Social TV and "Influencers": Different Users, Different Effects

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***Abstract*— TV broadcasters are increasingly adopting social TV strategies to affect the viewers' online behavior. The research done so far suggests that different drivers play different roles and their effects are different according to the specific type of online behavior. In order to extend this research, through hierarchical linear regression models, we compare the effects of the different drivers on the online behavior of "influencers", i.e., users having a large number of followers, and "ordinary" users. Despite some limitations, we show relevant differences between the online behaviors of these two kinds of users, particularly the social TV strategies do not affect the online behavior of the "influencers", while some of them affect the online behavior of "ordinary" users.**

Keywords-social TV; engagement; online behavior; influencer.

I. INTRODUCTION

In the context of the "Social TV" phenomenon [2], social networks, as Twitter, have gained a relevant role, by allowing viewers to share online their real-time viewing experiences [1]. On the other hand, broadcasters often use Social TV strategies [2][3][4] to prompt viewers to interact online during the TV programs [3] and then increase the viewers' involvement [5] and the online engagement around the TV programs, that is the amount of viewers' interactions occurring online [3]. Viewers can interact online through different types of behaviors: in particular, on Twitter they can post original tweets, share tweets (retweets), reply to tweets (replies). Previous research found a relationship between some viewers' online behaviors and specific TV programs and contents [13], while few studies have explored the effects of the Social TV strategies on viewers' online engagement. Reference [3] showed that displaying a TV show-related tweet on TV screen increases the number of retweets, while showing a hashtag increases the viewers' online engagement during commercial breaks. Furthermore, reference [9] demonstrated that the effects of Social TV strategies and TV contents on online engagement can be better explained by distinguishing the different kinds of online behaviors (i.e., generating original tweets, sharing tweets and replying to tweets). They found that some strategies positively affect the generation of original tweets and negatively affect retweets and replies, while the absence of a strategy has a negative effect on all kind of behaviors. Moreover, different TV contents have different effects on different kinds of online behaviors. In particular, during commercial breaks the generation of original tweets decreases, while retweets and replies increase.

However, in order to better examine the viewers' online engagement, relevant aspects of online social networks should be considered. In social networks' context, indeed, one of the most relevant aspect characterizing the online behavior is represented by the individual characteristics [10], specifically the influence a user exerts in his/her network to spread information further [10]. This kind of user is called "influencer" [8][10] (also "influential" or "opinion leader" [6]) and generally the behavior is different from the one of the other members of the network, called "ordinary" users [7]. For instance, by analyzing the online behaviors on a Google Groups' sample, reference [11] demonstrated that "influencers" are more likely to post messages and reply to other messages than other members of the network. Therefore, "influencers" are generally characterized by a different behavior in comparison with the remainder of the network. "Influencers" are identified by considering several metrics, such as the number of followers [7][8][10]. The distinction between "influencers" and "ordinary" users is valid also in the Social TV context but no studies have explored their behavior. In particular, no studies explored whether "influencers" and "ordinary" users show different reactions to the TV contents and the Social TV strategies. Therefore, our aim is to examine in depth the effects of Social TV strategies and TV contents on the online behaviors [9], by studying the difference between "influencers" and "ordinary" users.

The paper is structured as follows. The section II depicts the methodology of our research, in terms of dataset, variables' description and method applied to study the relationship between variables. The section III illustrates the preliminary results and conclusions.

II. METHODOLOGY

According to prior research, we want to study the effects of Social TV strategies and TV contents on the online behaviors of "influencers" and "ordinary" users. In order to do so, first we collected approximately 500,000 viewers' tweets during the entire 2015 edition of the Italian TV show "L'Isola dei Famosi", one of the most popular reality show using social TV strategies, where celebrities had to survive on a desert island. During the show (one episode a week for seven weeks), the broadcaster delivered several strategies on the second screen app dedicated to the program. The collected data were further distinguished between original tweets, retweets, replies and tweets generated through the second screen app. Then, we defined two different types of users: "influencers" and "ordinary" users. In order to do so, we measured the number of followers [7][8][10] of each

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user and we built a frequency distribution of the number of followers per user. Finally, we identified the group of "influencers" by considering the top 1% of users [12], which are the users with the highest number of followers. The rest of the network has been labeled as "ordinary" users.

In addition, for each minute of the show (including commercial breaks), we measured: the type of TV content shown on screen, the type of Social TV strategy used, the number of viewers, the number of total tweets further distinguished into original tweets, retweets, replies and tweets generated through the second screen app. According to previous research [9], we applied hierarchical multiple linear regressions using the following dependent variables: online engagement (OE), i.e., total number of tweets, and the different kinds of online behaviors, such as original tweets (OT), retweets (RT), replies (RP) and tweets generated through the second screen app (AT). The dependent variables were shifted by a time delay of one minute with respect to the measurement of independent variables [9]. The independent variables are: the TV content, i.e., (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; the Social TV strategy, i.e., (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 (the minute within the episode and the number of the episode within the season) as control variables.

III. RESULTS

In this section, we report the main results obtained from our models. For the sake of brevity, we just discuss the statistical significant results (p-value is lower than 0.1) as in [9], without showing any table. We found that viewership positively affects the OE generated by both "influencers" and "ordinary" users. We also found that during the season only the "ordinary" users increase all kinds of online behaviors, while during each episode only the "influencers" increase their online behaviors.

Concerning the Social TV strategies, the results show relevant differences between the two types of users. First of all, the absence of Social TV strategies (strategy 8) has a negative effect on the online behavior of the "ordinary" users, while it does not affect the online behavior of the "influencers". The Social TV strategies do not affect the online behaviors of the "influencers", while some of them, such as strategy (5), negatively affect the online behaviors of the "ordinary" users, and some other Social TV strategies, such as strategy (1), positively affect their posting behavior and negatively affect their sharing behavior.

Looking at the TV contents' effects, we found that some contents (such as content 2 or content 9) generate increases and decreases in different types of online engagement for the two groups of users. In particular, during commercial breaks, i.e., content (9), RT generated by both kinds of users increases. However, "ordinary" users decrease OT and increase both RT and RP, while "influencers" increase only RT. In other words, "influencers" and "ordinary" users react differently to different kinds of TV contents and, in particular, during the commercial breaks, only the "ordinary" users decrease the posting behavior.

In this paper, we have shown the preliminary results of our research, which aims at demonstrating that the distinction between "influencers" and "ordinary" users is useful to explore the effects of Social TV strategies and TV contents in the Social TV context. The results suggest that the two kinds of users are characterized by different behaviors: "influencers" increase the online behaviors during the episode, while "ordinary" users increase the online behaviors during the season. Moreover, "ordinary" users are more affected by Social TV strategies than "influencers", while different TV contents lead to different effects on the online engagement of the two groups of users. As next steps, we will observe in depth the difference between these two kinds of users, by further analyzing the two subsets. In particular, we will include further metrics suggested by the previous literature to identify "influencers" and "ordinary" users, including the "Pareto principle"). Furthermore, we will take into account other similar TV shows in order to confirm these results.

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