



When a luxury brand bursts: Modelling the social media viral effects of negative stereotypes adoption leading to brand hate

Eleonora Pantano

School of Management, University of Bristol, Office: HH4.11, Queens Avenue, BS81SD Bristol, UK

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ABSTRACT

In early 2020, the World Health Organization (WHO) developed the term “infodemic” to describe the velocity at which data can be exchanged among people, in a free virtual space where firms have limited control over the information diffusion. In particular, the diffusion of information on social media has analogies with the transmission (contagion) of social phenomena and infectious diseases. The aim of this research is to model the viral effects of a luxury marketing campaign when adopting negative stereotypes to increase the market share in a growing market. The campaign generated 506,127 likes of celebrity endorsers/influencers and 17,984 comments spread worldwide in a relatively short period, producing a “burst”. Findings revealed the unexpected social burst occurred with negative consumers’ evaluation, which has been amplified becoming dramatically damaging for the brand (brand hate).

1. Introduction

In early 2020, the World Health Organization (WHO) developed the term “infodemic” to describe “an over-abundance of information [...] that makes it hard for people to find trustworthy sources and reliable guidance when they need it”, similar to the huge number of users seeking massively information about the 2019-nCoV outbreak (WHO, 2020). To this end, WHO works 24/7 to identify the “news” that can potentially harm the public’s health (WHO, 2020). The “infodemic” concept synthesizes the velocity at which data can be exchanged among people, in a free virtual space where firms have limited control over the information diffusion process. For this reason, the diffusion of information across social media is a hot topic of investigation in many contexts. Meaningful examples are in public health to support the diffusion of vaccination, in national security to dispel the diffusion of malicious propaganda, and ultimately in marketing to promote the purchase of certain products and consumers’ loyalty.

Understanding how to take advantage from information diffusion and social influence in social media has acquired an important role in brand management (Aleti, Pallant, Tuan, & van Larer, 2019; Giglio, Pantano, Bilotta, & Melewar, *in press*). For instance, the selection of a certain endorser (celebrity) might influence the (positive) diffusion of advertising messages on social media, due to the higher authenticity and credibility which leads to a lower resistance to the message (Casalo, Flavian, & Ibanez-Sanchez, 2020; de Vries, Gensler, & Leeflang, 2012).

Through their posts, endorsers might positively impact consumers’ preference for specific brands and products, resulting in a sale increase (De Veirman, Cauberghe, & Hudders, 2017; Hsu, 2019; Stubb & Colliander, 2019). Indeed, social media marketing strategies can be successfully integrated in corporate marketing communication (Athwal, Istanbuluoglu, & McCormack, 2019; Melewar & Nguyen, 2014). Similarly, if a social media post displays a higher number of “likes”, it is perceived to be more credible by users, resulting in more positive attitudes towards the brand (Seo, Kim, Choi, & Li, 2019). Research in this sense is largely devoted to (i) understanding the characteristics of a post to become viral and shared (Aleti et al., 2019; Arora, Bansal, Kandpal, Aswani, & Dwivedi, 2019; Check & Huberman, 2010; Jin, Zhou, & Yu, 2019; Villarroel Ordenes et al., 2019), and (ii) discover the most influential entities (influencers and celebrity endorsers), within a certain (social) network, capable to lead a product to become viral (Kiss & Bichler, 2008; More & Lingam, 2019).

To the best of our knowledge, previous studies lack investigation of the massive diffusion/contagion of the negative opinions of a luxury marketing campaign through social media. The aim of this paper is to model the viral effects of a luxury marketing campaign, similarly to the transmission (contagion) of infectious diseases, when this adopts negative stereotypes to increase the market share in a growing market. To this end, the research focused on the case of Dolce&Gabbana 2018 marketing campaign to exploit further the Chinese market. The brand’s choice of certain stereotypes in the advertising produced 506,127 likes

E-mail address: e.pantano@bristol.ac.uk.

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and 17,984 (negative) comments worldwide in a very short time. The present research provides a model of the online contagion (viral effects) of adverse consumers' brand perception. This contagion further resulted in a "burst" with the unexpected consequence of brand hate.

This paper is organized as follows. The next section will discuss the theoretical background in terms of luxury brand management, and social media information diffusion. Subsequently, the paper introduces the methodology and the main findings, with emphasis on the emergence of the burst. It concludes discussing the contribution to the literature and the implications for practitioners, while proposing suggestions for future studies.

2. Theoretical background

2.1. Luxury brand management

A positive brand reputation synthesizes the positive opinion that brand's stakeholders (i.e., consumers, retailers, etc.) have about the brand (Varadarajan, DeFanti, & Busch, 2006), which exists as associations held in memory (Keller, 1993). Thus, products supported by favorable brand reputations are highly desired by consumers (Rapp, Beitelspacjer, Grewal, & Hughes, 2013).

Specifically, in the case of luxury brands, the reputation is more about what the brand represents (symbolic value), rather than about the technical qualities of the product (Wiedmann, Hennigs, & Siebels, 2009). In other words, consumers' choice of luxury brands is driven more by intangible benefits rather than by the functional utility of specific products (Beverland, 2019). Luxury products are usually perceived as high quality, capable of providing authentic value via desired benefits, with a prestigious image within the market, premium price, and capable of inspiring a deep connection with consumer (Ko, Costello, & Taylor, 2019). They are also able to evoke imageries of rich people who can afford the cost of luxury as the synthesis of exclusive/inaccessible and highly desired lifestyle (Kapferer & Laurent, 2016). Since consumers create an image of others on the basis of what branded products they wear (Willems et al., 2012), luxury products allow consumers to exhibit higher social status (Bian & Forsythe, 2012). As a consequence, luxury retailers might further generate a sense of "adoration" in their stores by consumers. For instance, many tourists go to the most famous Tiffany store in New York (US) to take a picture in front of the store and evoke the luxurious lifestyle of Tiffany customers. However, this means that consumers also have high expectations towards luxury brands, which might result either in high satisfaction or high disappointment (Wiedmann, Hennigs, & Siebels, 2007). As a consequence, the intrinsic features and intangible value of luxury brands always amplify the consumers' response (Wiedmann et al., 2007). Therefore, when negative incidents occur for luxury brands the effects of those can be extremely negative such as brand hate (Bryson, Atwal, & Hulten, 2013).

In this vein, social media play a critical role in amplifying consumers' opinion about brands and marketing campaigns. Indeed, consumers engage with luxury brands in social media for several reasons: (i) the perceived relevancy of the contents (including trendiness as the extent to which the luxury brand diffuses the latest and trendiest information about the brand), (ii) the quality of brand-customer relationship (including brand love), (iii) perceived enjoyment, (iv) aesthetic quality of the contents, and (v) brand equity and technical elements as ease of use and convenience (Bazi, 2020). Moreover, luxury brands should still maintain a certain distance from consumers in social media to maintain the sense of exclusivity and uniqueness (Athwal et al., 2019; Park, Im, & Kim, 2020). Indeed, luxury brands' social media activities might also lead to disadvantages (Mandler, Johenen, & Grave, in press), soliciting new investigations especially concerning users' negative reactions in social media. However, consumers' reaction on social media might vary across different cultural markets (Choi, Seo, Wagner, & Yoon, 2020). In this vein, recent studies (e.g., Ko et al., 2019) solicit for new

investigation on how social media can be successfully used to build luxury brand image, and how social media marketing for luxury brands should be different from the traditional one. Also, luxury brands would benefit from new advances in understanding the role of new technologies, with emphasis on social media, for the development of more successful corporate marketing communication campaigns (Choi et al., 2020).

2.2. Social media information diffusion

Predicting the diffusion of certain messages among users (consumers) might lead to positive marketing advantages such (positive) word-of-mouth communication, brand loyalty, more purchases, etc. (De Veirman et al., 2017; Stubb & Colliander, 2019). Consumers might contribute to the diffusion with "likes", "retweets", and "shares", based on the level of engagement, ultimately resulting into the amplification or dulling of subsequent marketing actions (Aleti et al., 2019; Riquelme, Rios, & Al-Thufery, 2018). For this reason, there is a huge deal of research in predicting the popularity (virality) of such messages (Araora et al., 2019; Check & Huberman, 2010; Hansen, Kupfer, & Hennig-Thurau, 2018).

Specifically, popularity is defined as a piece of online information receiving a certain level of attention in social media, which can be measured through the number users who actually viewed the message, or the number of comments achieved, likes, retweet, etc. The information shared online exhibits different popularity evolution, since it is impacted by many factors such as celebrity involvement, a certain event occurring in the real world, user interests, and so on (Hu, Hu, Fu, Fang, & Xu, 2017). Accordingly, recent studies tried to understand why certain information become more popular than others, by considering the richness in informational content (Araujo, Nijens, & Vliegenthart, 2015), vividness and interactivity (de Vries et al., 2012), emotional involvement (Pantano, Giglio, & Dennis, 2019), narrative styles (Aleti et al., 2019), originality and uniqueness (Casalo et al., 2020), and presence of certain visual elements (Villaruel Ordenes et al., 2019). Similarly, recent papers (Hansen et al., 2018) solicit the future studies on the impact of the massive and rapid diffusion of negative messages on brand management, specifying that the actual social media usage might generate different consumers' reactions if compared with the preliminary studies in this topic. Indeed, the ease of disseminating misinformation through social media might lead to the diffusion of fake news or wrong messages that can result in the adoption of incorrect behaviours (i.e., against vaccines movements).

The diffusion of some pieces of online information also shows analogies with the diffusion (transmission) of infectious diseases (contagion) (Rapp et al., 2013). In the both cases, the contagion starts with a number of entities/users who diffuse the virus/message (Hu et al., 2017). Subsequently, the number of users liking/commenting/replying to the message represents the number of users "infected" by the message, which becomes viral/highly popular as in the unlucky case of infectious diseases (Kiss & Bichler, 2008; Rapp et al., 2013).

In the case of infectious disease contagion, compartmental epidemic models such as the Susceptible-Infected-Susceptible (SIS) or Susceptible-Infected-Recovered (SIR) and contagion theory (Rapp et al., 2013) describe the evolution of disease transmission among individuals, where Susceptible are the persons who might contract the disease, Infected the persons who actually got the disease, and Recovered the persons who got it and recovered. In particular, these models portray how the individuals of a fixed population are Susceptible, Infected and Recovered in a certain period of time, by predicting how many individuals will get the disease (Osborne, Wang, & Tien, 2018). The information transmission among users follow similar dynamics (Bettencourt, Cintron-Arias, Kaiser, & Castillo-Chavez, 2006; Goffman & Newill, 1964), suggesting that individuals might engage in certain behavior because of their exposure to others' behavior (similar to the infectious disease exposure). In other words, if an individual is exposed to a certain

message or a certain behavior for a certain amount of time, they can be affected. For these reasons, epidemic models have been used to investigate the popularity evolution (contagion) of a certain message on social media as mediated by the frequency of online interaction with the brand and the brand reputation (Rapp et al., 2013); and to understand the *explosive* evolution in social networks if the contagion occurs too fast (Gomez-Gardenes, Lotero, Taraskin, & Perez-Reche, 2016). The quickest rate of increase of the popularity in the shortest time generates the “burst” event (Barabasi, 2005; Hu et al., 2017; Jung, 2017), without distinguishing if positive or negative burst occurs when associated with a positive or negative information. The burst is a sudden moment consisting of the quickest and highest level of popularity of certain information, which does not always follow traditional distribution curves (Barabasi, 2005; Hu et al., 2017).

It has been further argued that it is more complex to predict the spread of ideas than diseases (Monsted, Sapiezynski, Ferrara, & Lehmann, 2017). In the case of infectious disease it is possible to evaluate the R_t as the rate of reproducibility of the infecting virus, which helps understanding how many individuals will be infected in a certain time (Kucharski, Russel, Diamong, & Liu, 2020). In other words, if R_0 value is 1, each infected individual might infect another one, higher the value of R_0 higher the risk of the epidemic diffusion (Kucharski et al., 2020). According to the R_t value, Governments and National Health Services might choose to adopt containing measures to limit the diffusion (as severe lockdown in countries as in the case of COVID19 outbreak) (Pantano, Pizzi, Scarpi, & Dennis, 2020). In the case of information diffusion, the value of R_0 as the rate of reproducibility of the information (the number of individuals willing to share the information) is not known, and might vary according to several factors (Aleti et al., 2019; Araujo et al., 2015; de Vries et al., 2012; Pantano et al., 2019; Villarroel Ordenes et al., 2019). Moreover, in case of infectious diseases, countries

are usually prepared to communicate rapidly, regularly, and transparently with the population through existing public health communication networks, and train the staff accordingly with the support of World Health Organization (WHO, 2020). However, in the case of private companies, this kind of support is not available.

While some studies tried to predict the impact of a huge amount of negative message shared online in a short period of time (social media firestorms) (Hansen et al., 2018; Scholz & Smith, 2019), there are no studies modeling the diffusion when the firestorm evolves so quickly that the burst occurs, especially in the context of luxury brands. Thus, the burst event is potentially more dangerous for a company, and harder to be contained.

3. Methodology of research

3.1. Case research

Dolce&Gabbana is a luxury Italian brand established in 1985 by Domenico Dolce and Stefano Gabbana. The brand has a strong link with its country of origin in Southern Italy, particularly Sicily (the home region of the founders). Although the brand was already present in the Asian market, the growth of the market (Bu, Durand-Servoingt, Kim, & Yamakawa, 2017) pushed Dolce&Gabbana to duplicate the market share in China. To this end, in November 2018 the brand created an event in Shanghai to attract the interest of new Chinese consumers. Accordingly, the brand launched a social media marketing campaign based on Instagram, by creating the hashtag “#DGTheGreatShow”. Indeed, consumers show more favorable attitudes towards empowerment-campaign hashtags than brand-name hashtags (Kim & Phua, 2020). The marketing campaign used an Asian actress eating the most representative Italian food (i.e., pizza, cannolo, spaghetti with

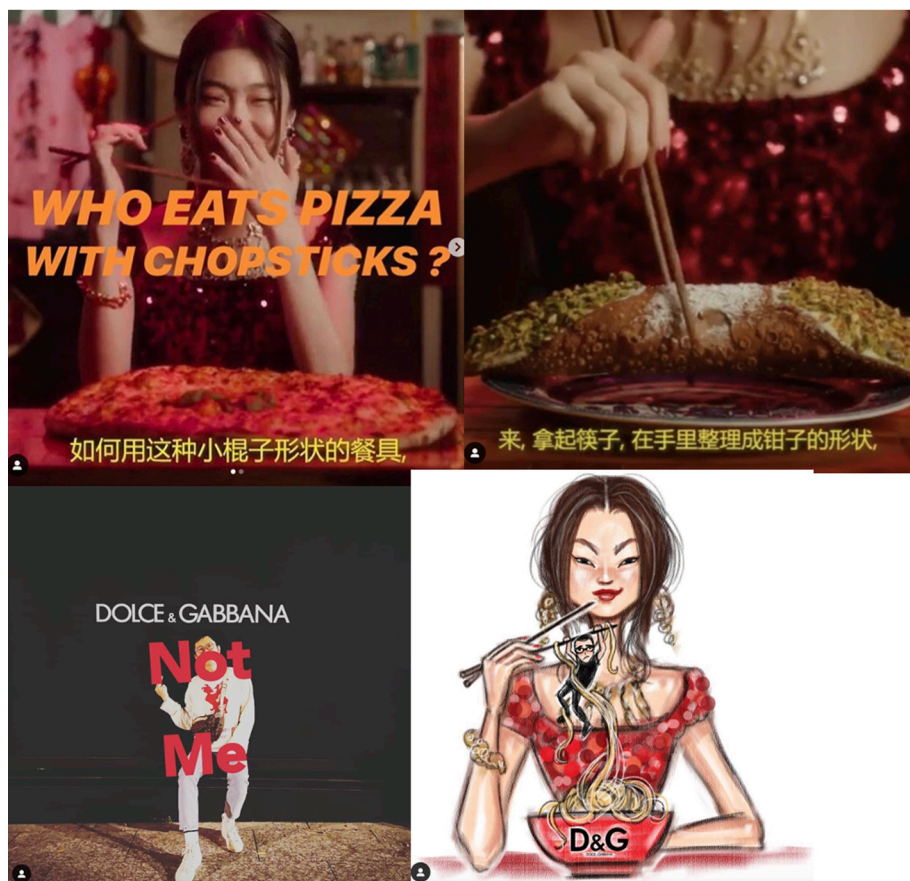


Fig. 1. Examples of images diffused by Instagram users to graphically show their reaction towards Dolce&Gabbana 2018 campaign for Chinese consumers.

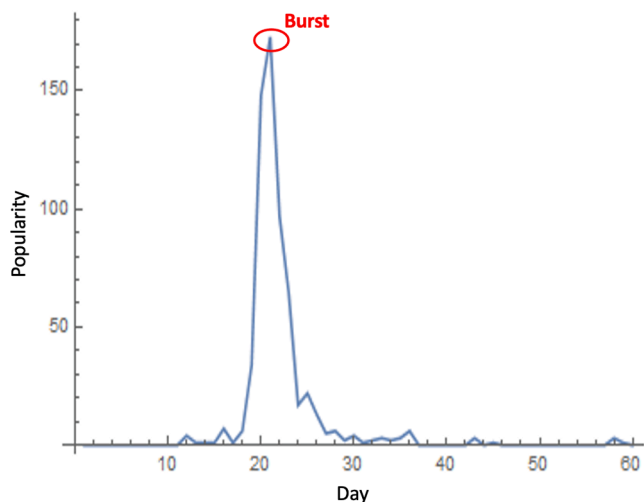


Fig. 2. Evolution of the posts including #DGTheGreatShow (across days), with clear evidence of a burst on Day 21.

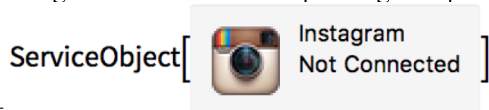
tomato sauce), pretending to conform to the national stereotype of an Asian model eating only with chopsticks. The marketing message led to negative consumers’ reactions towards the choice to show Italian food eaten with chopsticks, who started diffusing negative comments about the brand. The message was considered offensive for Chinese culture, since in consumers’ mind it embraced racial stereotypes such as the inability to eat with anything other than chopsticks. Since the integrated marketing communication principles guide the creative efforts of an advertising campaign (Kim, Kim, & Marshall, 2016; Porcu, del Barrio-Garcia, Kitchen, & Tourky, in press), Dolce&Gabbana usually tends to promote controversial advertising campaigns to generate debate. For instance, in some occasions the Italian Government even invited the brand to remove the campaign with sexist stereotypes. Thus, the Asian

accessible through search engines, and can be still shared among users. This means that the brand might potentially suffer for the consequences of this campaign in the future as well.

3.2. Data collection and procedure

The analysis of spontaneous information generated online by consumers is largely acquiring scholars’ interest because it provides a reliable source of insights for consumer research (Aleti et al., 2019; Arora et al., 2019; Athwal et al., 2019; Klostermann, Plumeyer, Boger, & Decker, 2018; Pantano & Stylos, 2020; Tellis, MacInnis, Tirunillai, & Zhang, 2019; Villarroel Ordens, Ludwig, De Ruyter, Grewal, & Wetzels, 2017), including the fashion industry (Pantano & Stylos, 2020; Walasek, Bhatia, & Brown, 2018). Since the analyses of users’ generated contents on Facebook, Instagram, Twitter allow determining how and how much certain concepts are mentioned and associated with by consumers (Walasek et al., 2018), analyzing specifically the contents provides deeper insights if compared with the traditional research based on surveys (Dindar & Yaman, 2018). Similarly, Instagram is recognized by recent researches as a powerful image-sharing network, where users share evaluations about their experience with brands, products, etc., rather than just to document their lives through pictures (Klostermann et al., 2018). Specifically, through the usage of hashtags, users mark content about a certain brand, indicating what concepts users associate with the brand (Klostermann et al., 2018). The present study exploits the hashtag “#DGTheGreatShow” to identify users’ contents associated with the event. Since this hashtag was initially launched by the brand on Instagram, as the favorite social media to promote the event, Instagram is the source for data collection. To this end, the research adopts Wolfram Mathematica software to collect all the posts including the hashtag #DGTheGreatShow generated by users on Instagram. In doing so, the software first starts a new connection with the social media by launching an authentication dialog, and then searches for the specific hashtag as it follows (1):

```
In[1]:= Instagram= ServiceConnect["Instagram"]
```



```
Out[1]=
```

```
In[2]:= instagram["UserSearch", {"Query" -> "#DGTheGreatShow"}]
```

(1)

campaign was consistent with the advertising background. However, it caused negative reactions. Fig. 1 shows examples of images diffused by users in Instagram against the campaign.

To stop the spreading, Stefano Gabbana on his personal Twitter profile declared that Chinese audience did not get the real message of the brand (now removed from social media). This comment generated even more (negative) reactions, since it was judged as rude and offensive by international audiences (i.e., “Italian food culture deemed racists”, “I don’t want to see your name anywhere in my house!!!”, “Shame on this stupid racist brand”). To further mitigate the online diffusion of negative messages towards the brand, Dolce&Gabbana cancelled the event in Shanghai and shut down social media usage in China. Simultaneously, Chinese and international e-commerce platforms and luxury retailers (i.e., Secoo, Yoox Net-a-Porter Group, Alibaba, JD.com, etc.) removed Dolce&Gabbana products from their platform. Although the brand made actions to cancel the hashtag (which means that no further posts can be uploaded with “#DGTheGreatShow”), the video of the Asian actress eating Italian food for Dolce&Gabbana is still available and freely

Secondly, the system collects all the posts published between the 1st of October 2018 (when the hashtag was created) and the 31st of December 2018 (when the hashtag was canceled), for a total of 653 posts, with 506,127 likes and 17,984 comments. Each hashtag also includes the exact time with the string “YEAR-MM-DD-HO:MI”, for instance “2018-11- 20-06:56” means year (2018) month (11) day (20) time (06.56).

To analyse the data, the research followed a two-step approach. Firstly, it evaluated the distribution of online information to understand the popularity evolution and the presence of a burst. In other words, it evaluated the number of posts including the hashtag “#DGTheGreatShow” that appeared online, and how this number evolved in the period of time. Secondly, the research focused on the automatic content analysis of the posts to identify what consumers said, in order to deeply understand the negative connotation of the information shared online.

4. Key findings

4.1. Modelling online information diffusion

To evaluate the distribution of the popularity across time (from October to December 2018), the software provides a set of machine learning algorithms that can be used to extract information from unstructured data like posts shared on social networks (Pantano & Stylos, 2020; Valdivia, Luzon, & Herrera, 2017). Machine learning algorithms are considered particularly efficient to extract patterns and make prediction on large data sets (as posts published online and shared among users) (Giglio et al., in press); in particular, the software provides the machine learning algorithms as pre-trained methods capable of manipulating and analyzing a wide range of unstructured data from different sources (Zotos, 2007).

In this paper, we consider the definition of information popularity provided by Hu et al. (2017) to evaluate the online evolution and the possible presence of burst. If we denote a generic piece of online information as i and we consider a certain period of time T (from October to December 2018), where T_i is the time of information i , $y_i(t)$ defines the popularity that the information i got at time t , $\forall t \in T$.

If $T_i \in \{1, 2, 3, \dots, T_i\}$ and $(y_i(T_i) - y_i(T_i - 1))$ is the largest element in $y_i(2) - y_i(1), y_i(3) - y_i(2), \dots, y_i(T_i) - y_i(T_i - 1)$, then, the burst of i occurs at time point T_i .

$$- y_i(T_i - 1)) \text{ is the largest element in } y_i(2) - y_i(1), y_i(3) - y_i(2), \dots, y_i(T_i) - y_i(T_i - 1), \text{ then, the burst of } i \text{ occurs at time point } T_i. \tag{2}$$

Drawing upon this definition, the software provides the graphical distribution of the online information (posts including the hashtag “#DGTheGreatShow”) across time in Instagram (Fig. 2), with the clear occurrence of a burst. Indeed, the number of posts rapidly increases on a certain day to decrease immediately after, thus the hashtag encountered the highest popularity on that day.

The highest number of posts occurs between the 17th and the 27th of November (2018), with a peak on the 21st day. In other words, in 10 days the spread of the negative messages related to the marketing campaign reached the highest number of consumers who shared the similar negative voice through Instagram, with the highest peak in one day.

Fig. 3 further shows the distribution of the posts at the specific time of the day (y axis) and the day of the month (x axis). Thus, on the 21st of November, consumers massively commented, shared and liked posts associated with the marketing campaign at any time of the day (like a firestorm), which evolved in a high and sudden peak (burst), by subsequently largely decreasing this activity to certain hours/days.

The probability density of the dataset further provides the probability distribution of the specific outcome (the information evolution to the burst event) as driven by the random variable consisting of the

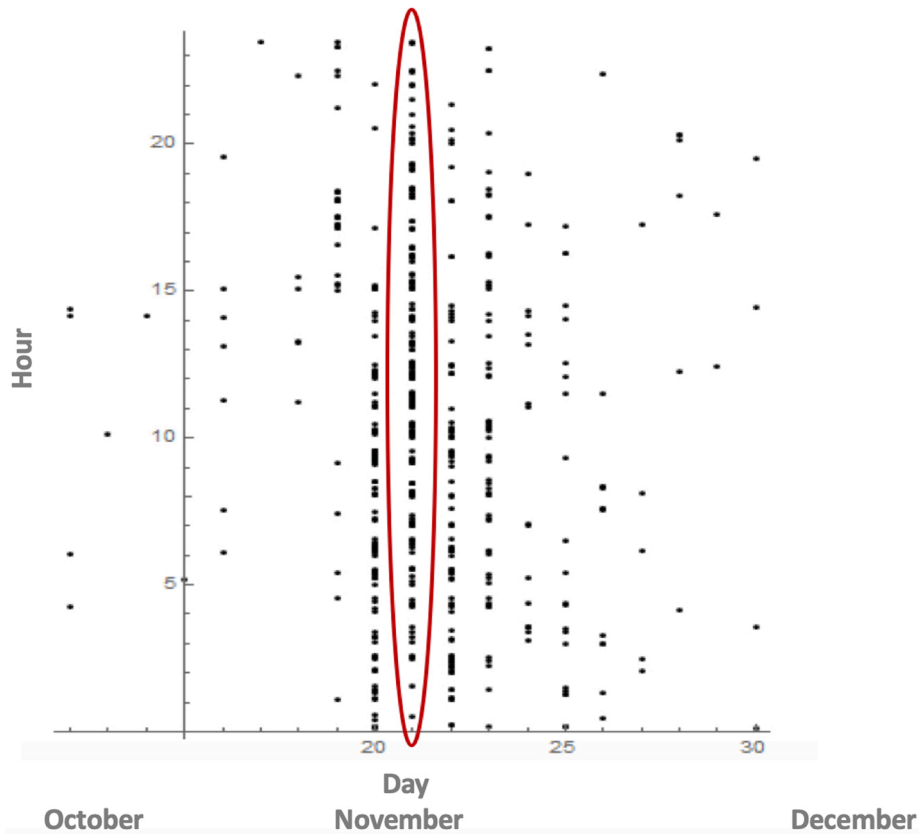


Fig. 3. Distribution of the posts including the hashtag #DGTheGreatShow (at exact time).

consumers’ messages to understand the likelihood of the burst event to occur. To identify the proper probability density function, Wolfram

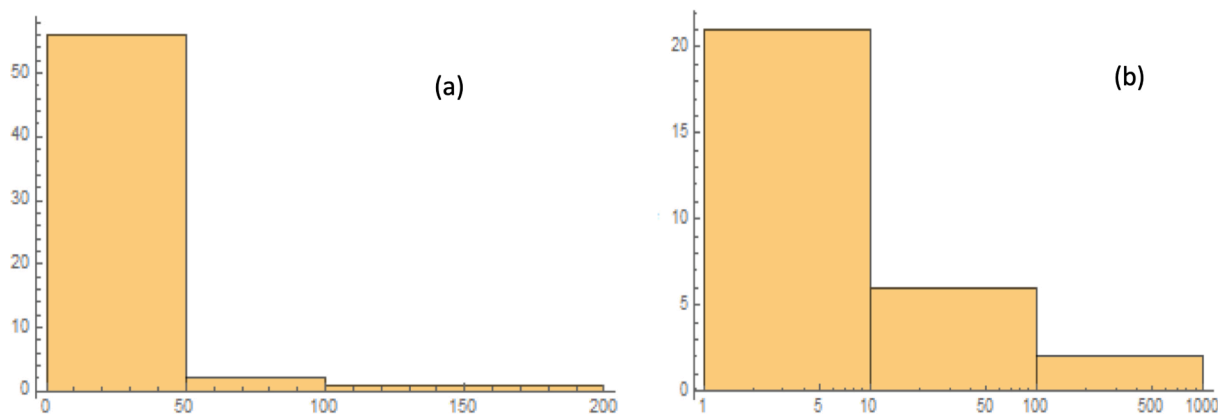


Fig. 4. (a) The linear distribution (on the left hand side), and (b) the logarithmic distribution (on the right hand side) of the posts evolution to the burst across time.

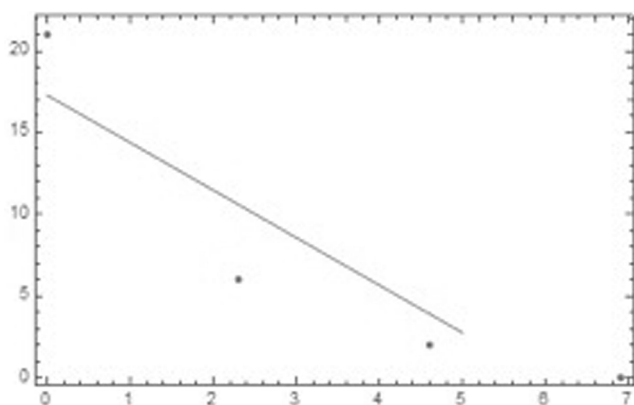


Fig. 5. The curve best fitting the evolution of posts in the referring period.

Mathematica provides the algorithm and Histogram plots to model the distribution of the data. Fig. 4 shows the probability density of the data sample in terms of linear distribution (a) (on the left hand side), and logarithmic distribution (b) (on the right hand side).

In order to find the mathematical function modelling the evolution of the posts including the hashtag (fitting the information evolution to a linear model), we used a fitting algorithm already available in Wolfram Mathematica software. To this end, the system automatically selects the function that best fits the data through the algorithm $f(x) = \text{LinearModelFit}[\text{data}, x, x]$. Thus, we obtain (3), showing the linear curve able to best fit the evolution of the posts, and Fig. 5 graphically visualizing the fit (considering the assumption of independent normal errors).

$$y(x) = 17.3 - 2.90977x \tag{3}$$

Table 1

Most frequent words appearing in the posts including the hashtag #DGTheGreatShow.

	FREQUENCY	NO. CASES	% CASES	TF • IDF
RACISM	125	104	15,95%	99,7
RACIST	85	67	10,28%	84,0
NOTME	46	46	7,06%	53,0
RESPECT	30	25	3,83%	42,5
DUMB	29	29	4,45%	39,2
LAME	29	29	4,45%	39,2
SHIT	24	22	3,37%	35,3
BOYCOTTDOLCE	18	17	2,61%	28,5
BOYCOTTDOLCEGABBANA	17	17	2,61%	26,9

4.2. Automated text analysis

The second step of the methodology of research is based on the deep understanding of the contents of the posts, in order to evaluate the positive or negative connotations of posts during the time period T . To this end, we followed the usual steps suggested by Humphreys and Wang (2018) for consumer research, by using automated text analysis to quantify qualitative data (like posts) in new methods of aggregating and displaying data. In this way, it is possible to identify patterns that might not be obvious at the granular level.

WordStat software helps to operationalize, analyse and validate the data. In particular, we used the software for the automatic extraction of the most important words from the text (the posts). This extraction resulted into the identification of the thematic structures of a text through the word frequency analysis, and the most frequent entities analysis (consisting of the words association with a meaning included in the “categorization dictionary” available in the software). This dictionary was obtained through a combination of natural language processing and statistical analysis. To ensure the stability of the factoring solution, all the entities with factor loadings higher than a specific criterion were considered as part of the extracted entity, thus low-frequency items were excluded.

Since some words are rarer than others but equally predictive, this it was necessary to weight them properly (Humphreys & Wang, 2018). Thus, if considering tf as the total frequency, and idf as i word in the document d (part of D total documents) frequency, formula (4) allowed to adjust the infrequently occurrence of words as (Humphreys & Wang, 2018):

$$tf \cdot idf = [1 + \log(\text{number of occurrences of word in } d)] \times \log\left(\frac{\text{total number of documents in } D}{\text{number of documents containing } w}\right) \tag{4}$$

Table 1 shows the results of the entities extraction from the text. In particular, the table clearly shows the negative attributes associated with the hashtag “#DGTheGreatShow”, where “racism” and “racist” emerges as the most frequent attributes. Thus, the posts related to the show on Instagram had a negative connotation.

5. Discussion

The present research aimed at modelling the viral effects of negative stereotypes adoption in a luxury brand’s marketing campaign when expanding in a growing market. To this end, it adopted a two step approach: (i) it evaluated the distribution of the posts related to a specific marketing campaign (identified with the hashtag “#DGTheGreatShow”); this diffusion of posts led to an unexpected burst on social media, which occurred when the evolution of the hashtag reached the highest number of users (highest level of popularity) in an extremely

short time; and (ii) the research automatically appraised the negative connotation of the posts related to the event, by identifying the racist association with the luxury marketing campaign (Table 1). In other words, the message related to the racist connotation of the specific marketing campaign spread among social media users (with emphasis on Instagram), by “infecting” a large amount of users in a short time as per an infectious disease leading to the burst, finally turning into brand hate. The specific information transmission among users can be modelled and represented by formula (3).

As consumers’ reaction on social media might vary across different cultural markets (Choi et al., 2020), these findings show that the luxury brand attempt in principle to develop an ad hoc marketing campaign for the Asian market. However, the campaign generated high volume of negative messages due to the stereotypes involved. Thus, findings modeled the disadvantages of the social media activities for a luxury brand, by replying to calls for further investigation concerning users’ negative reactions in social media with emphasis on the luxury context (Choi et al., 2020; Ko et al., 2019; Mandler et al., in press). Also, our research sheds light on the backfire effects (negative burst) of the usage of stereotypes in marketing communication campaigns.

Specifically, results also add knowledge to the investigation of burst (Barabasi, 2005; Gomez-Gardenes et al., 2016; Hu et al., 2017; Jung, 2017), with empirical evidence on the case of a real luxury brand failing to increase the market share in a growing market, due to the occurrence of a burst associated with negative users’ communications. In particular, the model of contagion proposed in this paper (3) shows the extent to which a piece of information quickly evolves across time, while specifying the negative connotation of the diffused messages (Table 1), which do not follow the traditional distribution curves (Barabasi, 2005; Hu et al., 2017). In this way, the research corroborates the analogies between the massive social media diffusion of a certain message (infectious) with the diffusion of infectious diseases (Kiss & Bichler, 2008; Rapp et al., 2013; WHO, 2020). Although the burst occurrence cannot be modeled with historical data, since it is considered a sudden and unexpected event (Barabasi, 2005; Jung, 2017; Monsted et al., 2017), the threat of burst event can be detected before the *explosion*. In other words, if a certain brand encounters a popularity evolution as the one modeled (Figs. 2 and 3), it might quickly evolve into a burst, with possible similar consequences to the ones of Dolce&Gabbana. In this case, the resulting brand hate evolved until the contagion become durable enough to push the brand to remove the hashtag, cancel the show and quit the market. The brand was not able to propose any inhibitory mechanism to stop the contagion before the burst, which effectively stopped almost one month after the burst (see Figs. 2 and 3). Similar to the compartmental epidemic models (Bettencourt et al., 2006; Goffman & Newill, 1964; Kiss & Bichler, 2008; Rapp et al., 2013), the contagion should be contained immediately, limiting users’ (consumers) further exposure to the message. Indeed, the information diffusion through social media makes the rate of reproducibility of the information (R_0) much higher than in the case of infectious diseases, rapidly leading to infodemic, as hypothesized by WHO (2020).

Results also demonstrate that the key factor responsible for the explosive contagion leading to the burst was the negative stereotypes associated with the campaign, which has been perceived as racist by consumers. Thus, especially the negative stereotypes associated with the messages contributed to the popularity (virality) of the message, thus extending the previous works on the characteristics of a message to become more popular (Aleti et al., 2019; Araujo et al., 2015; Casalo et al., 2020; de Vries et al., 2012; Pantano et al., 2019; Villarreal Ordenes et al., 2019). Similarly, our results show the impact of the massive and rapid diffusion of negative messages (burst) on the brand image, as solicited by Hansen et al. (2018), by modelling the consumers’ reactions towards a specific luxury brand marketing campaign.

Finally, drawing upon recent studies considering consumer generated contents on social media as trustable source for consumer research that mainly focused on Twitter (Aleti et al., 2019; Athwal et al., 2019;

Dindar & Yaman, 2018; Giglio et al., in press; Pantano & Stylos, 2020; Walasek et al., 2018), our study adds new knowledge on the evaluation of Instagram posts as data source, by confirming that also this platform might provide useful insights for marketing research. In this way, our study further extends the few works (Arora et al., 2019; Casalo et al., 2020; Riquelme et al., 2018), by describing how extracts consumers’ insights Instagram through new metrics and analytics, with emphasis on the specific sector of luxury brands.

While recent studies highlighted the link between brand popularity on social media and positive consumers’ attitude towards the brand (Arora et al., 2019; De Veirman et al., 2017; Seo et al., 2019; Stubb & Colliander, 2019), our study model the extent to which the higher number of social media (dis)“likes” (negatively) impacts the brand image. Indeed, boosting the number of “likes” is not always rewarding, while managers are required to distinguish between “likes” and (dis) likes, due to the dramatic effect of the burst of negative messages. Similarly, managers should consider the risky effect of using stereotypes in their campaigns, since the usage of racial stereotypes might rapidly evolve into brand hate (burst hate). Our results do not say that stereotypes always have this evolution, but they solicit manager attention towards the clear possibility of this rapid and hard to contain contagion. Finally, considering the evolution of the information as the contagion in the epidemic models would help managers to recover faster, as required by the exceptional rapidity of the burst.

6. Conclusion and future works

Informed by recent studies into social media marketing with emphasis on luxury brand management (Athwal et al., 2019; Bryson et al., 2013; Choi et al., 2020; Mandler et al., in press), and the information diffusion on social media similar to the diffusion of an infectious disease (Bettencourt et al., 2006; Goffman & Newill, 1964; Kiss & Bichler, 2008; Rapp et al., 2013), our study develops a novel perspective (burst model) of the way the negative stereotypes exerts negative influence on brand image in the context of a luxury brand aiming to massively increase the sales in a growing market.

In particular, the present study would support luxury brands towards a better understanding of the backfire effects of social media on luxury branding, by advising about the potential risk of a negative burst on social media like Instagram. This research further supports scholars and practitioners’ understanding of the viral effect of negative stereotypes among existing and prospective consumers, by pushing to consider actions to undertake to contain the contagion before the (negative) burst occurs. Indeed, the diffusion of the contagion also after the burst might lead brands to the dramatic decision to quit an existing market as in the case of Dolce&Gabbana. Nevertheless, the largely impossible ability to hide past action on the internet, and the incessant documentation that can always be retrieved and used with negative consequences for individual and society (Eichhorn, 2020) imply that the brand might suffer for the consequences of this campaign even further. Hence, the consequences might potentially be even larger in the future. Thus, luxury brands should systematically identify and monitor the most prevalent threats on social media, and rebut accordingly.

Despite the contributions, some limitations should also be taken into account. First, the present study only focused on a *negative* burst. However, future research might focus on a *positive* burst, in order to identify the different evolution of positive and negative messages for luxury brands. In other words, have the positive bursts a different popularity evolution if compared with the negative ones? If the negative one resulted in brand hate, do the positive ones result into brand love? Second, our results show that the negative connotation of the brand messages drove it to become extremely popular. However, the proposed model does not consider the characteristics of information as linguistics, the presence of videos, and the narrative styles of the original posts that might have contributed to the virality of the posts. Concerning the epidemic models, our model does not distinguish the characteristics of

users who have been “infected” and those who did not. New research would add supporting evidence on the relationship between the negative stereotypes, the characteristics of the information and individuals to model the contagion process more efficiently. Similarly, new studies might develop measurement scales to identify the “susceptible” consumers, in terms of the characteristics of the individual who will show the highest willingness to share certain information. Also, a measure of the R_t as the rate of reproducibility of certain negative messages, would help predicting the online evolution of information (contagion).

Third, this research only evaluated the diffusion among users across time, without considering the geographical diffusion of the information, which is also considered in the epidemic models. Thus, further studies might consider also the geographical evolution of the message among consumers, by including the geographical position of the posts published online when collecting data, to provide a more comprehensive model.

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Eleonora Pantano is Senior Lecturer (Associate Professor) of Marketing at University of Bristol since 2018. Her research activities mainly relate to the development of new customer solutions to improve retail analytics, strategies and management, with emphasis on the role of artificial intelligence, emotional analytics, and machine learning algorithms. She held Ph.D. in “Psychology of Programming and Artificial Intelligence” (2008), M.Eng. in Management (2005), and PG Cert in Higher Education Teaching and Supporting Learning (2016). She is also fellow of the Academy of Higher Education. Her findings appear in several books and textbooks, and in international peer-reviewed journals (i.e., *Computers in Human Behavior*, *Tourism Management*, *Journal of Business Research*, *Psychology and Marketing*). Her papers (more than 80) have also consistently pushed the frontiers in the area of marketing and have become highly cited by academics in the field (h-index 21, Scopus), by frequently achieving the award of “highly commended paper”.

She has always been curious about the world and the phenomena related to human dynamics in retail context, and feels lucky since her passion has become her work!