The Influence of Social TV Strategies and Contents on TV Online Engagement

Angela Fortunato, Michele Gorgoglione, Umberto Panniello
Dipartimento di Meccanica, Matematica e Management
Politecnico di Bari
Bari, Italy
e-mail: angela.fortunato@poliba.it

***Abstract*—The phenomenon of social TV is gaining importance in both industry and research. TV broadcasters are increasingly adopting social TV strategies both on first and second screen to increase the viewers' online engagement. The research done so far suggests quite simple models of the phenomenon, identifying and studying separately the effects of different variables on online engagement. This research represents one of the first attempts to develop a better research model. We analyzed a large dataset related to a popular Italian TV show using social strategies to engage viewers on Twitter. Through hierarchical linear regression models we studied the relationships among social strategies, TV contents, viewership, time and different kinds of viewers' online behavior. We demonstrate that (i) different factors play different roles in affecting the viewers' online engagement and (ii) the phenomenon can be better explained if we look at different kinds of online behavior that represent online engagement, such as posting original comments, sharing or replying to them. Despite some limitations, we think that this work's findings may be important for researchers to develop a holistic research model of social TV, and for practitioners to realize how to balance the factors affecting the viewers' online engagement in an effective way.**

Keywords-Social TV; social networks; viewers' online engagement.

I. INTRODUCTION

The phenomenon of Social TV has gained a striking importance in the last years. Increasing the amount of discussion associated with TV show's contents, i.e., the online engagement of TV viewers, has become a major goal of the companies in this industry. TV broadcasters encourage viewers interacting in real time with the TV shows and sharing online comments through "second screen" devices (smartphones and tablets). They do this through several social strategies, which can be delivered on both screens. Examples of strategies on the first screen include showing Twitter hashtags and recent viewers' comments on the TV screen during a show, or let the show hosts reply to some of the viewers' tweets. Second screen strategies include posting comments on a social network or delivering online messages to invite viewers polling a show's contestants. The main reason behind the use of these strategies is the idea that they can increase the viewers' online engagement in online communities, such as Twitter, which is the most popular social network in both research and industry domains. In the recent past, scholars have studied this phenomenon [34][35] examining the changes in the relationship between the broadcasting industry and its audience, thus considering the new ways of audience engagement through the integration of the technology. Particularly, recent research investigated the relationship between online engagement and social strategies. They showed that using social TV strategies on the first screen can be predictive of various types of online engagement [15]. Other works [5][10][12][32][33] have highlighted the existence of several variables, which can play an important role in driving the TV viewers' online engagement, such as viewership, time and the show contents. Moreover, recent studies [3][7][15][27][29][32] have identified different kinds of behavior, which can represent online engagement, such as posting tweets or sharing them. However, the approach used in these works suggests a quite simple model of the phenomenon, where the use of a certain social strategy can have an effect, potentially positive, on the online engagement of viewers. This research represents the first step in the development of an appropriate research model to study the phenomenon of social TV online engagement (OE). The goal of this research is to demonstrate that a change in the OE of TV viewers cannot be simply explained by the use of social TV strategies, rather different variables play different roles in the phenomenon. Based on prior research we have identified several variables, which can be included in a model. Firstly, three main factors can affect OE: the use of *social strategies*, the type of TV *content* on air, the *online behavior* of other viewers. Secondly, three variables may influence OE and have to be controlled: *viewership*, time during an *episode*, time during the *season*. Finally, OE can be represented by three different kinds of behavior: generation of *original* tweets, sharing tweets (*retweets*), *replies* to tweets. We studied the relationships among these variables by analyzing the behavior of viewers on Twitter during "L'Isola dei Famosi", a popular Italian TV show. We used hierarchical linear regression models. We have found that the phenomenon of OE can be better explained if we look at different kinds of behavior separately, namely generating original tweets, sharing tweets (retweets), replying to tweets. In this paper, we show the following main results: (1a) viewership affects the overall number of original tweets, as expectable; however, it does not affect retweets and replies; (1b) online engagement decreases with time during each episode, while it increases during the season; (2a) the effect of *social strategies* is different for different kinds of behavior: they increase generation while decrease retweets and replies; (2b) the effect of *TV contents* depends on the kind of content: commercial breaks decrease generation while increase retweets and replies, “challenges” always decrease OE. We also found that (3) an increase in the number of original tweets generated is correlated to an increase in retweets and replies. The contributions of this work are the following. First, we demonstrate that different factors play different roles in the phenomenon and their effect to online engagement is more complex than what research has shown so far. Second, we show that these effects depend of the type of online behavior we use to represent online engagement. Third, to our best knowledge this is one of the first attempts to develop a complex research model of the phenomenon of online engagement in the context of social TV. Despite some limitations in our research, we think that its findings may be important from the business viewpoint because they contribute to clarify the real factors affecting the phenomenon and help managers properly design TV shows and social strategies in order to drive viewers online and keep them engaged. The paper is structured as follows. Section II provides a description of the existing literature on social television. Section III depicts the methodology of our research, in terms of dataset, variables’ description and the propositions we explored in our research. Section IV illustrates the results and Section V describes their implications from research and managerial viewpoints and limitations of this work.

II. 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 [20][21][30]. Moreover, it affects viewers’ behavior [26] in terms of shaping, reinforcing or changing their reactions [16]. This depends on factors, such as the type of contents or messages [22][26]. 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 [13]. Social networks have gained a relevant role, since they allow viewers to share online their real-time viewing experiences [6], by interacting around the TV contents. Therefore, viewers can be affected by social interactions in online networks during a viewing experience [16][28]. Research has studied several aspects of Social TV. Some authors studied viewers’ motivations and the different ways to interact on social network sites during viewing [9][18][32]. Notably, some scholars analyzed the use of hashtags. For instance, [4] stated that hashtags are used to group tweets by topic, thus allowing people to follow and contribute to conversations on topics of interest, e.g., during televised political debates in the U.S. presidential primaries. Others studied how viewers’ messages are related to what viewers are watching and observed particular behavioral patterns focusing on specific TV programs and contents [5][12][32]. Moreover, viewers can deliver different types of messages (tweets) when using Twitter, which are generally studied separately: original tweets, when posting a message for the first time; replies, when responding to an existing message, and retweets, when sharing an existing message [3][7][15][27][29][32]. A major topic is the analysis of the Social TV Strategies that broadcasters often use during a show. These strategies may consist in adopting program’s official hashtags [8], displaying on the first screen social media elements such as viewers’ tweets [13][15] or in leveraging the use of second screen applications dedicated to the program to deliver several types of trigger [2][5][19]. These strategies aim at attracting people’s interest towards the live shows [24] and increase the viewers’ involvement towards the programs [31]. They are used to prompt real-time viewers to interact online with the TV programs and to share online messages [13][14][15]. A few studies have reported the effects of the Social TV Strategies on viewers’ behaviors. For instance, reference [15] analyzed the effect of the social TV strategies in the American show “The Voice”. They studied the effects of different social strategies displayed on the first screen: showing a show-related tweet on the screen increases the number of retweet, while showing a hashtag on the screen increases the viewers’ online engagement, i.e., the amount of discussions associated with the TV show’s contents [15], during commercial breaks. Another study [10] showed that in certain circumstances online engagement can be predicted by the show contents rather than by the use of social strategies and that the overall number of tweets is highly correlated to the number of viewers. Another work has examined viewers’ visual attention while interacting with synchronized second-screen applications and found that the presence of the second screen dramatically decreased the attention towards TV contents [17]. Each one of these works has studied the influence of one single type of variable on OE. This entails the use of very simple models, which, in our opinion, cannot explain a complex social phenomenon properly. Researchers, indeed, have not built yet a complex model to explain the whole phenomenon of the viewers’ online behavior. Building and testing such models is important because it would clarify the factors affecting online engagement and, in turn, the source of business value related to social TV and second screen applications. Our research represents the very first step in the attempt of filling this gap.

III. METHODOLOGY

In this section, we report the methodology followed for our experiments. In particular, we discuss the dataset used to perform analyses, the variables measured during our study and the propositions to explore.

A. Dataset

We collected data from the 2015 edition of the Italian TV show “L’Isola dei Famosi”, a reality show where celebrities have to survive on a desert island. The show had one episode a week and lasted 7 weeks, from the 2nd of February to the 23th of March, each episode lasted around 170 minutes. The TV broadcaster delivered several social strategies during the show on the second screen app dedicated to the program (see next section for the list). Viewers interacted on Twitter during the show using the official TV show hashtag. First of all, we acquired approximately 500,000 tweets, including the official TV show hashtag. The tweets in our dataset included original tweets, retweets and replies. We used the tweet time-stamp to associate each tweet with a minute during the show. Second, we structured in our dataset the type of TV content that viewers were watching minute by minute for the 1,242 minutes of show (including commercial breaks). Third, we collected the type of social strategy that the broadcaster was delivering on the second screen app minute by minute. Fourth, we gathered the number of viewers who were tuned on the show also minute by minute (viewership), provided by Auditel s.r.l.. In conclusion, we collected 1,242 observations corresponding to as many minutes and each observation included information on tweets, TV contents, social strategies and viewership.

B. Measurements

Based on the literature reviewed in the previous section, we have identified several variables, which can be included in a model of the Social TV phenomenon. Three main factors can generate OE, (1) the use of social strategies, (2) the type of TV content, (3) the online behavior of other viewers (the tweets generated). Three variables may influence OE and have to be controlled: (4) viewership (the number of TV viewers), (5) time (measured both during each episode and during the whole season). OE can be represented by three different kinds of behavior: (7) posting original comments, (8) sharing comments, (9) replying to comments. The dependent variable in our models is the online engagement (OE). According to the research we have reviewed, we have defined OE as the amount of discussions around the TV show's content, measured by the total number of tweets including the TV show's official hashtag. In addition we classified the tweets as follows: original tweets (OT), measured by the total number of tweets posted for the first time; original tweets from app (AT), measured by the total number of tweets posted for the first time, but delivered through the second screen application (AT represents a subset of OT); retweets (RT), measured by the total number of retweets, i.e., the share of existing tweets; replies (RP), measured by the total number of replies to existing tweets. According to prior research [15] the measurement of dependent variables is shifted by a time delay of one minute with respect to the measurement of independent variables. The independent variables in our models are the TV content and the social strategy. TV content is defined as a nominal variable that describes what type of contents viewers are watching on the TV screen and takes nine values: (1) general contents, (2) challenge, (3) nomination, (4) week summary, (5) contestant's elimination, (6) appearance of eliminated contestant in studio, (7) visit in "Playa Desnuda", (8) start of voting, (9) commercial break. Social strategy is defined as a nominal variable describing what message the broadcaster delivered to viewers through the second screen app. It takes eight values: (1) call to comment, (2) survey/quiz, (3) call to predict, (4) photo gallery, (5) call for appreciation, (6) call to vote, (7) displaying related information, (8) absence of strategy. Finally, we considered viewership and time (episode and season) as control variables. We measured viewership as the number of viewers in each minute. Since we observe the aggregate phenomenon of online interaction, a change in the number of viewers may affect the overall number of tweets. In addition, since a variation in OE may be caused by time [15], we used two measures of time: the minute in each episode and the number of episode. We included these measures of time 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.

C. Propositions development

According to prior research, we developed three main propositions that we want to explore:

P1: *Viewership and time affect OE*.

P2: *TV contents and social strategies affect OE*.

P3: *OT affect RT and RP*.

We explored these propositions through hierarchical multiple linear regression models [1][11], using SPSS. In general, we first built a linear regression considering one dependent variable a time, checked the significance, then added more dependent variables and checked again the significance of the model. We repeated this procedure for each dependent variable. Dependent and control variables are metric, while we codified the nominal independent variables as dummy (binary) variables.

IV. RESULTS

In order to explore P1, we built models having viewership, episode and minute as independent variables: first, we built simple linear regressions considering only one of the described variables, then we used all variables together. We iteratively repeated this procedure one dependent variable a time, i.e., OT, AT, RT and RP. Table I reports the results. We also ran regressions measuring viewership in a log scale. For lack of space we do not report these results. As expected, we found that viewership positively affects the online engagement. Looking at the three kinds of behavior, we observed that viewership positively affects the number of original tweets (both OT and AT), while it does not affect the number of RT and RP. We also found that the online engagement decreases minute by minute during each episode. Looking at the three kinds of behavior, the decrease holds for AT, RT and RP while OT increase. In addition, only the number of RT and RP increases during the season (episode by episode), while there is no effect for OT. Therefore, we found that P1 is valid, however the relationship between viewership, time and OE changes depending on what kind of online behavior we measure. In order to explore P2 we ran the models with

Copyright (c) IARIA, 2015. ISBN: 978-1-61208-443-5

TV contents and social strategies as independent variables. First, we built the models considering only one independent variable and then all variables together, including viewership and time variables as control variables. We iteratively repeated this procedure one dependent variable a time. Table II reports the results of the final model. As expected, we found that TV contents and social strategies affect the online engagement. In particular, some contents (challenge), strategies (call to vote) and the absence of a strategy negatively affects the OE, while some contents (contestant's elimination, commercial break, displaying related information) positively affects the OE. Looking at each kind of online behavior, we found more clear patterns. If we consider the TV contents, the "challenge" decreases all kinds of behaviors (OT, RT and RP); the "contestant's elimination" increases the original tweets; the "appearance of eliminated contestant in studio" increases the number of RP. Interestingly, during "commercial breaks" the number of OT increases while the number of RT and RP decreases. If we consider the social strategies, we found that the "call to comment" has a positive effect only on the number of tweets from app (which is expectable because strategies were only shown on the second screen app) while it has a negative effect on the number of RT and RP. The "call for appreciation" and the "call to vote" have a negative effect on the number of RT, while the "displaying related information" has a positive effect on the AT. Finally, the "absence of strategy" has a negative effect on all kind of behaviors. Again, our models show that P2 is valid, however the relationships change depending on the way OE is measured. In order to explore P3, we ran the models with OT and original AT as independent variables. We included viewership and time as control variables. We used RT and RP as dependent variables. Table III reports the results of the final model, with all variables together. We found that the number of OT and the number of AT positively affects both the number of RT and RP. In this case, the models confirm the validity of P3.

V. DISCUSSION AND CONCLUSIONS

In this section, we present and discuss the findings and their implications from research and managerial viewpoints. First, we have shown that the phenomenon of OE can be better explained if we look at different kinds of online behavior separately (namely generating original tweets, sharing tweets and replying to tweets). In fact, we confirmed the influence of viewership on OE: the higher the number of viewers tuned into the program, the higher the number of tweets posted. However, looking at the different kinds of online behaviors, we found that the viewership affects the number of OT while it does not affect the number of RT and RP. We also found that the OE changes during each episode and during the season. During each episode, the number of RT and RP decreases while the number of OT increases. Finally, the number of RT and RP increases during the season, while the OT do not. Second, we have shown that TV contents and social strategies affect OE. Also in this case, the relationship between contents and OE as well as the relationship between the use of social strategies and OE changes depending on what online behavior is used as measure of OE. On the one hand, we found that some strategies have a positive effect on the generation of OT and a negative effect on RT and RP, while the absence of a strategy has a negative effect on all kind of behaviors. On the other hand, we found that different TV contents have different effects on the online behavior. During challenges, all kinds of OE decrease. During commercial breaks the generation of OT decreases while RT and RP increase. During the elimination, OT and RP increase. Finally, we found that the generation of OT positively affects sharing and replying behaviors: the number of OT generated is correlated with the number of RT and RP. This research has clearly some limitations. The main are the use of one dataset only, the fact that the social strategies in our setting were only delivered by the second screen app, and the use of "simple" regression models. Despite this, our findings may have interesting implications from both a research and a managerial viewpoint. For researchers, it is interesting to develop a consistent interpretation of viewers' behavior to build a holistic research model. For instance, when viewers are watching a challenge they decrease each form of OE, but this is offset by an increase in the willing to post new comments when contestants are eliminated. Viewers seem to be willing to share comments and reply to comments during breaks. Challenges are likely to attract more attention towards the first screen, while commercial breaks attract viewers to the second screen: however, since viewers are not provided with any content to tweet about, they tend to read and react to existing tweets. From a managerial viewpoint, our results suggest that TV contents remain a major factor affecting OE. However, social strategies may increase the generation of OT, which, in turn, are a factor affecting RT and RP. Broadcaster should then carefully balance the use of social strategies with TV contents in order to drive the viewers' online behavior effectively. In the next research steps, we plan to develop a behavioral interpretation of the phenomenon and test hypotheses through the use of more datasets and the use of more sophisticated statistical models. Moreover, we plan to analyze the relationship between contents and strategies and understand the effect of *combinations* of contents and strategies.

ACKNOWLEDGMENT

We wish to thank Telecom Italia for funding this research, Auditel for allowing the authors to access viewership data, Media Consultants for providing the viewership datasets.

REFERENCES

[1] R. M. Baron and D. A. Kenny, "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," Journal of Personality and Social Psychology, vol. 51, no. 6, Dec. 1986, pp. 1173-1182, doi: http://dx.doi.org/10.1037/0022-3514.51.6.1173.

[2] S. Basapur, G. Harboe, H. Mandalia, A. Novak, V. Voung, and E.C. Metcalf, "Field trial of a dual device user experience for iTV," The 9th International Interactive Conference on

Interactive Television (EuroITV '11), ACM, June 2011, pp. 127-136, ISBN: 978-1-4503-0602-7

[3] D. Boyd, S. Golder, and G. Lotan, “Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter,” The 43th Hawaii International Conference on System Sciences (HICSS), Jan. 2010, pp. 1-10, ISSN: 1530-1605

[4] A. Bruns and J. E. Burgess, “The use of Twitter hashtags in the formation of ad hoc publics,” The 6th European Consortium for Political Research (ECPR) General Conference, 2011.

[5] C. Buschow, B. Schneider, and S. Ueberheide, “Tweeting Television: Exploring communication activities on Twitter while watching TV,” Communications - The European Journal of Communication Research, vol. 39, no. 2, Jun. 2014, pp. 129-149, doi: 10.1515/commun-2014-0009.

[6] P. Cesar and D. Geerts, “Past, Present and Future of Social TV: A Categorization,” The IEEE Consumer Communications and Networking Conference, Jan. 2011, pp. 347-351, ISBN: 978-1-4244-8789-9

[7] G. M. Chen, “Tweet this: A uses and gratifications perspective on how active Twitter use gratifies a need to connect with others,” Computers in Human Behavior, vol. 27, no. 2, Mar. 2011, pp. 755-762, doi: 10.1016/j.chb.2010.10.023.

[8] R. Deller, “Twittering On: Audience Research and Participation Using Twitter,” Participations: Journal of Audience &Reception Studies, vol. 8, no. 2, May 2011.

[9] M. Doughty, D. Rowland, and S. Lawson, “Who is on your sofa?: TV audience communities and second screening social networks,” The 10th European conference on Interactive tv and video, July 2012, pp. 79-86, ISBN: 978-1-4503-1107-6

[10] A. Fortunato, M. Gorgoglione, and U. Panniello, “What Drives TV Online Engagement? The Influence of Social Strategies and Contents,” The 12th International Conference on Web Based Communities and Social Media, July 2015.

[11] P. A. Frazier, A. P. Tix, and K. E. Barron, “Testing Moderator and Mediator Effects in Counseling Psychology Research,” Journal of Counseling Psychology, vol. 51, no. 1, Jan. 2004, pp. 115-134, doi: http://dx.doi.org/10.1037/0022-0167.51.1.115.

[12] F. Giglietto and D. Selva, “Second Screen and Participation: A Content Analysis on a Full Season Dataset of Tweets,” Journal of Communication, vol. 64, no. 2, Apr. 2014, pp. 260-277, doi: 10.1111/jcom.12085.

[13] G. Harboe, “In Search of Social Television,” in Social Interactive Television: Immersive Shared Experiences and Perspectives, P. Cesar, D. Geerts and K. Chorianopoulos, IGI Global, USA, 2009, pp. 1-13.

[14] G. Harboe, C. Metcalf, F. Bentley, J. Tullio, N. Massey, and G. Romano, “Ambient Social TV: Drawing People Into a Shared Experience,” The 26th Annual SIGCHI Conference on Human Factors in Computing Systems, Apr. 2008, pp 1-10, ISBN: 978-1-60558-011-1

[15] S. Hill and A. Benton, “Social TV: Linking TV Content to Buzz and Sales,” The International Conference on Information Systems (ICIS), Dec. 2012.

[16] R.L. Holbertand and J.M. Tchernev, “Media Influence as Persuasion,” in The SAGE Handbook of Persuasion: Developments in Theory and Practice, J. Dillard and L. Shen, Eds. SAGE Publications Inc., 2012, pp. 36-52.

[17] M. E. Holmes, S. Josephson, and R. E. Carney, “Visual attention to television programs with a second-screen application,” The Symposium on Eye Tracking Research and Applications, Mar. 2012, pp. 397-400, ISBN: 978-1-4503-1221-9

[18] N. C. Krämer, S. Winter, B. Benninghoff, and C. Gallus, “How «social» is Social TV? The influence of social motives and expected outcomes on the usage of Social TV applications,” Computers in Human Behavior, vol. 51, no. A, Oct. 2015, pp. 255-262, doi: 10.1016/j.chb.2015.05.005

[19] M. Lochrie and P. Coulton, “Sharing the Viewer Experience through Second Screens,” The 10th European Interactive TV Conference (EuroITV), July 2012, pp. 199-202, ISBN: 978-1-4503-1107-6

[20] M. Morrison and D. Krugman, “A look at mass and computer mediated technologies: Understanding the roles of television and computers in the home,” Journal of Broadcasting & Electronic Media, vol. 45, no. 1, pp. 135–161, 2001, doi: 10.1207/s15506878jobem4501_9

[21] H. Newcomb, Television: The critical view, Fifth edition. New York: Oxford University Press, 1994.

[22] W. J. Potter, Media Effects. SAGE Publications Inc., 2012.

[23] S. Schirra, H. Sun, and F. Bentley, “Together Alone: Motivations for Live-Tweeting a. Television Series,” The SIGCHI Conference on Human Factors in Computing Systems, Apr. 2014, pp. 2441-2450, ISSN: 2308-4138, ISBN: 978-1-4503-2473-1

[24] M. Proulx and S. Shepatin, Social Tv: How Marketers Can Reach and Engage Audiences by Connecting Television to the Web, Social Media, and Mobile. Wiley, 2012.

[25] L. Rossi and M. Magnani, “Conversation Practices and Network Structure in Twitter,” The Sixth International AAAI Conference on Weblogs and Social Media, AAAI Press June 2012, pp. 563-566.

[26] L. J. Shrum, “Television and Persuasion: Effects of the Programs between the Ads,” Psychology and Marketing, vol. 16, no. 2, Mar. 1999, pp. 119-140, doi: 10.1002/(SICI)1520-6793(199903)16:2<119::AID-MAR4>3.0.CO;2-R

[27] D. Sousa, L. Sarmento, and E. M. Rodrigues, “Characterization of the Twitter @replies Network: Are User Ties Social or Topical?,” The 2nd International Workshop on Search and Mining User-generated Contents (SMUC), Oct. 2010, pp. 63-70, ISBN: 978-1-4503-0386-6

[28] B.G. Southwell and M.C. Yzer, “The roles of interpersonal communication in mass media campaigns,” in Communication Yearbook, C. Beck Ed., Lawrence Erlbaum Associates, New York, 2007, pp. 419-462.

[29] B. Suh, L. Hong, P. Pirolli, and E. H. Chi, “Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network,” The IEEE Second International Conference on Social Computing, Aug. 2010, pp. 177-184, ISBN: 978-1-4244-8439-3

[30] C. Tichi, “Electronic hearth: Creating an American television culture,” New York: Oxford University Press, 1991.

[31] J. Torrez-Riley, “The Social TV Phenomenon: New Technologies Look to Enhance Television’s Role as an Enabler of Social Interaction,” 2011, available at: http://www.torrezriley.com/projects/researchpaper/SocialTVpaper.pdf, [retrieved: September, 2015].

[32] D. Y. Wohn and E.-K. Na, “Tweeting about TV: Sharing television viewing experiences via social media message stream,” First Monday, vol. 16, 2011, pp. 3 – 7.

[33] S.Hill and A. Benton, “The Spoiler Effect?: Designing Social TV Content That Promotes Ongoing WOM,” The Conference on Information Systems and Technology (INFORMS), Oct. 2012.

[34] J. Jones, “Emerging platform identities: Big Brother UK and interactive multi-platform usage,” in Big Brother International: Format, Critics, and Publics, E. Mathijs and J. Jones, London: Wallflower Press, 2005, pp. 210-231, ISBN: 9781904764199

[35] J. Roscoe, “Multi-platform event television: Reconceptualizing our relationship with television,” The Communication Review, vol. 7, no. 4, 2004, pp. 363-369.

TABLE I. EFFECT OF VIEWERSHIP AND TIME ON ONLINE ENGAGEMENT: UNSTANDARDIZED COEFFICIENTS (STANDARD ERRORS).

	OE	**OT**	**AT**	**RT**	**RP**
Episode	3.110 (3.055)	-1.962 (1.934)	0.027 (0.048)	5.072 (1.754)**	0.297 (0.061)***
Minute	-0.218 (0.120) (*)[a]	0.163 (0.076)*	-0.005 (0.002)**	-0.381 (0.069)***	-0.014 (0.002)***
Viewership	6.076e-5 (0.000)***	5.522e-5(0.000)***	2.368e-7 (0.000)*	5.542e-6 (0.000)	1.508e-7 (0.000)
Constant	62.089 (39.298)	-105.969 (24.880)***	0.791 (0.616)	168.058 (22.564)***	4.285 (0.787)***
R^2	0.173	0.201	0.038	0.077	0.091
Adjusted R^2	0.171	0.200	0.036	0.075	0.089

a. Statistical significance: "***"*p<0.001; "**"p<0.01; "*"p<0.05; "(*)"p<0.1*.

TABLE II. EFFECT OF SOCIAL STRATEGIES AND CONTENTS ON OE: UNSTANDARDIZED COEFFICIENTS (STANDARD ERRORS).

	OE	**OT**	**AT**	**RT**	**RP**
Episode	1.679 (3.107)	0.469 (1.992)	0.140 (0.045)**	1.211 (1.691)	0.194 (0.061)**
Minute	-0.257 (0.129)*[b]	0.031 (0.083)	-0.010 (0.002)***	-0.288 (0.070)***	-0.013 (0.003)***
Viewership	7.181e-5 (0.000)***	4.815e-5 (0.000)***	-1.098e-7 (0.000)	2.366e-5 (0.000)***	4.842e-7 (0.000)**
Content 1 +					
Content 2	-89.090 (18.573)***	-47.754 (11.906)***	-0.224 (0.266)	-41.335 (10.109)***	-1.155 (0.366)**
Content 3	19.524 (18.890)	14.164 (12.109)	-0.100 (0.271)	5.360 (10.282)	-0.196 (0.373)
Content 4	-77.901 (61.385)	-40.600 (39.348)	-0.203 (0.880)	-37.301 (33.411)	-0.674 (1.211)
Content 5	151.100 (56.434)**	174.917 (36.175)***	0.887 (0.809)	-23.817 (30.717)	0.054 (1.113)
Content 6	13.422 (21.886)	17.141 (14.029)	0.369 (0.314)	-3.719 (11.913)	2.036 (0.432)***
Content 7	80.358 (60.334)	35.494 (38.675)	-0.580 (0.865)	44.865 (32.840)	0.499 (1.190)
Content 8	39.721 (80.547)	44.395 (51.632)	0.839 (1.154)	-4.674 (43.841)	0.789 (1.589)
Content 9	50.111 (15.708)**	-25.972 (10.069)*	0.061 (0.225)	76.083 (8.550)***	2.246 (0.310)***
Strategy 1	-14.593 (17.560)	3.858 (11.256)	4.317 (0.252)***	-18.451 (9.558) (*)	-0.889 (0.346)*
Strategy 2 +					
Strategy 3	14.274 (17.216)	14.213 (11.035)	0.321 (0.247)	0.061 (9.370)	0.150 (0.340)
Strategy 4	11.410 (14.599)	-3.317 (9.358)	-0.153 (0.209)	14.727 (7.946) (*)	-0.119 (0.288)
Strategy 5	-27.977 (14.578) (*)	-7.523 (9.345)	0.059 (0.209)	-20.455 (7.935)*	-0.460 (0.288)
Strategy 6	-63.054 (27.231)*	-27.674 (17.455)	-0.404 (0.390)	-35.379 (14.822)*	-0.522 (0.537)
Strategy 7	40.869 (24.504) (*)	25.961 (15.707) (*)	0.885 (0.351)*	14.908 (13.337)	0.518 (0.483)
Strategy 8	-130.203 (54.290)*	-38.319 (34.800)	-1.519 (0.778) (*)	-91.885 (29.550)**	-2.295 (1.071)*
Constant	12.204 (44.225)	-62.773 (28.349)*	2.117 (0.634)**	74.978 (24.071)**	2.736 (0.872)**
R^2	0.239	0.246	0.260	0.237	0.189
Adjusted R^2	0.228	0.235	0.249	0.226	0.177

b. Statistical significance: "***"*p<0.001; "**"p<0.01; "*"p<0.05; "(*)"p<0.1*. *+omitted*

TABLE III. EFFECT OF ORIGINAL TWEETS AND APP TWEETS ON RETWEETS AND REPLIES: UNSTANDARDIZED COEFFICIENTS (STANDARD ERRORS)

	RT	**RP**
Episode	5.740 (1.490)***[c]	0.315 (0.056)***
Minute	-0.456 (0.059)***	-0.016 (0.002)***
Viewership	-1.950e-5 (0.000)***	-5.006e-7 (0.000)***
OT	0.474 (0.022)***	0.012 (0.001)***
Constant	213.270 (19.279)***	5.461 (0.728)***
R^2	0.335	0.232
Adjusted R^2	0.333	0.229

	RT	**RP**
Episode	4.791 (1.727)**	0.289 (0.061)***
Minute	-0.343 (0.068)***	-0.013 (0.002)***
Viewership	4.393e-6 (0.000)	1.162e-7 (0.000)
AT	6.533 (1.023)***	0.196 (0.036)***
Constant	161.012 (22.237)***	4.073 (0.779)***
R^2	0.107	0.113
Adjusted R^2	0.104	0.110

c. Statistical significance: "***"*p<0.001; "**"p<0.01; "*"p<0.05; "(*)"p<0.1*.