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The interrelations between TV consumption, engagement actors, and engagement content

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Abstract

Purpose – The purpose of this paper is to explore the interrelationship between television (TV) consumption (viewing ratings), engagement behaviors of different actors on Twitter (TV programs, media, celebrities and viewers) and the content of engagement behaviors (affective, program-related and social content).
Design/methodology/approach – TV ratings and Twitter data were obtained. The content of tweets was analyzed by means of a sentiment analysis. A vector auto regression model was used to understand the interrelationship between tweets of different actors and TV consumption.
Findings – First, the results showed a negative interrelationship between TV viewing and viewers' tweeting behavior. Second, tweets by celebrities and media exhibited similar patterns and were both affected mostly by the number of tweets by viewers. Finally, the content of tweets matters. Affective tweets positively relate to TV viewing, and program-related and social content positively relates to the number of tweets by viewers.
Research limitations/implications – The findings help us understand the online engagement ecosystem and provide insights into drivers of TV consumption and online engagement of different actors.
Practical implications – The results indicate that content producers may want to focus on stimulating affective conversations on Twitter to trigger more online and offline engagement. The results also call for rethinking the meaning of TV metrics.
Originality/value – While some studies have explored viewer interactions on Twitter, only a few studies have looked at the effects of such interactions on variables outside of social media, such as TV consumption. Moreover, the authors study the interrelations between Twitter interactions with TV consumption, which allows us to examine the effect of online engagement on offline behaviors and vice versa. Finally, the authors take different actors into account when studying real-life online engagement.

Keywords Engagement, Twitter, Sentiment analysis, Second screen, TV viewing

Paper type Research paper

Introduction

The ways in which television (TV) programming is consumed are changing tremendously, with significant consequences for program creators and the companies that use TV programs as vehicles for their messages. A recent report by Nielsen (2013) finds that adults (18+) in the USA spend around 11 h every day consuming media from linear and digital devices. Nearly 90 percent of US adults watch live and time-shifted TV. While live TV is consumed for around 4 h every day, the duration for time-shifted TV is much smaller,

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around 35 min each day. Consuming live TV, therefore, still seems to be an important ritual in people's lives.

The most interesting development is that smartphones have an extremely high penetration rate irrespective of race and ethnicity (Pew Research Center, 2018). Smartphones provide consumers with easy access to social media platforms and thus enable viewers to multitask on multiple platforms. Using an additional screen while watching TV has become a part of the viewing experience (Segijn, Voorveld, Vandeberg, Pennekamp and Smit, 2017). Especially in the case of live TV shows, social conversations using smartphones and other portable devices can occur in real time, enhancing audience experience and driving viewers' engagement. Twitter is particularly well suited for this purpose; it keeps people up-do-date and facilitates a quick information flow (Voorveld, van Noort, Muntinga and Bronner, 2018). It allows TV content producers to interact with audiences in real time, and to use different channels and modes of information delivery and processing. In addition, the role of the TV viewer changes; they are no longer passive audiences but often (inter)active participants that engage in media-related conversations.

Engagement has attracted substantial attention from both academics and marketers. Although we still lack a universally and broadly agreed definition of engagement, most scholars are of the opinion that it comprises cognitive, emotional and behavioral component (Brodie *et al.,* 2011; Hollebeek *et al.,* 2014). In an online context, engagement can be divided into consuming, contributing, and creating (Muntinga *et al.*, 2011). In the current study, we explore the interrelations between TV programming and engagement on Twitter. Thus, engagement can be seen as watching TV (i.e. consuming), commenting on what others are saying on social media about the TV show (i.e. contributing) and posting a new comment about the program on Twitter (i.e. creating).

To understand and provide implications for content creators on what kind of content stimulates engagement, the current study focuses on the dynamic interactions between engagement elements using real-life data. Particularly, we explore the interrelations of several engagement elements: TV consumption, the Twitter participation of different actors (i.e. TV programs, celebrities, media and viewers), and the content of the tweets. While there is an expanding body of literature on engagement, empirical papers studying the dynamic interactions constituting engagement are still rare. Only a few studies have tried to measure engagement dynamics, most of them using surveys (e.g. Hollebeek *et al.,* 2014). However, several aspects of engagement can be better studied using behavioral data (e.g. Viswanathan *et al.,* 2017). For instance, the amount and valence of engagement can be used to represent the cognitive and affective aspects of engagement. While some previous studies have explored audience interactions on Twitter (e.g. Kim *et al.,* 2015; Lin *et al.,* 2014; Liu *et al.*, 2016), only few studies looked at the effects of such interactions on variables outside of social media, such as brand memory (Angell *et al.,* 2016), political engagement (Vaccari *et al.*, 2015) or voting decision (Maruyama *et al.,* 2014). Finally, we answer the call for the use of real-life data, which enables us to analyze actual social media content and prevent self-report measurement issues (Voorveld, 2019).

Liu *et al.* (2016) also explored the effect of online platforms (e.g. Twitter) on TV consumption. They found a positive relation between volume of tweets and exposure, and they found that information content (i.e. I am planning to watch show X) adds predictive power. However, they did not look into dynamic two-way relationships. Exploring these interrelations allows for studying the effect of Twitter on TV consumption (or other economic/social phenomena), as well as the simultaneous reverse effect of TV consumption on Twitter engagement. Therefore, the current study will include interrelations to the model. In addition, Liu *et al.* (2016) did not look at different actors posting on Twitter. By including engagement actors, engagement content, and TV consumption, we have more insight in who is participating, what they talk about on

Twitter and how this relates to TV consumption. This information could provide valuable insights for TV producers and marketers about which actors and which conversations can stimulate the viewer's engagement with TV events and ultimately TV consumption. The latter is important for both TV producers and advertisers because ad pricing and reach may differ depending on the TV consumption.

To date, we have limited understanding of how the aspects of consumer engagement with TV programming (i.e. program viewing and discussions on Twitter) affect each other and which actors and what content stimulates greater engagement. This is important considering that previous studies find that content creators should use more consumer engagement strategies on earned media (Lovett and Staelin, 2016). In addition, audience participation on Twitter can be an important indicator of viewer engagement (Jenkins, 2006; Liu *et al.*, 2016), and as such can provide marketers, political parties, or other content creators with directions on targeting. In sum, the aim of the study is to explore the dynamic interrelations between offline engagement (i.e. TV consumption), Twitter engagement of different actors (i.e. TV program, celebrities, media, and viewers) and the content of the tweets.

Theoretical framework

Viewer engagement

Engagement is a concept with a long tradition in psychology and organizational behavior (e.g. Maslach and Jackson, 1981). Even though it has received considerable attention in the literature, there is no agreement on how to define and operationalize it. Engagement has been discussed in a variety of contexts, leading to the establishment of various engagement types, such as brand engagement in self-concept (Sprott *et al.,* 2009), customer engagement (Brodie *et al.,* 2011), media engagement (Peck and Malthouse, 2010) and music engagement (Hollebeek *et al.,* 2016). Most of the literature agrees that engagement can be described using three dimensions: cognitive, affective and behavioral dimensions (Brodie *et al.,* 2011; Hollebeek *et al.,* 2014; Islam *et al.,* 2018). In addition, the literature agrees that it involves dynamic interactions with a specific object (Hollebeek *et al.,* 2014). It is also quite widely accepted that engagement has a motivational component (Mollen and Wilson, 2010). The motivations driving individuals' behaviors stem from their experiences with an object, that is, thoughts and emotions evoked by the object (Calder *et al.,* 2015). Therefore, we can say that engagement represents an individual's motivations, resulting from his or her experiences with an object, which manifest in object-oriented behaviors. These behaviors have been referred to as customer engagement behaviors (van Doorn *et al.*, 2010) or brand-dialogue behaviors (Maslowska *et al.*, 2016) and have been argued to occur as "interactions between the focal object and/or other actors" (Jaakkola and Alexander, 2014, p. 248). Therefore, the behavioral aspect of engagement can be directly observed in individuals' interactions with the object but also in object-related interactions with other individuals.

Focusing on the online context, Muntinga *et al.* (2011) divide engagement behaviors into consuming, contributing and creating. Applying that to our context, individuals can interact with the TV programming by simply watching it (i.e. consuming), commenting on what others are saying about it on social media (i.e. contributing) or posting their own reviews of the program (i.e. creating). More passive engagement behaviors, such as consuming, are less likely to create deep experiences and as such are not that beneficial for content producers. Conversely, more active engagement behaviors, such as contributing or creating, are more personally relevant and more interactive, which means they require more cognitive and emotional investment, and as such may reflect higher levels of engagement (cf. Maslowska *et al.,* 2016). Creating may be especially engaging because it produces particularly elaborate experiences.

A specific form of creating, namely tweeting about TV programming, has become especially popular (Nielsen, 2013). Such interactions transform audiences from passive receivers of TV content into participants actively interacting with TV content, and constitute "a catalyst to a new, more engaged viewing audience" (Doughty *et al.,* 2012, p. 80). Marwick and boyd (2011) discuss the tweeting audience as a network of groups and individuals who are highly engaged not only in the consumption but also production of content. Watching a program and chatting about it at the same time can enhance viewers' experiences (Weisz *et al.,* 2007) and increase program involvement (Segijn, Voorveld and Smit, 2017), which, in turn, can enhance engagement (Hollebeek *et al.,* 2014). Several studies show that active related social media behavior (e.g. commenting live on TV content or engaging with conversations via Twitter hashtags) results in positive effects on several outcome variables, such as brand memory (Angell *et al.,* 2016; Segijn, Voorveld and Smit, 2017) and political engagement (Maruyama *et al.,* 2014; Vaccari *et al.,* 2015). Furthermore, social media could serve as a first point of contact for potential viewers or as a reminder to watch a program (Lovett and Staelin, 2016). Social media could inform potential viewers about what is happening on TV and even spark their interest in watching a TV show, working as informative advertising (Gong *et al.,* 2017).

The extent of engagement might differ depending on different factors. We argue that it can be influenced by different actors and the content of the discussion on social media. In the next section, we will first discuss the different actors that may play a role in engagement behaviors on social media, followed by a discussion on how content could influence engagement behaviors.

Four types of actors of engagement behaviors

In today's communication between content providers and audiences, especially online, the content provider does not control messages anymore, meaning that it may be media users who create and/or distribute messages. Moreover, all of the engagement behaviors, such as message sharing, can not only be directed at the existing media users but also at other actors. The role of other actors is recognized in the engagement ecosystem (Maslowska *et al.,* 2016) – a conceptual model of engagement that comprises in brand actions, other actors, customer brand experience, shopping behaviors, brand consumption and brand-dialogue behaviors. Building on the service-dominant logic (Vargo and Lusch, 2016), the model argues that engagement does not only concern the focal object and an individual but rather encompasses relationships between different actors that co-create value. Thus, different actors can participate in TV-related social media conversations. Viewers are becoming active communicators when consuming media content, such as TV shows. Therefore, engagement does not only entail the TV program sending a message, but also includes viewers and other actors (Maslowska *et al.,* 2016), such as celebrities and the media. In the social media context, attention has been mostly paid to so-called opinion leaders or influential users as actors. They have been broadly studied in the literature on innovation diffusion and word of mouth (WOM). Opinion leaders can be described as "information brokers between the mass media and the general population" (Araujo *et al.,* 2017, p. 498). In the context of Twitter, the highly influential users are often celebrities, public figures, or the news media (Cha *et al.,* 2010). In line with the engagement ecosystem and research on opinion leaders, we focus on four groups of Twitter users: the TV program, celebrities, media and viewers.

First, the TV program can interact with different actors on social media in various ways. It can post on social media to promote the show and affect viewers' motivations and experiences by posting additional content from behind the scenes or comments by the presenters. The TV program may also engage in the conversation by addressing issues discussed by viewers or posting questions and contests as incentives for viewers to participate in the conversation. As discussed earlier, such actions can not only remind viewers about the program leading them to tune in but could also enhance their experience of the program (Vaccari *et al.,* 2015).

Second, celebrities often participate in conversations about popular TV programs and can sometimes even endorse them. According to the source attractiveness model, the persuasiveness of a message depends on the source's familiarity, likeability and similarity (McGuire, 1985). This suggests that attractive sources, such as celebrities, are more influential in terms of affecting attitudes and behaviors (see Erdogan, 1999 for a discussion). Early studies into the effects of celebrity endorsement show that celebrities can enhance attitudes and purchase intentions (e.g. Atkin and Block, 1983; Petty *et al.,* 1983). Also, more recent research shows that celebrities' tweets about brands can influence consumers' attitudes and intentions (Jin and Phua, 2014).

Third, media – media-related actors other than the TV show itself, such as broadcasters, journalists or other media outlets such as newspapers – also often comment on events aired on TV. The source credibility model states that information coming from a credible source can affect individuals' attitudes and behaviors via internalization (Erdogan, 1999). According to the Hovland version of the model, message persuasiveness depends on the expertness and trustworthiness of the source (Hovland *et al.,* 1953). Media, such as newspapers and journalists, are expected to be trustworthy sources of information and hence influential participants in the conversation taking place on social media.

Finally, viewers play a crucial role in engagement. Viewers turn to social media motivated by the need for connectedness and for self-presentation purposes. They want to share their experiences with similar others. According to the WOM literature, people pay significant attention to other people's behaviors and often imitate it (Libai *et al.,* 2010). In addition, information coming from similar others is more persuasive, since it does not present a persuasive intent, and, as such, might not activate persuasion knowledge (McGuire, 1985). Therefore, we expect viewers to be especially influential in conversations on social media.

Content of engagement behaviors

Besides number of tweets, engagement behaviors can be described in terms of their content, that is, what different actors post about the program. We argue that affective, program-related and social aspects of the content of the tweet could play an important role in affecting viewers' engagement with the TV program. Besides linear relationships, we are also interested in examining non-linear relationships for the following reasons. First, it is theoretically interesting to include non-linear relationships because too many tweets may overload people (Sasaki *et al.,* 2016) or satisfy people's need for information (Voorveld, van Noort, Muntinga and Bronner, 2018), and therefore they may not need to watch the event anymore (U-shape). Conversely, only a few tweets may suggest a TV event is boring or not interesting enough (inverted U-shape). Second, literature on the effects of other research fields, such as electronic WOM, shows that message valence, number of tweets per day, number of hashtags and photos in tweets, and message length can have a non-linear effect (e.g. Kim *et al.*, 2017; Maslowska *et al.*, 2017; Mudambi and Schuff, 2010; Soboleva *et al.*, 2017). Finally, because of the explorative nature of the current study, including both linear and non-linear relationships will provide us more detailed information on the interrelationships between TV consumption, actors and content (i.e. affective, program-related and social aspects).

First, affective content is expected to influence engagement behaviors. Voorveld, van Noort, Muntinga and Bronner (2018) showed that Twitter engagement is associated with negative emotions. Based on the theory of selection and diffusion in news media, it is argued that negative sentiment enhances virality (Hansen *et al.,* 2011; Heimbach *et al.,* 2015). Conversely, others have shown positive news to be more shareable (e.g. Berger and Milkman, 2012). Positive content may be shared more because it reflects positively on the sender (Berger and Heath, 2007). However, we do not know if it would affect other behaviors equally. Also, some have found no effect of valence (Liu *et al.,* 2016). As Berger and Milkman (2012) suggest, it may be more about the emotionality (i.e. arousal) of the content, rather than its sentiment. In line with such reasoning, Seiler *et al.* (2017) showed that it is the emotional engagement that affects TV viewership not the positive vs negative sentiment. Therefore, we focus on the more general affect expressed in the tweets.

Second, when it comes to the topic, we expect that the more relevant the conversations, the more positive the effect on behavior. In our research context, more relevant content would contain words referring to the TV event and more specifically to music, because we study a music TV event. Thus, tweets containing words related to music might provoke more tweeting and more TV consumption. In addition, we expect music to trigger more social interactions because music plays a particularly strong social function. Feelings of co-presence can influence communication patterns (Kim *et al.,* 2015). While watching a music TV event, viewers may experience the feeling of co-presence – a feeling of closeness, collective awareness, which may lead them to engage in social activities. Another reason to expect music to trigger more social media activity lies in the self-identity. One of the functions of music is the establishment of self-identity (North *et al.,* 2000). As Rentfrow and Gosling (2003) propose, music preferences can be used to affect self-perception and reinforce identity. People tend to share content on social media driven by similar motives, that is, for self-presentation and to cultivate a certain image (Wojnicki and Godes, 2008). Individuals express their identity with music and can further boost it when they share their music experiences with others.

Finally, words of social tone can drive engagement behaviors. These words are related to social aspects like friends, family, people, communication, etc. Research into socio-emotional experiences shows that individuals can experience socially-oriented emotions through consumption. For example, Stieler and Germelmann (2016) showed that individuals watching a football game experienced feelings of connectedness with other crowd-members. Individuals mostly discuss their emotional experiences with others to make sense of them or to establish or deepen social connections (see Berger and Milkman, 2012 for a discussion). Therefore, the social function of experiences may drive consumers to engage in more conversations on social media.

In sum, in this study we will test the interrelationships between the consumption of the TV event (i.e. TV ratings) and online engagement behaviors (i.e. amount and content) with the event expressed on Twitter. To this end, we will explore the interrelations between TV consumption, engagement actors and content of engagement behaviors, as presented in Figure 1.

Method

Research context

For this study, we focused on a live music TV event (i.e. Eurovision Song Contest) because such programing is not only extremely popular in the studied market, where it was the most

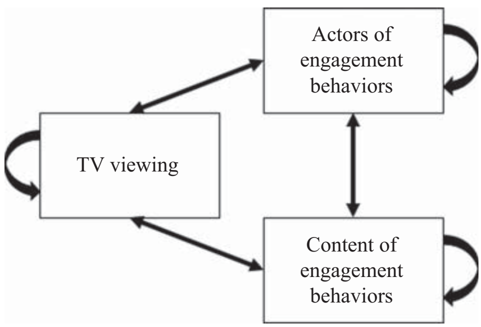


Figure 1.
A conceptual model of interactions between engagement elements

watched TV program that year, but also creates deep experiences for audiences. The event therefore creates an opportunity for TV networks to increase viewers' engagement with the event. The Eurovision Song Contest is a live TV event in which singers from different European countries compete. The event is broadcasted in all European countries, but also in countries outside of Europe (e.g. Australia, the USA). In this study, we focus on the final of the 2016 edition of the contest, which took place in May. Around 204m people watched the final (Ritzen, 2017), making it one of the most watched shows in many countries. The show consists of performances of the different countries, introductions of each country, short interviews with the artists, and the results of the contest at the end of the show. The show is not interrupted by any commercial breaks, which is typical for a public broadcaster in the Netherlands and other European countries (Media Act, 2008).

Data collection

TV ratings. The TV ratings were retrieved from the Netherlands Public Broadcasting, the official organization that keeps track of TV rating in the Netherlands. The viewing rates were provided for every minute of TV programming, starting at 9:00 p.m. up until 00:45 a.m. were included, which gave us access to the viewing rates for almost 4 h of TV on that channel on the night of the 2016 Eurovision finale. On average, about 4,286,000 people were watching the music TV event at the same point in time in the Netherlands.

Twitter data. Twitter data was collected from the social media monitoring tool Coosto, and included tweets containing words associated with the Eurovision Song Contest, namely words used to refer to the contest on Twitter (esc2016, esc16, eurovision, esf), and also tweets mentioning the social media accounts of the Dutch singer in the competition (teamdouwe, douwe_bob). We used the start time of the commercial break broadcasted before the show and the end time of the commercial break broadcasted after the show in order to account for the time lag in the analyses. The first tweet included in the sample was posted at 8:55 p.m. and the last tweet at 00:58 a.m. As the focus of this study was Twitter activity about Eurovision in the Netherlands, and considering that not all tweets are properly tagged with location, this study took a two-step conservative approach when it comes to collecting Twitter activity. First, only tweets in Dutch (according to Twitter's own automatic language classification) were collected. While this may have eliminated tweets that may also have been tweeted in the Netherlands in other languages that could be detected because of their location, doing so was deemed appropriate to prevent missing tweets in these other languages that may also have been tweeted in the Netherlands but not properly tagged with location, thus biasing the data collection. In this first step, therefore, 136,513 tweets in Dutch (according to Twitter's categorization) were retrieved in the monitoring tool using the words associated with the contest. From these tweets, as a second step, 17,905 were deemed to be from Belgium because of the location informed by the user in her or his profile. A total of 118,608 tweets were then included in the final sample.

Actors of engagement behaviors. In line with our theoretical framework, the accounts were assigned to one of the four categories: the TV program (Eurovision), media, celebrities, and viewers. Eurovision included the official Twitter account of the Eurovision song contest, as well as the broadcaster (i.e. AVROTROS), the presenters of the show and the performers. This category (including the performer from the Netherlands), however, tweeted primarily in English during the show. As such, given the small sample of tweets in Dutch, the category Eurovision could not be included in the analysis. Media contained the accounts of journalists, specific media outlets/vehicles, and also the social media channels of other TV shows. The category Celebrity contained all famous people (e.g. actors, singers, politicians, athletes) who did not fall into the category of Eurovision or Media. All other users were assigned to the Viewer category. Unverified accounts were also assigned to this category.

All accounts were coded by the first author. In addition, a subsample of the verified accounts ($n = 100$, 42.7 percent) were coded by an independent coder. Krippendorff's α showed good intercoder reliability (0.85) with a 91 percent agreement.

Content of tweets. Twitter sentiment analysis was performed using automated content analysis. The Linguistic Inquiry and Word Count (LIWC) software (Pennebaker *et al.*, 2015) was used. LIWC can automatically detect different dimensions of psychological expressions in text (Tausczik and Pennebaker, 2010), and has been used in studies about social media posts in a wide variety of contexts (e.g. Araujo and Kollat, 2018; Kim *et al.*, 2018; Huang and Yeo, 2017; Kim *et al.*, 2016). The Dutch 2007 version of its dictionary (Zijlstra *et al.*, 2004) was employed. We focused on the three categories affect, music (i.e. program-related), and social. Affect included positive emotions, positive feelings, negative emotions and several specific emotional states, such as optimism, energy, anxiety, anger, sadness. Music included words like singing, song, guitar, etc. Social included words related to communication, friends, family, people and references to other people.

The descriptive statistics for the variables mentioned above are in Table I. The statistics for the number of tweets by different actors are reported for a short interval of 10 s. As one can observe from the table, the average number of tweets by viewers is much greater than the number of tweets by celebrities and media. For context, the total number of tweets from celebrities and media in our sample is 385 and 789 respectively. However, the total number of tweets from individuals over the duration of the event is 117,431. The scores for social and affect too are generally much higher than that for music. These numbers throw some light on the nature and scope of activity by different actors during the TV event.

Control variable. Highfield *et al.* (2013) observed a variation in spikes of Twitter activity about Eurovision, which focused on the performance itself, but also included current social and political discussions. Favorability toward some countries can be driven by, for example, their proximity to the Netherlands. Also, previous research has shown that individuals respond differently when listening to music that is characteristic to their own culture vs an unfamiliar culture (Morrison *et al.*, 2003; Schlosser *et al.*, 1998). We accounted for time-invariant country-specific factors by including a dummy variable to consider the effects specific to each country including its performance.

Estimation methodology

We used a vector auto regression (VAR) model to investigate the relationships between the variables. Consistently with the theoretical framework, we considered tweets by different actors, namely media, celebrities, and viewers as endogenous. We also considered TV ratings as they could be influenced by tweets of different actors. We used the mean scores for affect, music, and social from the sentiment analysis as exogenous variables. We also included a quadratic effect for these three variables to check for their non-linear effects, either U-shape or inverted U-shape, on the endogenous variables. Other exogenous variables include fixed effects that account for the content during the performance of each country.

	Mean	SD	Minimum	Maximum
Tweets by viewers ($y1$)	81.211	40.930	3.000	217.000
Tweets by celebrities ($y2$)	0.266	0.526	0.000	3.000
Tweets by media ($y3$)	0.546	0.788	0.000	5.000
TV Rating in '000 ($y4$)	4,286.460	326.163	2,661.000	5,268.000
Social	3.716	1.024	0.055	8.139
Music	0.432	0.358	0.000	3.703
Affect	3.920	1.357	0.190	9.343

Table I.
Descriptive statistics

Content is classified as talk, video introduction or music performance. To avoid the dummy variable trap, talk during the introduction of the show is coded as 0.

The model can therefore be specified as:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{bmatrix} + \sum_{K=1}^{k} \begin{bmatrix} b_{11}^K & b_{12}^K & b_{13}^K & b_{14}^K \\ b_{21}^K & b_{22}^K & b_{23}^K & b_{24}^K \\ b_{31}^K & b_{32}^K & b_{33}^K & b_{34}^K \\ b_{41}^K & b_{42}^K & b_{43}^K & b_{44}^K \end{bmatrix} \begin{bmatrix} y_{1t-k} \\ y_{2t-k} \\ y_{3t-k} \\ y_{4t-k} \end{bmatrix} + \boldsymbol{\beta_z} \begin{bmatrix} social_t \\ social_t^2 \\ affect_t \\ affect_t^2 \\ music_t \\ music_t^2 \\ country\_video_c \\ country\_music_c \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}, \quad (1)$$

where, t is the time interval of 10 s, y_1 is the number of tweets from viewers, y_2 is the number of tweets from celebrities, y_3 is the number of tweets from media and y_4 is the TV rating. The vector **A** comprises of the four intercept terms for each of the four endogenous variables; b is a matrix of coefficients that capture the effects of the endogenous variables with k lags. The tweets from different actors are aggregated at time interval t of 10 s. Since the ratings of the show are captured only every minute, we assume the ratings are the same for every interval t in that minute. β is a vector of z coefficients for the exogenous variables comprising of the mean affect score and its quadratic term, the mean music score and its quadratic term, dummy variables ($country\_video_c$) to capture a video being played to introduce country c before the musical performance and, finally, another set of dummy variables ($country\_music_c$) that capture the musical performance of artists from each country c. The model error is captured in ε which is assumed to be MVN(0, Σ).

We first checked for the presence of unit roots in the endogenous variables. The presence of a unit root suggests that a variable is evolving and hence not stationary. In such cases, it is preferable to use the first difference value of the variable rather than the absolute value of the variable. The Twitter activities for all three actors were found not to have a unit root. However, TV rating had a unit root and we hence used the first difference value of this variable in the model. We also conducted tests to determine the optimum number of lags k in the model (Table II). Here, we evaluated different metrics such as likelihood ratio, final prediction error, Akaike information criterion, Schwarz criterion and Hannan–Quinn information criterion criterion. The FPE and AIC suggested that a model with $k = 7$ lags best explains the model, while the SC and HQC supported a model one

Lag	LogL	LR	FPE	AIC	SC	HQC
1	−14,213.64	1,539.20	29,423.03	21.64	22.67	22.03
2	−14,144.22	131.58	27,166.52	21.56	22.65	21.97
3	−14,119.53	46.65	26,817.73	21.55	22.70	21.98
4	−14,094.83	46.51	26,473.48	21.53	22.75	21.99
5	−14,057.44	70.20	25,642.62	21.50	22.78	21.98
6	−13,780.44	518.40	17,360.73	21.11	22.45*	21.61*
7	−13,759.03	39.95	17,222.61*	21.10*	22.50	21.63
8	−13,750.25	16.32	17,411.49	21.12	22.58	21.66

Notes: LR, likelihood ratio; FPE, final prediction error; AIC, Akaike information criterion; SC, Schwarz criterion; HQC, Hannan–Quinn information criterion. *Denotes the minimum value for the criterion

Table II.
Lag selection criteria

with $k = 6$ lags. There is no change in the substantive results from two models with these different lag structures. Below, we explain the results from a model estimated with $k = 7$ lags.

Results

The interrelations between various actors

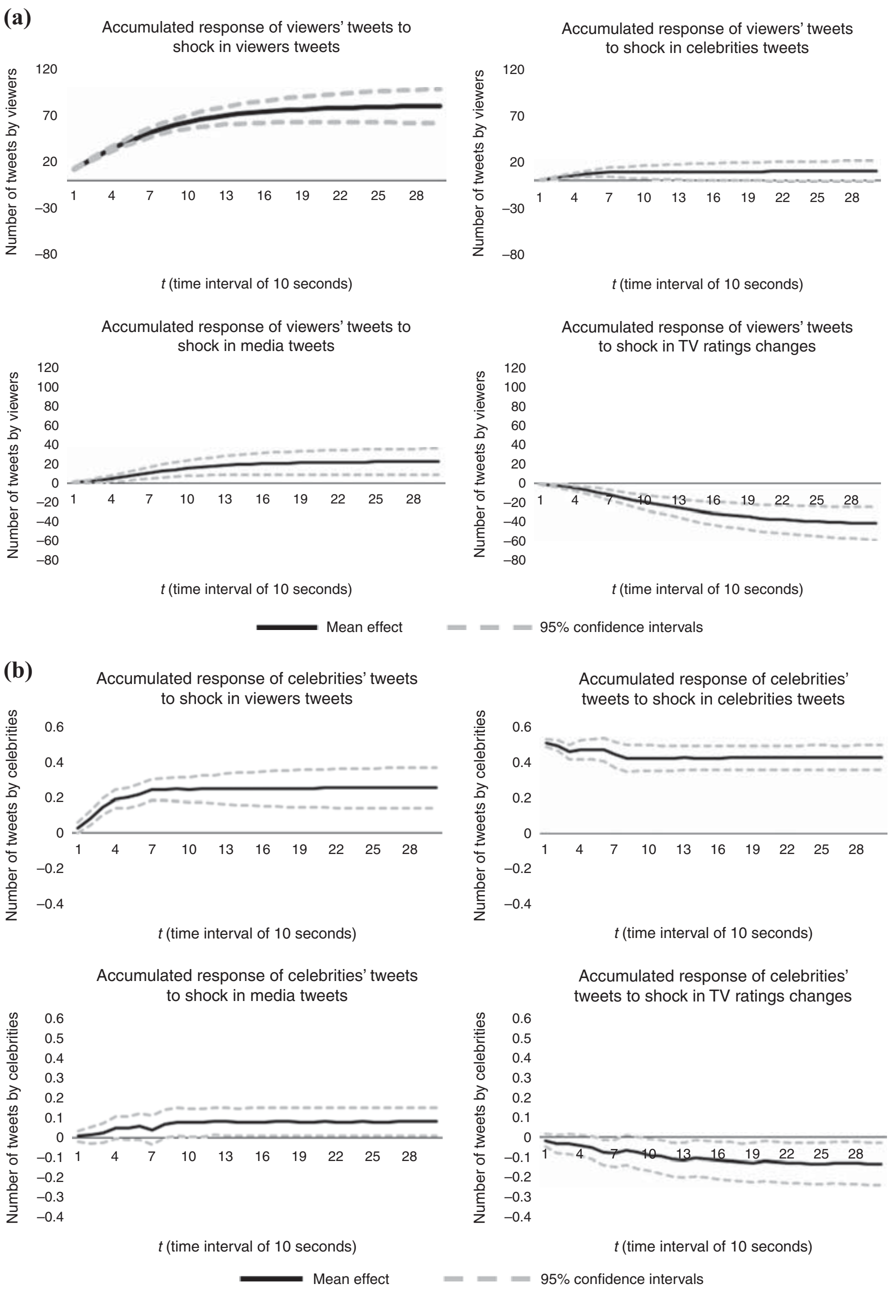
We used a VAR model to examine the interrelations between various actors and TV consumption (i.e. TV ratings). The model that explains the number of tweets from individuals has an adjusted R^2 of 89.2 percent. The adjusted R^2 for tweets from celebrities is 11.27 percent while that for tweets from media is 10.06 percent. The model for TV ratings has an adjusted R-square of 44.24 percent. In a VAR model, the estimates of the endogenous variables are by themselves not easy to interpret (Sims, 1980). The estimates are rather used to calculate the impulse response functions (IRF) (Sims and Zha, 1999) that capture the direct and indirect effects of a shock to one of the endogenous variables (say, tweets by viewers) on the other endogenous variables in future time periods. To calculate the IRF, we shock an endogenous variable by increasing its value over the average by 1 standard deviation (SD). We then capture the change in the values of the other endogenous variables for each of the next thirty time periods (i.e. 5 min). We chose to estimate the effects over this time duration since the effects of activities on Twitter for a live TV event are normally short and fleeting. In order to capture the net effect of this shock, we sum the IRFs for each time period to calculate the accumulated impulse response function (A-IRF). The standard errors for these shocks are calculated using Monte Carlo simulations. Figure 2 provides a visual depiction of the A-IRF values.

First, we examine how the number of tweets from viewers changes in response to a 1 SD increase in each of the other endogenous variables one at a time. From the plots in Figure 2 (a), we can observe that while increasing activity on Twitter by viewers has a positive effect on itself, the response stabilizes after around 12 time periods (i.e. 2 min). An increase in the number of tweets from celebrities does not seem to have a significant effect on the number of tweets from viewers since the confidence intervals overlap zero. However, an increase in the number of tweets from media seems to have a positive effect on the number of tweets from viewers. Interestingly, an increasing change in TV rating (i.e. viewership) results in a drop in the number of tweets from viewers.

Second, we examine how the number of tweets from celebrities changes in response to a 1 SD increase in each of the other endogenous variables one at a time. From the plots in Figure 2(b), we observe that a shock to the number of tweets from viewers has a positive effect on the number of tweets from celebrities. As celebrities tweet more, there is a sustained effect on tweets from celebrities in future time periods. An increase in the number of tweets from media does not significantly affect the number of tweets from celebrities. Finally, as the change in TV ratings increases, this results in a lower number of tweets from celebrities.

Third, we examine how the number of tweets from the media actors changes in response to a 1 SD increase in each of the other endogenous variables one at a time. In Figure 2(c), we find that a shock to the number of tweets from viewers seem to increase the number of tweets from media. There is no effect of the shock to the number of tweets from celebrities, however, on the number of tweets from media. The plot on the bottom left (Figure 2(c)) seems to suggest that there is a sustained positive effect of increasing tweets from media in future time periods. Finally, increasing TV ratings result in a lower number of tweets from media.

Finally, we examine how changes in viewing ratings vary in response to a 1 SD increase in each of the other endogenous variables (Figure 2d). We find that an increase in the number of tweets from viewers has a negative effect on changes in TV ratings.



(continued)

Figure 2.
A visual depiction of the A-IRF values

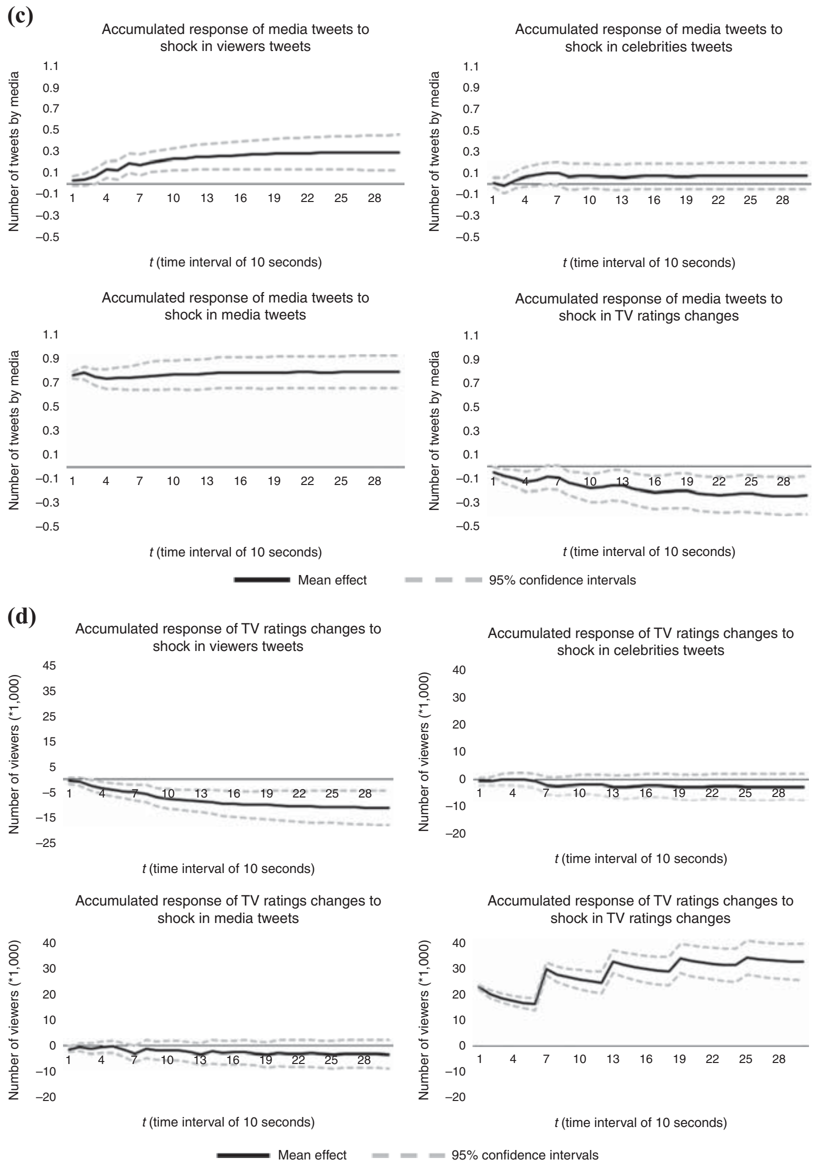


Figure 2.

Notes: (a) Accumulated response of viewers' tweets; (b) accumulated response of celebrities' tweets; (c) accumulated response of media tweets; (d) accumulated response of TV ratings changes. Accumulated response to generalized 1 standard deviation shocks ±2 standard error

However, the effects of the shock to the number of tweets from celebrities and media on changes in TV ratings are not significant. Finally, we observe that an increasing change in TV ratings has a positive effect on TV ratings that stabilizes after around 20 time periods (i.e. around 3 min).

While the A-IRF plots reveal the absolute change in the response variable, it is also interesting to look at the percentage changes. Table III displays the percentage change in the values of endogenous variable in response to a shock from another endogenous variable and we report only the results with sizeable effects here. From the first row of this table, we can observe that a 1 SD shock in y_3, the number of tweets from media, results in a 0.22 percent increase in the number of tweets from viewers y_1. A shock to the number of tweets from viewers y_1 results in a 0.93 percent increase in y_2, the number of tweets from celebrities, and a 0.54 percent increase in y_3, the number of tweets from media. It therefore seems that celebrities are affected to a larger extent than media by tweets from viewers. Celebrities are also influenced more by tweets from media (0.23 percent) than the other way around (0.10 percent). In fact, an increase in the number of tweets from media influences celebrities (0.23 percent) marginally more than viewers.

The effects of content of engagement behaviors

The estimates for the intercept and the exogenous variables affect, music, and social are in Table IV. We find that tweets that contain more content on social aspects have a marginally positive effect on the number of tweets from viewers. Social content does not seem to have an effect on tweets by other actors. Tweets that are about music have an inverted U-shape effect on the number of tweets from viewers. As the average score for music (obtained from a sentiment analysis of tweets) increases, the number of tweets increases but only up to a point. As the mean value of music increases beyond a certain threshold value, the number of tweets from viewers starts decreasing. However, the effect for tweets that carry affective content is different in that affective content has a U-shape effect on the number of tweets from media. While the number of tweets from media decreases with increasing affect score, the Twitter activity from this group starts increasing as content with affect increases beyond a certain value. Affect also has an inverted U-shape effect on TV ratings. As the mean value of affect increases, there is an increasing change in TV ratings, but only up to a point. Beyond a certain value of affect, the changes in TV ratings start decreasing. The number of tweets from viewers increases during the musical performance of the Dutch team. There was also a marginal increase in the number of tweets from celebrities during the introduction of the Dutch team. Viewership increased significantly during the musical performance of the Dutch team. These results for the Dutch team seem reasonable and lend face validity to the model and estimation technique.

Discussion

TV consumption patterns are shifting from passive consumption behaviors to interactive engagement behaviors. Despite that Twitter engagement while watching TV becomes more popular (Nielsen, 2013), previous research has only rarely looked into the interactions between engagement behaviors on Twitter and other engagement behaviors, such as media

Table III. Percentage change in response to 1 SD generalized impulse

	Generalized impulse 1 SD			
	*y*1	*y*2	*y*3	*y*4
% change until t+30				
y_1	0.9735	0.0656	0.2244	−0.4603
y_2	0.9338	1.5437	0.2346	−0.4060
y_3	0.5365	0.1007	1.4179	−0.3305
y_4	−0.0026	−0.0004	−0.0007	0.0076

Notes: y_1, tweets by viewers; y_2, tweets by celebrities; y_3, tweets by media; y_4, TV ratings

	y_1	y_2	y_3	y_4
A (intercept)	11.603**	−0.057	1.291***	−7.688
	5.774	0.225	0.337	10.247
Social	3.480*	0.030	0.003	2.168
	2.028	0.079	0.119	3.599
Social^2	−0.413	−0.004	−0.003	−0.365
	0.267	0.010	0.016	0.474
Music	8.994***	0.011	0.073	3.727
	3.457	0.135	0.202	6.136
Music^2	−7.345***	−0.006	−0.088	−3.131
	2.681	0.105	0.157	4.758
Affect	0.098	0.021	−0.254***	9.351***
	1.425	0.056	0.083	2.528
Affect^2	0.074	−0.006	0.028***	−1.314***
	0.155	0.006	0.009	0.276
Netherlands_video	−4.299	0.303*	0.054	8.802
	4.318	0.168	0.252	7.663
Netherlands_music	17.017***	0.224	0.425	27.035**
	6.601	0.257	0.386	11.714
Model fit				
Adj. R^2 (%)	89.20	11.27	10.06	44.24
Log Likelihood	−5,291.968	−944.895	−1,486.527	−6,060.543

Notes: y_1, tweets by viewers; y_2, tweets by celebrities; y_3, tweets by media; y_4, TV ratings. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table IV. Results for exogenous variables from VAR model estimates and respective standard errors

consumption (e.g. TV ratings). However, we know from previous research that online activities drive individuals' offline choice behaviors (e.g. Godes and Mayzlin, 2004; Yoon *et al.,* 2017) and vice versa (Kessler and Guenther, 2017; Voorveld, Araujo, Bernritter, Rietberg and Vliegenthart, 2018). Thus, it is important to understand how engagement behaviors on Twitter interact with offline engagement. Therefore, the aim of the current study was to explore the dynamic interrelations between offline engagement (i.e. watching TV) and Twitter engagement of different actors (i.e. TV program, celebrities, media and viewers) and the content of the tweets. By combining real-life data of TV ratings and Twitter data, we explored how the engagement behaviors of different actors can drive each other. This resulted in three main conclusions.

First, the results showed a negative interrelation between number of tweets by viewers and TV ratings. As the changes in TV ratings become smaller, the more viewers tweet and vice versa. Thus, it seems that viewers' engagement on Twitter can cannibalize TV viewing, that is, following the event on Twitter may be a substitute for watching the event live on TV. Another way of interpreting this finding is that Twitter can attract more people to be engaged with a TV event who are not necessarily going to watch the event on TV. It appears that viewers are being strategic while choosing only one medium to engage with during the event. These results suggest that live TV shows are more likely to engage viewers on one platform.

This result differs from the findings of Liu *et al.* (2016), who found that volume of tweets positively impacts TV consumption. Some possible explanations are the type of event (TV shows vs TV event), online platforms (four online platforms (including Twitter) vs Twitter only), and the country of research (the USA vs the Netherlands). Liu *et al.* (2016) collected data from US Twitter usage and TV ratings, while the current study is conducted in the Netherlands. This could lead to differences because research into the use of multiple media at the same time showed that this behavior is the most prevalent in the USA and the least in the Netherlands (Segijn and Kononova, 2018; Voorveld *et al.*, 2014). Future research is needed to further examine the differences and how they can affect the relationship between Twitter usage and TV consumption.

Second, the results showed that the drivers of the number of tweets by celebrities (i.e. famous people other than people working for the show or the media) and the media (e.g. journalists, broadcasters, newspapers) show similar patterns. The results showed that both of these types of actors have a sustained effect on their own tweeting behaviors. More importantly, the results showed that the number of tweets by these actors is positively affected by the number of tweets by viewers. Thus, the number of tweets by celebrities and media increase when the number of tweets by viewers increases. Conversely, the number of tweets of both actors is negatively affected by the TV ratings. Thus, the TV show itself is not a driver for tweeting behavior of celebrities and media. However, the number of tweets by viewers is. Since the number of tweets by viewers is more visible at the moment of tweeting/viewing, a possible explanation could be that the number of tweets by viewers is a cue for popularity and visibility. Celebrities and the media might be more likely to tweet when the event is perceived as more important in order to gain more publicity. The number of tweets by viewers can serve as an indication of the relative importance of the media event. Therefore, the more tweets by viewers a program receives, the more celebrities and media actors will also engage in online conversation. Although these two actors show similar patterns, the number of tweets by celebrities (vs media) were more affected by the number of tweets by viewers.

Third, the results showed that the content of the tweets also matters in driving engagement behaviors. In the current study, we looked into affect, program-related and social content in tweets. Affect has a positive inverted U-shape relation with TV ratings, meaning that the more tweets containing emotional words, the incremental change in TV ratings also increases. However, an increasing affect in tweets beyond a certain point only results in a decreasing change in TV ratings. Furthermore, tweets containing program-related and social content are related to number of tweets by viewers. The relation between program-related words and number of tweets by viewers has an inverted U-shape. The more tweets that contain program-related contents, the more viewers will tweet but only up to a point. Furthermore, tweets that contain more social aspects are positively related to the number of tweets by viewers.

Theoretical and practical implications

The findings of this study have at least two implications for theory. First, the results of the current study have implications for the engagement literature. Focusing on engagement behaviors in the online context, we made a distinction between consuming (e.g. TV watching), contributing (e.g. commenting on what others are saying on Twitter) and creating (e.g. posting on Twitter) (Muntinga *et al.,* 2011). The finding of the negative interrelation between TV ratings and number of tweets by viewers suggests that consuming (i.e. TV watching) and creating (i.e. tweeting) behaviors can be isolated activities. The engagement ecosystem places engagement behaviors on a continuum of resources invested. The more resources consumers invest in their behavior and the more interactive the behavior is, the stronger is the consumers' engagement (Maslowska *et al.*, 2016). TV watching requires less resources than tweeting, which would suggest a lower level of engagement of those engaging in watching than tweeting. In addition, the Ecosystem postulates that the three categories of behaviors are not exclusive, but often integrated, meaning that media users often engage in all three activities or in a combination of two (Shao, 2009). Our findings show that they are rather exclusive. It may be that media users engage in the different behaviors consecutively, but not at the same time. The effort required to engaging in both activities at the same time may be too huge for the level of engagement observed in our study. Future research could investigate whether that is the case by applying experimental designs.

Second, although not measured, the results tell us something about motivations of different actors. Building on uses and gratification perspective, Muntinga *et al.* (2011) investigated motivations driving the three categories of engagement behaviors and showed that consuming is driven by information, entertainment and remuneration; contributing is driven by personal identity, integration and social interaction, and entertainment; and creating is driven by personal identity, integration and social interaction, empowerment, and entertainment. In the current study, the results on the drivers for the number of tweets by viewers may indicate the "integration and social interaction" motive. This need for belonging is shown by the results that the number of tweets of viewers is mostly driven by itself. This finding strengthens the belief that social media constitute a participative environment in which viewers can engage with each other and co-create meaning (Okazaki *et al.,* 2015). Also, that mainly viewers (vs celebrities and media) respond to content of tweets tells us something about the possible use of social media by the different media actors. That the number of tweets of celebrities are not related to the content of the tweets might be an indication of a more active rather than interactive role that celebrities have. They respond to TV content but seem to be less interactive participants in the conversations that are taking place on social media (i.e. they seem to focus on exposure rather than interacting). The number of tweets of viewers, on the other hand, is affected by the content of tweets. This could be an indication that viewers are more interactive engagement actors because they not only respond to TV content but also respond to other actors' content on social media.

In addition to theoretical implications, the current study also has practical implications. First, content of tweets matters when stimulating viewers' engagement behaviors on Twitter. The results showed that the number of tweets was positively related with social and program-related content in tweets. This finding would suggest that stimulating program-related conversations on Twitter can be beneficial to viewer engagement. Research on multiscreening has found positive effects on brand memory (Angell *et al.,* 2016; Segijn, Voorveld and Smit, 2017) and political engagement (Vaccari *et al.,* 2015) when viewers engage in program-related conversations while watching. Thus, stimulating program-related conversations might be relevant for the TV industry in order to increase viewer engagement behaviors on Twitter and to attract brands that want to advertise around their shows. Also, the TV industry may want to stimulate affective conversations on Twitter. Although the results show cannibalizing effects of the number of tweets and TV consumption, the content of tweets positively relates to TV consumption. Therefore, content producers may want to focus on stimulating affective conversations on Twitter, when shows are known for their viewers' frequent social media use.

Second, dividing attention between media can have implications for media experiences, such as enjoyment (Chinchanachokchai *et al.,* 2015) or engagement as shown in the current study. Vaccari *et al.* (2015) found that social media can make people aware of political debates happening on TV without watching or listening to the live debates. Thus, social media could inform viewers about the developments in the TV program. The results of the current study suggest that tweets about the aired event may fulfill viewers' need of staying up to date with the event, without having to watch it. In such cases, a metric that captures the overall level of engagement of the audience (e.g. TV ratings and social media usage) may be a more appropriate measure of success than a number of viewers or number of tweeters separately. The TV industry is already debating on whether or not to include watching on different screens, platforms, and extended watching into viewing metrics (Poggi, 2018). The results of the current study contribute to this debate by suggesting to also include social media engagement.

It is important to note, however, that the study followed Twitter behaviors of different actors during the live event only. It is quite possible that viewers' behaviors differ for different kinds of content or that they continue to tweet about the event even after the show ends. For example, Seiler *et al.* (2017) suggest complementarity of TV viewing and microblogging. Not tracking social media activities before, during and after the event can be seen as a limitation of the study. Furthermore, the study is limited by the availability of Dutch tweets. Therefore, we need to be careful in drawing causal conclusions about the relations between number of tweets and TV watching. Moreover, even though we have taken several steps to remove tweets from Belgium, considering that the location information on Twitter is a text field, there is a risk that some tweets not created in The Netherlands may be in the sample – especially when users do not mention a city or a country in their location. Also, the current study only examined one media event. Thus, replicating the findings on different shows or different genres is necessary to further validate the relations found. In this light, the results of the current study must be interpreted as a first exploration on the interrelations between TV consumption, different engagement actors and content of engagement behaviors. Future studies to examine activity on social media before, during, and after an event and replicate the findings for other events are necessary.

Conclusion

In conclusion, different strategies are being used to increase consumers' engagement with TV programs in order to bring back audiences who are shifting to online content. Social media, such as Twitter, are often seen as a means to achieve that, which, if true, may have incremental consequences for TV content producers, advertisers and other content creators. However, our research shows that the engagement dynamics are rather complex. Most importantly, they suggest a substitution effect between engagement on social media and TV consumption.

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