confirm the effects of the control variables, i.e. positive effect of viewership and episode on all the OE metrics. In addition, the results show that both TV contents and Social TV strategies have different effects on OE metrics. In particular, I found that the commercial breaks generate a significant reduction of the number of original tweets, while they generate a positive and significant effect on the number of retweets and replies. I also found that some contents (i.e., live performance, web room and choice) generate a significant increase of the original tweets, while some other contents (i.e., coaches' comment and steal) generate a significant reduction of the original tweets. I did not find significant effects of the TV contents on the number of retweets and replies with the exception of a slight positive effect of the Web Room content. Similarly, I found that some strategies (i.e., Name, T+Vote, N+T+V) generate a positive and significant effect on the number of original tweets. I did not find significant effects of the Social TV strategies on the number of retweets and replies with the exception of a spurious negative effect of the Team strategy.

The partial models report the same results of the ones described in Table 3. In particular, Tables A1 in appendix shows the results of the model built by considering only the control variables and TV contents as independent variables, while Table A2 in appendix shows the results of the model built by considering only the control variables and Social TV strategies as independent variables. These additional results confirm that during commercial breaks the number of original tweets decreases, while the number of retweets and replies increase. In addition, TV contents and Social TV strategies affect the number of original tweets, and the effect may be positive or negative depending on the specific TV content or strategy, while they do not affect retweets and replies (with few exceptions).

5. Discussion

Previous research on Social TV has shown that the usage of Social TV strategies may lead to an increase of the viewers' online engagement. It has been also demonstrated that several variables (such as time, TV contents and commercial breaks) can play an important role in this phenomenon. However, to the best of my knowledge, none of these studies explored the phenomenon by considering all these variables altogether. In this paper, I aim at filling this gap. In particular, I ran an extensive set of hierarchical linear regressions in order to deeply explore which variables affect the online engagement of TV show's viewers and to build a model explaining the effects of the social TV strategies on TV viewers. In order to do so, I collected data coming from an Italian TV show using Social TV strategies. In particular, I gathered the number of viewers, the online activity, the TV content and the Social TV strategy used minute by minute.

I found that both Social TV strategies and TV contents affect different types of online activities. In particular, viewers seem to increase sharing and replying activities during commercial breaks while reducing the posting activity. I also found that both TV contents

and Social TV strategies affect the posting activity, but they do not affect sharing and replying activities (with few and slightly significant exceptions). TV contents can generate a significant increase or a significant reduction of the original tweets, while Social TV strategies generate a positive and significant effect on the number of original tweets.

Moreover, I confirmed the influence of viewership on all kind of OE metrics: the higher the number of viewers tuned into the program, the higher the number of original tweets, retweets and replies. I also found that all kinds of OE increase episode by episode during the season.

These results are characterized by several limitations. First, the classification of TV contents and Social TV strategies is strictly related to the TV program considered in this study. As next step, it could be useful to develop a more general classification, which could be valid at least within the TV program's category (i.e., reality or talent show). Similarly, I cannot generalize results, since they are related to a specific TV program, but I could apply the analytical model to other programs in order to extend its validity.

Despite these limitations, the findings of this paper have some important managerial implications. They suggest relevant insights to TV broadcasters about how to balance TV contents and Social TV strategies in order to effectively lead the viewers' online engagement. Indeed, the online engagement is affected both by Social TV strategies and TV Contents, designed by broadcasters, but in different ways. However, since the effects on the three types of online activity are different, broadcasters should carefully define what kind of online reactions they aim at increasing, in order to effectively design Social TV strategies and TV contents. In addition, the increasing effect of online activities during the commercial breaks highlights the existence of a controversial phenomenon. Indeed, during breaks viewers increase their online activity by reading, sharing and replying messages dedicated to the TV show: it can be considered a positive effects for the TV broadcasters, but a negative

effect for TV advertisers, since they seem to lose the viewers' attention towards the ads. Therefore, since broadcasters prompt viewers to interact also during the commercial breaks to keep the viewers' interest towards the TV program, TV advertisers should carefully plan their strategy (online or on TV screen) to avoid the decline of interest towards the commercials.

In the next research steps, I plan to replicate these analyses on new datasets in order to compare and generalize the results, investigate the role of other viewers' activity and explore the process related to the generation of online engagement during the commercial breaks.

6. Future Research

This PhD thesis merely represents the first step concerning the exploration of the social TV phenomenon. The collection and the analyses of such a large number of data, freely accessible on social networks, the so-called big data, allow to obtain useful insights, as shown in the second chapter. However, looking at the whole dataset valuable differences can remain hidden within the general trends, without providing a real comprehension of the phenomenon. For instance, the results shown within this chapter highlight the need to separate specific kinds of online activities in order to deeply understand the different relationships between online activity and TV contents and Twitter elements. Indeed, the whole phenomenon needs to be explored not only by considering the general number of tweets, but also by identifying and separating different kinds of viewers, which can be characterized by different kinds of online activities. Therefore, in order to further explore the different kinds of viewers, the whole dataset has been also analyzed by considering several settings concerning the viewers' online activity. For instance, Fig. 5 shows that the most part of viewers of the TV show (62.61%) interacted on Twitter just during one episode

of the show, while the percentage of viewers that interacted during several episodes is equal to 37.39%.
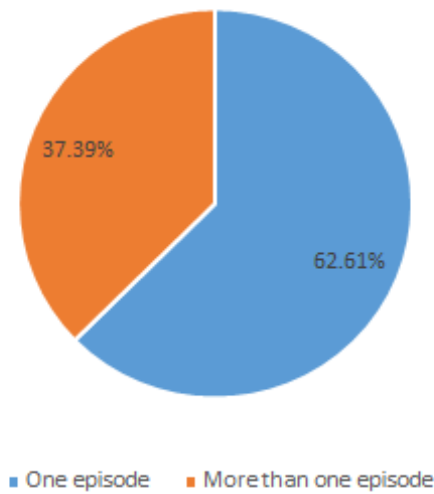

Figure 5. Percentage of viewers interacted during the TV show: during one and more than one episode.
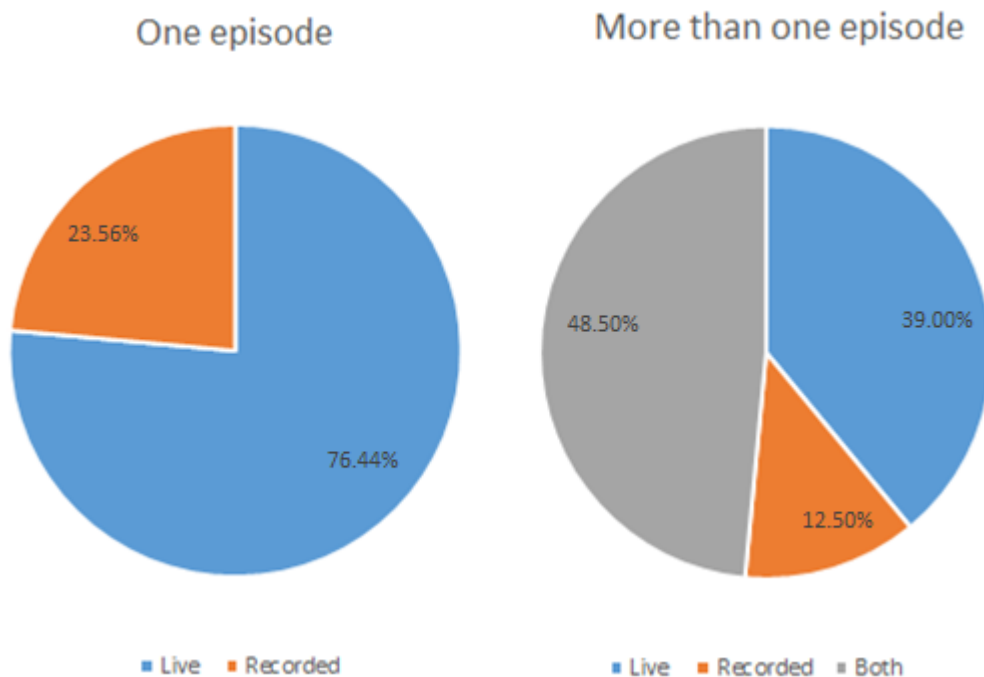

Figure 6. Percentage of viewers interacted during live and recorded episodes per group.

These two groups are also characterized by further different behaviors. Since the TV show has been built by including nine episodes previously recorded, while the last five have been

live broadcasted, the viewers belonging to the first group (see Fig. 6, graph on the left) are mainly represented by those who decided to watch only live episodes of the show (76.44%). On the other hand, the viewers belonging to the second group (graph on the right) are mainly represented by those who followed the overall season, specifically both live and recorded episodes (48.50%).

These analyses highlight also that, by considering the whole dataset, the most part of viewers (47.86%) interacted on Twitter just during one of the live episodes of the TV show (Fig. 7). These groups are characterized by different kinds of online activities (Fig. 8). Particularly, viewers that interacted just during one episode or during live episodes have posted more retweets than original tweets, while viewers that interacted during more than one episode have posted more original tweets than retweets.
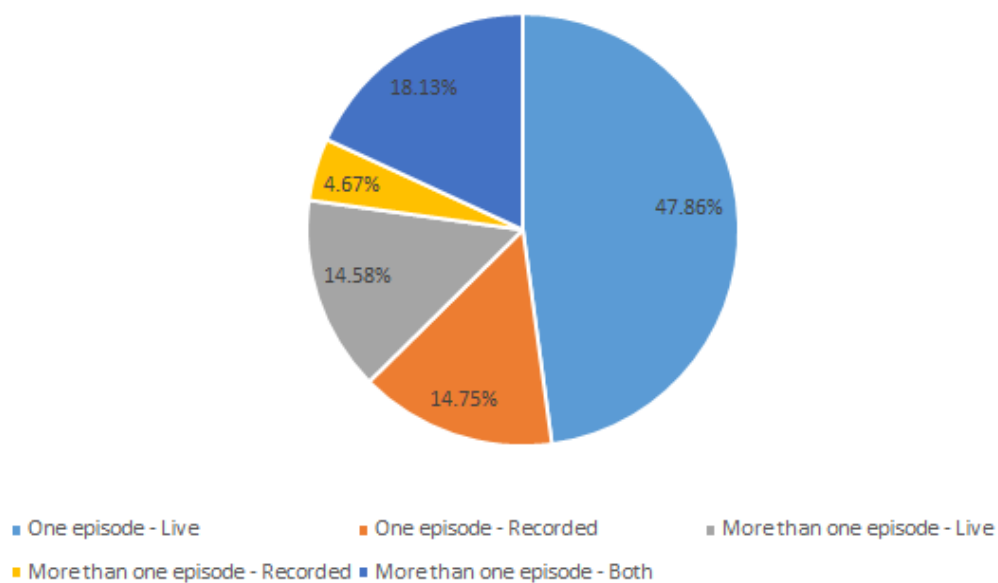

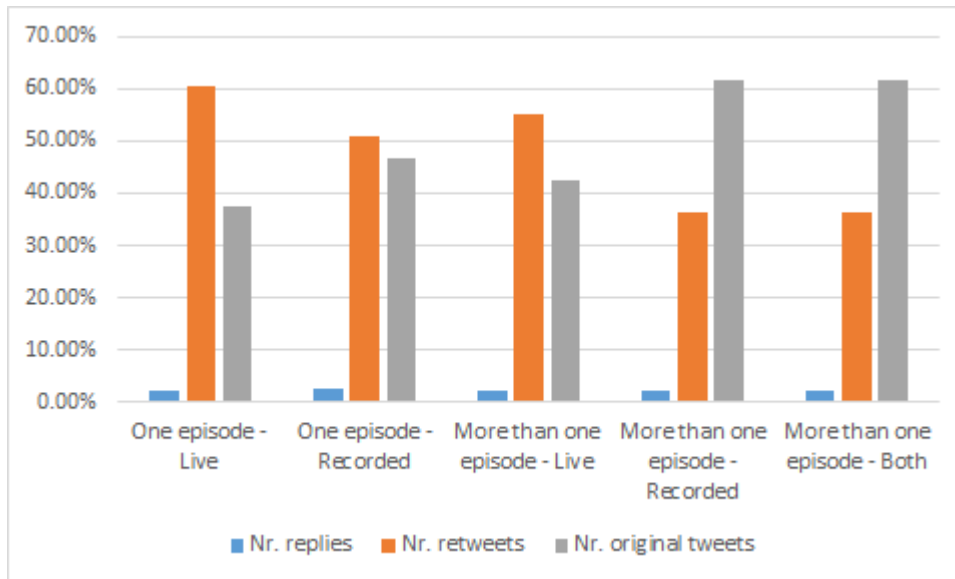Figure 7. Percentage of viewers interacted during the TV show per group.

Figure 8. Different kinds of online activity per group of viewers.

Consequently, the whole dataset needs to be seen as a sum of very different contributions and, therefore, these different contributions need to be further explored in order to understand the different effects of TV contents and Twitter elements on viewers' online activity and, in general, to extract valuable insights concerning the viewers' behavior on Twitter.

Another interesting topic concerns the distinction between viewers, according to loyalty and frequency of Twitter activity. By defining loyalty as the number of episodes during which viewers interacted on Twitter, and frequency as the mean of tweets posted by them per episode, I ran some preliminary analyses in order to identify different viewers' behaviors. Particularly, several levels of loyalty and frequency have been defined. Loyalty levels are described in Table 8, as well as the number of viewers that interacted on Twitter, the number of tweets generated by viewers and the relative percentage for each level. The most part of viewers (62.61%) interacted just during one episode, while the viewers that interacted during the whole season correspond to only 0.15%. However, the most part of online activity is not generated by the viewers belonging to the first level of loyalty, on the contrary by the viewers

that interacted during several episodes, particularly from 2 to 13 episodes (second and third levels, respectively 47.04% and 29.55%).

Table 8. Number and percentage of viewers and tweets per level of loyalty.

LOYALTY				
Nr. of episodes during which viewers interacted on Twitter:	**Nr. viewers**	**% viewers**	**Nr. Tweets**	**% Tweets**
Level 1: just during one episode	41996	62.61%	112014	16.89%
Level 2: 2 to 7	23112	34.46%	311904	47.04%
Level 3: 8 to 13	1866	2.78%	195935	29.55%
Level 4: all episodes	102	0.15%	43249	6.52%
Total	67076		663102	

Concerning the frequency (see Table 9), the most part of viewers posted only 1-2 tweets per episode (62.19%), while the most part of tweets (61.54%) is generated by viewers which posted more than 6 tweets per episode (15.59%). These analyses confirm that the whole dataset is characterized by different kinds of behaviors and consequently different kinds of viewers, according to the levels of loyalty and frequency. The identification of these kinds of viewers highlights the need to deeply examine the behaviors of different groups of viewers, as well as their reactions to TV contents and Twitter elements.

Table 9. Number and percentage of viewers and tweets per level of frequency.

FREQUENCY				
Mean of tweets posted by viewers per episode:	**Nr. viewers**	**% viewers**	**Nr. Tweets**	**% Tweets**
Level 1: 1-2 tweets	15598	62.19%	98626	17.90%
Level 2: 3 to 5 tweets	5572	22.22%	113262	20.56%
Level 3: 6 to 245 tweets	3910	15.59%	339060	61.54%
Total	25080		550948	

For instance, Table 10 reports the results of regressions between Twitter elements and TV contents and the viewers' online activity belonging to each level of loyalty and frequency.

Table 10. Coefficients of regressions per level of loyalty and frequency.

	LOYALTY				FREQUENCY		
	Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3
Constant	-84,39978***	-99,70621***	Ns	**6,360082***	-20,98032***	-26,78873***	-44,22805***
Episode	**5,723523***	**8,746601***	-0,7330658***	-0,4401872***	**2,207869***	**2,296643***	**2,989975***
Minute	ns	ns	-0,0463497***	-0,0201366***	ns	ns	ns
Viewership	**0,0000295***	**0,0000446***	**0,0000203***	**2,81e-06***	**0,0000132***	**0,0000151***	**0,0000392***
Twitter element	ns	ns	**5,818617***	**1,283023***	-3,808913(*)	ns	**11,7429***
Break	-17,39293***	ns	**15,89599***	**4,871249***	ns	ns	**19,41111***
Show	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*
Perf	-21,93217***	ns	**26,22076***	**6,095184***	ns	**4,368584(*)	**33,82633***
Coach	-23,55372***	ns	**15,11021***	**4,284331***	ns	ns	**18,1655***
Choice	-18,31028*	ns	**17,95472***	**4,624172***	ns	ns	**20,67106**
Steal	-47,99198*	-67,78179**	Ns	ns	-22,06786(*)	-20,30121*	-35,04367*
WebRoom	**32,57585(*)	**61,41921*	**22,94117**	**6,646583***	ns	**16,50869*	**59,24449***

Notes: *Stat. sign. ***p<0.001; **p<0.01; *p<0.05; (*)p<0.1*

Particularly, the online activity is measured as the total number of tweets generated during the TV show, while the independent variable "Twitter element" means the presence of any Twitter elements on the screen. Table 10 reports only the statistical significant results, whose positive coefficients are reported in bold, while not significant results are reported as "ns". Results show that viewers belonging to higher levels of loyalty and frequency are characterized by positive relationships with both TV contents and the presence of Twitter elements. These analyses represent the first step to highlight the existence of different viewers within the whole dataset and therefore the need to explore their behaviors and the effects of TV contents and Twitter elements on each group separately. Indeed, they draw the

research directions within the context of social TV, which can be based on the exploration of different kinds of viewers and relative behaviors in order to deeply understand the phenomenon.

CONCLUSION

The main goal of this PhD thesis is to provide an analysis of the social TV phenomenon from a managerial viewpoint, supported by an empirical analysis focused on a specific TV show's case, i.e., "The Voice of Italy". Particularly, the empirical analysis demonstrates how the huge number of data generated around television can be used to produce valuable information for TV broadcasters and producers. Indeed, they can extract interesting insights to understand how to design the TV program, specifically its contents as well as the social strategies useful to encourage viewers to interact online.

The research is structured in three main phases presented through three chapters. First, following the methodology developed by Tranfield, Denyer & Smart (2003), I review the several contributions concerning the social TV literature, belonging to different research areas, in order to build an overview of all aspects that have been already analyzed. Particularly, I consider also the so-called "grey literature", since important sources of information has been presented as conference proceedings, dissertations and theses (Adams, Smart, & Huff, 2016). Literature findings have been organized considering two main aspects concerning the social TV: "technologies", concerning all the aspects related to the development of social TV applications, systems, functionalities and services, and "viewers' behaviors", focused on the exploration of behaviors of viewers within a specific TV context. Consequently, a summary of the main gaps and future research directions is provided. Results show that the most part of previous work in the social TV research has been focused on the technological aspects, particularly on the sense of connectedness created by the social TV design, while few authors focused on behavioral differences, motivations and reactions to social TV initiatives or strategies. The literature review highlights the need of further research concerning the social TV phenomenon. Despite the larger number of applications already developed and tested, it emerges the need of further general research, specifically

focusing on a specific program genre. It would be relevant also to systematically analyze the factors influencing the viewers' behavior on social media while watching TV. Finally, despite the huge number of data generated around TV shows, it is not clear the value that social TV represents for TV producers and broadcasters, thus needing a deep exploration.

The objective of the second phase, indeed, is to provide a first empirical analysis of data concerning a specific TV show, in order to demonstrate that the social TV phenomenon can be positioned within the big data issues. Indeed, the huge number of interactions on online social networks allows TV producers to collect data and obtain relevant insights to effectively design the TV shows. Indeed, social media represent one of the main sources of big data generating a large amount of knowledge about customers' preferences and reactions to provide valuable insights for organizations. However, it is not clear how to extract new insights, particularly concerning the social TV phenomenon. Therefore, in order to obtain valuable knowledge concerning all the different elements of the TV show, I analyze the viewers' interactions on social media, which lead to the generation of social media traffic around TV contents. Findings highlight that producers have to consider the trends and behaviors within the whole TV to better design the TV show's contents as well as the social media elements to increase the Twitter traffic. In the specific case, results suggest that they should dedicate a wider space within the TV show to specific TV contents, such as the performances and the web room, since they increase the social media traffic.

Finally, in the third phase, data concerning the same TV show are deeply analyzed by considering the different kinds of interactions occurring on Twitter. Specifically, I show that, in order to obtain valuable insights, it is useful to consider the different kinds of interactions and then how specific TV contents and social strategies can affect different kinds of viewers' interactions. Indeed, viewers can interact through different ways on Twitter: they can post tweets, thus generating original tweets, they can share existing tweets, thus generating the

so-called retweets and, finally, they can reply to existing tweets, thus generate a reply. Results show that viewers increase or decrease their posting behavior while they do not modify their sharing behavior according to specific TV contents. On the other hand, social strategies have a positive effect on the number of original tweets, while they do not affect retweets and replies. Therefore, TV producers should consider the different types of online activities, because TV contents and social strategies have a different impact according to the type of online activity.

In conclusion, this PhD project offers new important insights concerning the social TV phenomenon, specifically from a managerial viewpoint. Findings suggest how TV producers can analyze social media data generated around TV show in order to reach their aim and underline the value of insights derive from this kind of analysis.

REFERENCES

Abreu, J., Almeida, P., Afonso, J., Silva, T., & Dias, R. (2011). Participatory Design of a Social TV Application for Senior Citizens. In *Proceedings of the International Conference on Enterprice Information System*, pp. 49-58. Springer Berlin Heidelberg.

Adams, R. J., Smart, P., & Huff, A. S. (2016). Shades of Grey: Guidelines for Working with the Grey Literature in Systematic Reviews for Management and Organizational Studies. *International Journal of Management Reviews*.

Almeida, P., Ferraz, J., Pinho, A., & Costa, D. (2012). Engaging viewers through social TV games. In *Proceedings of the 10th European conference on Interactive tv and video (EuroITV '12),* pp. 175-184. New York, NY. Association for Computing Machinery.

Ardito, L., Messeni Petruzzelli, A., & Albino, V. (2015). From Technological Inventions to New Products: A Systematic Review and Research Agenda of the Main Enabling Factors. *European Management Review*, 12(3), 113-147.

Baron, R. M. & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology,* 51(6), 1173-1182.

Basapur., S., Harboe, G., Mandalia, H., Novak, A., Vuong, V., & Metcalf, C. (2011) Field trial of a dual device user experience for iTV. In *Proceedings of the 9th international interactive conference on Interactive television,* pp. 127-136. New York, NY. Association for Computing Machinery.

Basapur, S., Mandalia, H., Chaysinh, S., Lee, Y., Venkitaraman, N., & Metcalf, C. (2012). Fanfeeds: evaluation of socially generated information feed on second screen as a tv show companion. *In Proceedings of EuroiTV '12*, pp. 87–96.

Baym, N. K. (2000). *Tune In, Log On: Soaps, Fandom and Online Community*. Thousand Oaks, CA: SAGE Publications, Inc.

Bellman, S., Robinson, J. A., Wooley, B., & Varan, D. (2014). The Effects of Social Tv on Television Advertising Effectiveness. *Journal of Marketing Communications*, 1-19.

Berchicci, L. (2013). Towards an open R&D System: Internal R&D Investment, External Knowledge Acquisition and Innovative Performance. *Research Policy,* 42(1), 117–127. doi: 10.1016/j.respol.2012.04.017

Boyd, D., Golder, S., & Lotan, G. (2010) Tweet, tweet, retweet: conversational aspects of retweeting on Twitter. In *Proceedings of the 2010 43rd Hawaii international conference on system sciences*, pp. 1-10. IEEE.

Bruns, A. & Burgess, J. E. (2011) The use of Twitter hashtags in the formation of ad hoc publics. In *Proceedings of the 6th European consortium for political research (ECPR) general conference.*

Buschow, C., Schneider, B., & Ueberheide, S. (2014). Tweeting television: exploring communication activities on Twitter while watching TV. *Communications - The European Journal of Communication Research,* 39(2), 129-149.

Carpenter, M. A., Li, M., & Jiang, H. (2012). Social network research in organizational contexts: A systematic review of methodological issues and choices. *Journal of Management*, 38, 1328–1361.

Carroll, J. M. (1997). Human-computer interaction: psychology as a science of design. *Annual Review of Psychology*, 48, 61–83.

Cassiman, B. & Valentini, G. (2016). Open Innovation: Are Inbound and Outbound Knowledge Flows really Complementary? *Strategic Management Journal*, 37(6), 1034-1046. doi: 10.1002/smj.2375

Cesar, P. & Geerts, D. (2011). Past, present, and future of social TV: a categorization. In *Proceedings of the consumer communications and networking conference (CCNC),* pp. 347-351. IEEE.

Chen, G. M. (2011). Tweet this: a uses and gratifications perspective on how active Twitter use gratifies a need to connect with others. *Computers in Human Behavior, 27*(2), 755-762.

Chesbrough, H. W. & Appleyard, M. (2007). Open Innovation and Strategy. *California Management Review*, 50(1), 57-76. doi: 10.2307/41166416

Chorianopoulos, K. (2008). User Interface Design Principles for Interactive Television Applications. *International Journal of Human-Computer Interaction*, 24, 6.

Chorianopoulos, K. & Lekakos, G. (2008). Introduction to social TV: Enhancing the shared experience with interactive TV. *International Journal of Human Computer Interaction*, 24(2), 113–120.

Chua, A. Y. K. (2011). How Web 2.0 Supports Customer Relationship Management in Amazon. *International Journal of Electronic Customer Relationship Management, 5*(3-4), 288-304. doi: 10.1504/IJECRM.2011.044693

Chua, A. Y. K. & Banerjee, S. (2013). Customer Knowledge Management via Social Media: the case of Starbucks. *Journal of Knowledge Management*, 17(2), 237–249. doi: 10.1108/13673271311315196

Coppens, T., Trappeniers, L., & Godon, M. (2004). AmigoTV: towards a social TV experience. In *Proceedings of EuroITV 2004*, University of Brighton, U.K.

Crossan, M. M. & Apaydin, M. (2010). A Multi-dimensional framework of organizational innovation: A systematic review of the literature. *Journal of Management Studies*, 47, 1154–1191.

Cruz González, J., López-Sáez, P., Navas-López, J. E., & Delgado-Verde, M. (2015). Open Search Strategies and Firm Performance: The Different Moderating Role of Technological Environmental Dynamism. *Technovation,* 35, 32-45. doi: 10.1016/j.technovation.2014.09.001

Dan, O., Feng, J., & Davison, B. (2011). Filtering Microblogging Messages for Social TV. In *Proceedings of the 20th International Conference Companion on World Wide Web*, pp. 197-200. New York, NY, Association for Computing Machinery.

Deller, R. (2011). Twittering on: audience research and participation Using Twitter. *Participations: Journal of Audience & Reception Studies,* 8(1). Available at http://www.participations.org/ volume%208/Issue%201/deller.htm.

Dezfuli, N., Khalilbeigi, M., Mühlhäuser, M., & Geerts, D. (2011). A study on interpersonal relationships for social interactive television. In *Proceedings of EuroITV '11*, pp. 21-24.

Doughty, M., Lawson, S., & Rowland, D. (2011). Co-Viewing Live TV with Digital Backchannel Streams. In *Proceedings of EuroITV2011.* New York, NY. Association for Computing Machinery.

Doughty, M., Rowland, D., & Lawson, S. (2012). Who is on your Sofa?: TV Audience Communities and Second Screening Social Networks. In *Proceedings of the 10th European conference on Interactive TV and video—EuroiTV 2012*, pp. 79–86. New York, NY. Association for Computing Machinery.

Ducheneaut, N., Moore, R.J., Oehlberg L., Thornton, J. D., & Nickell, E. (2008). Social TV: Designing for distributed sociable television viewing. *International Journal of Computer–Human Interaction*, 24, 136–54.

Dutta, S. (2010), What's your Personal Social Media Strategy? *Harvard Business Review,* 88(11), 127-130.

Felin, T. & Zenger, T. R. (2014). Closed or Open innovation? Problem Solving and the Governance Choice. *Research Policy,* 43(5), 914–925. doi: 10.1016/j.respol.2013.09.006

Fortunato, A., Gorgoglione, M., & Panniello, U. (2015). What drives TV online engagement? The influence of social strategies and contents. In *Proceedings of the 12th international conference on web based communities and social media.*

Frazier, P. A., Tix, A. P., & Barron, K. E. (2004). Testing Moderator and Mediator Effects in Counseling Psychology Research. *Journal of Counseling Psychology,* 51(1), 115-134, doi: http://dx.doi.org/10.1037/0022-0167.51.1.115.

Fuchs, R. (2012). The 2nd Screen: Transforming video consumption. *The 2nd Screen Society*. Available at https://www.media-tech.net/fileadmin/templates/association/Las_Vegas_2012/Presentations/fuchs2.pdf

Gallaugher, J. & Ransbotham, S. (2010). Social Media and Customer Dialog Management at Starbucks, *MIS Quarterly Executive,* 9(4), 197-212.

Garavelli, A. C., Messeni Petruzzelli, A., Natalicchio, A., & Vanhaverbeke, W. (2013). Benefiting from Markets for ideas – an Investigation across Different Typologies. *International Journal of Innovation Management,* 17(6), 1-37. doi: 10.1142/S1363919613400173

Geerts, D. (2006). Comparing voice chat and text chat in a communication tool for interactive television. In *Proceedings of NordiCHI 2006*, pp. 461-464. New York, NY, Association for Computing Machinery.

Geerts, D., Cesar, P., & Bulterman, D. (2008). The implications of program genres for the design of social television systems. In *Proceeding of the International Conference on Designing Interactive User Experiences for TV and Video (UXTV)*, pp. 71–80.

Geerts, D. & De Grooff, D. (2009). Supporting the social uses of television: Sociability heuristics for social TV. In *Proceedings of the International Conference on Human Factors in Computing Systems*, pp. 595–604.

George, G., Haas, M. R., & Pentland, A. (2014). Big Data and Management. *Academy of Management Journal,* 57(2), 321–326. doi: 10.5465/amj.2014.4002

Giglietto, F. & Selva, D. (2014). Second screen and participation: a content analysis on a full season dataset of tweets. *Journal of Communication,* 64(2), 260-277. doi:10.1111/jcom.12085.

Gross, T., Fetter, M., & Paul-Stueve, T. (2008). Toward advanced social TV in a cooperative media space. *International Journal of Human-Computer Interaction*, 24(2), 155–173.

Guo, M. & Chan-Olmsted, S. M. (2015). Predictors of social television viewing: how perceived program, media, and audience characteristics affect social engagement with television programming. *Journal of Broadcasting & Electronic Media,* 59(2), 240-258.

Gurrin, C., Lee, H., Ferguson, P., Smeaton, A. F., O'Connor, N. E., Choi, Y.-H., & Park, H. (2010). Social recommendation and visual analysis on the TV. In *Proceedings of the 18th ACM International conference on Multimedia,* pp. 1513–1514. Association for Computing Machinery.

Hamaguchi, N., Fujisawa, H., Miyazaki, M., Yonekura, R., & Nishimura, S. (2012). Investigating trends in social TV services based on user participating experiments. In

Proceedings of the 15th International Conference on Network-Based Information Systems, pp. 873-878.

Harboe, G. (2009). In Search of Social Television. In P. Cesar, D. Geerts, & K. Chorianopoulos (Eds.) *Social Interactive Television: Immersive Shared Experiences and Perspectives* (pp. 1-13). USA: IGI Global.

Harboe, G., Massey, N., Metcalf, C.J., Wheatley, D., & Romano, G. (2008). The Uses of Social Television. *Computers in Entertainment*, 6, 1.

Harboe, G., Metcalf, C. J., Bentley, F., Tullio, J., Massey, N., & Romano, G. (2008). Ambient social tv: drawing people into a shared experience. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 1-10. New York, NY. Association for Computing Machinery.

Harrington, S., Highfield, T., & Bruns, A. (2013). More than a backchannel: Twitter and television. *Participations: Journal of Audience &Reception Studies,* 10(1). Available at http://www.participations.org/Volume%2010/Issue%201/

Hess, J., Ley, B., Ogonowski, C., Wan, L., & Wulf, V. (2011). Jumping between Devices and Services: Towards an Integrated Concept for Social TV. In *Proceedings of EuroITV '11,* pp. 11–20. New York, NY. Association for Computing Machinery.

Hill, S. & Benton, A. (2012). Social TV: Linking TV Content to Buzz and Sales. In *Proceedings of the International Conference on Information Systems (ICIS)*, Orlando, FL, USA.

Hill, S. & Benton, A. (2013). Designing Social TV content that promotes ongoin WOM. In *Proceedings of the Winter Conference on Business Intelligence,* Snowbird, Utah, March 2013.

Holbert, R. L. & Tchernev, J. M. (2012). Media influence as Persuasion. In Dillard J and Shen L (eds) *The SAGE Handbook of Persuasion: Developments in Theory and Practice.* SAGE Publications Inc., 36-52.

Holmes, M. E., Josephson S., & Carney, R. E. (2012). Visual attention to television programs with a second-screen application. In *Proceedings of the symposium on eye tracking research and applications,* March 2012, pp. 397-400. New York, NY. Association for Computing Machinery.

Hu, H., Huang, J., Zhao, H., Wen, Y., Chen, C. W., & Chua, T.-S. (2014). Social tv analytics: a novel paradigm to transform tv watching experience. In *Proceedings of the 5th ACM Multimedia Systems Conference*, pp. 172–175. Association for Computing Machinery.

Huang, E., Harboe, G., Tullio, T., Novak, A., Massey, N., Metcalf, C., & Romano, G. (2009). Of social television comes home: a field study of communication choices and practices in tv-based text and voice chat. In *Proceedings of the 27th international conference on Human factors in computing systems (CHI '09),* pp. 585-594. New York, NY, Association for Computing Machinery.

Huron, S., Vuillemot, R., & Fekete, J.-D. (2013). Bubble-TV: Live Visual Feedback for Social TV Broadcast. *ACM CHI 2013 Workshop: Exploring and enhancing the user experience for television*, Paris, France.

Hussinger, K. & Wastyn, A. (2011). In Search for the Not-invented-here Syndrome: The Role of Knowledge Sources and Firm Success. *ZEW Discussion Papers*, no. 11-048. Retrieved from http://ftp.zew.de/pub/zew-docs/dp/dp11048.pdf

Hwang, Y. & Lim, J. S. (2015). The impact of engagement motives for social TV on social presence and sports channel commitment. *Telematics and Informatics*, 32(4), 755-765.

Jacobson, S. (2013). Does Audience Participation on Facebook Influence the News Agenda? A case study of The Rachael Maddow Show. *Journal of Broadcasting & Electronic Media,* 57(3), 338-355, doi: 10.1080/08838151.2013.816706

James, S. D., Leiblein, M. J., & Lu, S. (2013). How firms capture value from their innovations. *Journal of Management*, 39, 1123–1155.

Jin, Y., Xie, T., Wen, Y., & Xie, H. (2013). Multi-screen cloud social TV: Transforming TV experience into 21st century. In *Proceedings of the 21st ACM International conference on Multimedia,* pp. 435-436. Association for Compunting Machinery.

Keupp, M. M., Palmié M., & Gassmann, O. (2012). The strategic management of innovation: A systematic review and paths for future research. *International Journal of Management Reviews*, 14, 367–390.

Kim, J. W., Kim D., Keegan, B., Kim, J. H., Kim, S., & Oh, A. (2015). Social Media Dynamics of Global Co-presence during the 2014 FIFA world cup. In *Proceedings of the 33rd annual ACM Conference on Human Factors in Computing Systems*, pp. 2623-2632. New York, NY. Association for Computing Machinery.

Krämer, N. C., Winter, S., Benninghoff, B., & Gallus, C. (2015). How "Social" is Social TV? The Influence of Social Motives and Expected Outcomes on the Usage of Social TV Applications. *Computers in Human Behavior*, 51(PA), 255-262. doi: 10.1016/j.chb.2015.05.005

Lee, K. Y., Seong Cho, K., & Ryu, W. (2011). Social TV Service: A case study. In *Proceedings of the 2011 IEEE International Conference on Consumer Electronics (ICCE),* pp. 287-288. IEEE.

Lim, J. S., Hwang Y. C., Kim, S., & Biocca, F. A. (2015). How social media engagement leads to sports channel loyalty: mediating roles of social presence and channel commitment. *Computers in Human Behavior,* 46, 158-167.

Laursen, K. & Salter, A. (2006). Open for Innovation: the Role of Openness in Explaining Innovation Performance among UK Manufacturing Firms. *Strategic Management Journal,* 27, 131–150. doi: 10.1002/smj.507

Laursen, K. & Salter, A.J. (2014). The Paradox of Openness: Appropriability, External Search and Collaboration. *Research Policy,* 43(5), 867-878. doi: 10.1016/j.respol.2013.10.004

Levy, M. (2009). Web 2.0 Implications on Knowledge Management. *Journal of Knowledge Management,* 13(1), 120-134. doi: 10.1108/13673270910931215

Lochrie, M. & Coulton, P. (2012). Sharing the viewing experience through second screens. In *Proceedings of the 10th European conference on interactive tv and video,* July 2012, pp. 199-202. New York, NY. Association for Computing Machinery.

Magnier-Watanabe, R., Yoshida, M., & Watanabe, T. (2010). Social Network Productivity in the use of SNS. *Journal of Knowledge Management,* 14(6), 910-927. doi: 10.1108/13673271011084934

Mantzari, E., Lekakos, G., & Vrechopoulos, A. (2008). Social TV: Introducing Virtual Socialization in the TV Experience. In *Proceedings of UXTV'08*. Association for Computing Machinery.

Marasanapalle, J., Vignesh, T. S., Srinivasan, P. K., & Saha, A. (2010). Business Intelligence from Twitter for the Television Media: a case study. In *Proceedings of the 2010 IEEE International Workshop on Business Applications of Social Network Analysis BASNA*, pp. 1–6. IEEE.

Martins, F., Peleja, F., & Magalhães, J. (2012). SentiTVchat: Sensing the mood of Social-TV viewers. In *Proceedings of the 10th European Interactive TV Conference*, pp. 4-6.

McKinsey Global Institute (2011). *Big data: The next Frontier for Innovation, Competition, and Productivity*. Lexington, KY: McKinsey & Company.

Meier, M. (2011). Knowledge management in strategic alliances: A review of empirical evidence. *International Journal of Management Reviews*, 13, 1–23.

Metcalf, C., Harboe, G., Tullio, J., Massey, N., Romano, G., Huang, E. M., & Bentley, F. (2008). Examining presence and lightweight messaging in a social television experience. *ACM Transactions on Multimedia Computing, Communications, and Applications*, 4(4) article 27.

Mitchell, K., Jones, A., Ishmael, J., & Race, N. J. (2010). Social TV: toward content navigation using social awareness. In *Proceedings of EuroITV*, pp. 283-292.

Moriarty, S. E. & Everett, S.-L. (1994). Commercial breaks: a viewing behavior study. *Journalism & Mass Communication Quarterly,* 71(2), 346-355.

Morrison, M. & Krugman, D. M. (2001). A look at mass and computer mediated technologies: understanding the roles of television and computers in the home. *Journal of Broadcasting & Electronic Media,* 45(1), 135-161.

Mukherjee, P. & Jansen, B. J. (2014). Social TV and the social soundtrack: significance of second screen interaction during television viewing. *Presented at SBP*, Springer, pp. 317-324.

Nagy, J. & Midha, A. (2014). The value of earned audiences: How social interactions amplify TV impact. *Journal of Advertising Research*, 54(4), 448-453.

Nakazawa, M., Erdmann, M., Hoashi, K., & Ono, C. (2012). Social Indexing of TV programs: Detection and Labeling of significant TV scenes by Twitter Analysis. In

Proceedings of the 26th International Conference on Advanced Information Networking and Applications Workshops, pp. 141–146.

Nee, R. C. (2013). Social TV and the 2012 election: exploring political outcomes of multiscreen media usages. *Electronic News* 7(4), 171–188.

Newcomb, H. (1994). *Television: The critical view*. Fifth edition. New York: Oxford University Press.

Newman, A. A. (2013). Mob City' Uses Twitter to Build Suspense for a Premiere. *The New York Times*. Available at: http://www.nytimes.com/2013/12/02/business/media/mob-city-uses-twitter-to-build-suspense-for-a-premiere.html

Nielsen, Nielsen Social (2016). TV Season in Review 2015-2016: Biggest Social TV Moments. Available at: http://www.nielsensocial.com/tv-season-in-review-2015-2016-biggest-social-tv-moments/

Nielsen Neuro, (2015). Brain Activity Predicts Social TV Engagement – Neuro-Twitter TV Linkage Study. Retrieved from Nielsen Web site: http://www.nielsen.com/content/dam/nielsenglobal/co/docs/Reports/2015/Nielsen%20Neuro%20Report%20April%202015.pdf

Pagani, M. & Mirabello, A. (2011). The influences of personal and social-interactive engagements in social TV Web sites. *International Journal of Electronic Commerce*, 16(2), 41–67.

Palacios-Marqués, D., Merigo, J.M., & Soto-Acosta, P. (2015). Online Social Networks as an Enabler of Innovation in Organizations. *Management Decision*, 53(9), 1906–1920. doi: 10.1108/MD-06-2014-0406

Palviainen, J., Kuusinen, K., & Väänänänen-Vainio-Mattila, K. (2013). Designing for Presence in Social Television Interaction. In *Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia*, pp. 1- 10.

Pan, Z. (2012). Opinions and Networks: How do They Effect Each Other. *Computational Economics,* 39(2), 157–171. doi: 10.1007/s10614-010-9241-z

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management*, 38, 1115–1166.

Potter, W. J. (2012). *Media Effects*. SAGE Publications Inc.

Proulx, M. & Shepatin, S. (2012). *Social TV: How Marketers can Reach and Engage Audiences by Connecting Television to the Web, Social Media, and Mobile.* New Jersey: Jon Wiley & Sons.

Pynta, P., Seixas, S. S., Nield, G. E., Hier, J., Millward, E., & Silberstein, R. B. (2014). The power of social television: Can social media build viewer engagement? A new approach to brain imaging of viewer immersion. *Journal of Advertising Research,* 54(1), 71–80. http://dx.doi.org/10.2501/JAR-54-1-071-080

Ross, S. M. (2008). *Beyond the Box: Television and the Internet.* Malden, Md.: Blackwell.

Sahami Shirazi, A., Rohs, M., Schleicher, R., Kratz, S., Müller, A., & Schmidt, A. (2011). Real-time nonverbal opinion sharing through mobile phones during sports events. In *Proceedings of CHI 2011*, pp. 307–310.

Schirra, S., Sun, H., & Bentley, F. (2014). Together alone: motivations for live-tweeting a television series. In *Proceedings of the 32nd annual ACM conference on human factors in computing systems*, pp. 2441-2450. New York, NY. Association for Computing Machinery.

Shin, D.-H. (2013). Defining sociability and social presence in social TV. *Computers in Human Behavior*, 29(3), 939–947.

Shrum, L. J. (1999). Television and persuasion: effects of the programs between the ads. *Psychology and Marketing* 16(2), 119-140.

Sigala, M. & Chalkiti, K. (2014). Investigating the Exploitation of Web 2.0 for Knowledge Management in the Greek Tourism Industry: An Utilisation–Importance Analysis. *Computers in Human Behavior,* 30(1), 800–812. doi: 10.1016/j.chb.2013.05.032

Sokoler, T. & Svensson, M. S. (2008). Presence remote: Embracing ambiguity in the design of social tv for senior citizens. In *Prooceedings of the 6th European Conference EUROITV*, pp. 158–162.

Soto-Acosta, P. Perez-Gonzalez, D., & Popa, S. (2014). Determinants of Web 2.0 Technologies for Knowledge Sharing in SMEs. *Service Business,* 8(3), 425–438. doi: 10.1007/s11628-014-0247-9

Sousa, D., Sarmento, L., & Rodrigues, E. M. (2010). Characterization of the twitter @replies network: are user ties social or topical? In *Proceedings of the 2nd international workshop on search and mining user-generated contents,* pp. 63-70. NY: ACM.

Southwell, B. & Yzer, M. C. (2007). The roles of interpersonal communication in mass media campaigns. In Beck, C. (eds) *Communication Yearbook*. New York: Lawrence Erlbaum Associates, 419-462.

Spiekermann, S. & Corina, P. (2000). Motivating HumanAgent Interaction : Transferring Insights from Behavioral Marketing to Agent Design. In *Proceedings of the 3rd International Conference on Telecommunications and Electronic Commerce, ICTEC3*, pp. 387-402.

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. In *Proceedings of the 2010 IEEE Second International Conference on Social Computing (SocialCom)*, pp. 177-184. IEEE.

Thomke, S. & von Hippel, E. (2002). Customers as Innovators: a New Way to Create Value. *Harvard Business Review,* 80(4), 5-11.

Tichi, C. (1991). *Electronic hearth: Creating an American television culture*. New York: Oxford University Press.

Torrez-Riley, J. (2011). The social TV phenomenon: new technologies look to enhance television's role as an enabler of social interaction. Available at: http://www.torrezriley.com/projects/researchpaper/SocialTVpaper.pdf

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14, 207–222.

Tse, A. C. B. & Lee, R. P. (2001). Zapping behavior during commercial breaks. *Journal of Advertising Research,* 41(3), 25–29.

Tullio, J. & Harboe, G. (2008). Investigating the Use of Voice and Text Chat in a Social Television System. In *Proceedings of EuroITV 2008.* Springer.

Zanjani, M., Rouzbehani, R., & Dabbagh, H. (2008). Proposing a Conceptual Model of Customer Knowledge Management: a Study of CKM Tools in British Dotcoms. *International Journal of Human and Social Sciences,* 3(5), 363-367.

Zhao, L.Z., Wickramasuriya, J., & Vasudevan, V. (2011). Analyzing twitter for social tv: Sentiment extraction for sports. In *Proceedings of the 2nd International Workshop on Future of Television*.

Zott, C., Amit, R., & Massa, L. (2011). The business model: Recent developments and future research. *Journal of Management*, 37, 1019–1042.

Wakamiya, S., Lee, R., & Sumiya, K. (2011). Crowd-powered TV Viewing Rates: Measuring Relevancy between Tweets and TV Programs. In *Proceedings of the 16th*

International Conference on Database Systems for Advanced Applications, DASFAA'11, pp. 390–401. Springer-Verlag.

Wilson, S. (2015). In the living room: second screens and TV audiences. *Television and New Media,* 17(2), 174-191.

Wohn, D. Y. & Na, E.-K. (2011). Tweeting about TV: sharing television viewing experiences via social media message stream. *First Monday,* 16, 3-7. Available at http://firstmonday.org/ojs/index.php/fm/article/view/3368/2779

Wu, Y., Zhang, Z., Wu, C., Li, Z., & Lau, F. C. (2013). Cloudmov: Cloudbased mobile social TV. *IEEE Trans. Multimedia*, 15(4), 821–832.

APPENDIX

The following tables show the results of the regression models built considering the TV contents (Table A1) and Social TV strategies (Table A2) as independent variables.

Table A1. Coefficients of hierarchical regression models, TV contents.

	Total tweets (TT)	Original tweets (OT)	Retweets (RT)	Replies (RP)
Constant	-184.25(18.713)***	-50.063 (7.815)***	-134.462 (14.287)***	-3.353 (0.615)***
Minute	0.028(0.068)	-0.072 (0.028)(*)	0.1 (0.052)	-0.001 (0.002)
Episode	13.165(0.987)***	4.671 (0.412)***	8.494 (0.754)***	0.383 (0.032)***
Viewership	90.964E-5(0.000)***	4.878E-05 (0.000)***	5.086E-05 (0.000)***	1.774E-06 (0.000)***
Break	1.133(12.461)	-31.002 (5.203)***	32.136 (9.513)***	1.484 (0.41)***
Show	*omitted*	*omitted*	*omitted*	*omitted*
Perf	17.112(9.603)(*)	25.185 (4.01)***	-8.072 (7.332)	0.319 (0.316)
Coach	-8.424(10.715)	-5.147 (4.475)	-3.277 (8.181)	0.227 (0.352)
Choice	8.018(15.997)	13.222 (6.68)(*)	-5.204 (12.213)	0.86 (0.526)
Steal	-116.327(46.595)*	-63.436 (19.458)***	-52.891 (35.574)	-2.472 (1.532)
WebRoom	124.672(45.165)**	37.433 (18.86)(*)	87.239 (34.482)(*)	3.569 (1.485)(*)
R^2	0.536	0.598	0.173	0.156
Adj. R^2	0.288	0.358	0.170	0.153

Notes: *Stat. sign. ***p<0.001; **p<0.01; *p<0.05; (*)p<0.1*

Table A2. Coefficients of hierarchical regression models, Social TV strategies.

	Total tweets (TT)	Original tweets (OT)	Retweets (RT)	Replies (RP)
Constant	-175.148 (18.072)***	-56.913 (7.561)***	-118.236 (13.849)***	-2.435 (0.596)***
Minute	.033(.068)	-0.059 (0.028)(*)	0.093 (0.052)	-0.001 (0.002)
Episode	13.081(1.008)***	3.841 (0.422)***	9.24 (0.773)***	0.381 (0.033)***
Viewership	9.693E-5(0.000)***	5.106E-05 (0.000)***	4.587E-05 (0.000)***	1.601E-06 (0.000)***
None	*omitted*	*omitted*	*omitted*	*omitted*
Hashtag	-4.075(13.846)	11.711 (5.793)(*)	-15.787 (10.61)	-0.441 (0.457)
Name	23.570(17.050)	24.269 (7.134)***	-0.699 (13.066)	-0.215 (0.563)
H+N	89.139(122.166)	20.437 (51.113)	68.703 (93.618)	0.044 (4.032)
Team	-70.998(20.508)**	-11.304 (8.58)	-59.694 (15.716)***	-2.265 (0.677)***
H+T	-101.109(77.308)	-30.764 (32.345)	-70.345 (59.243)	-2.636 (2.551)
T+Vote	25.970(15.035)(*)	32.173 (6.291)***	-6.203 (11.522)	0.566 (0.496)
N+T+V	78.298(23.536)**	92.56 (9.847)***	-14.263 (18.036)	0.794 (0.777)
H+T+V	11.637(46.690)	24.432 (19.535)	-12.795 (35.779)	0.91 (1.541)
R^2	0.536	0.359	0.171	0.154
Adj. R^2	0.288	0.356	0.167	0.150

Notes: *Stat. sign. ***$p<0.001$; **$p<0.01$; *$p<0.05$; (*)$p<0.1$*