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Content analysis and message characteristics of Twitter: a case study of high-end makeup

Análisis de contenido y características del mensaje en Twitter: el caso del maquillaje de lujo

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ABSTRACT

This paper seeks to understand the impact of social media user interactions on luxury makeup brands' strategies. We used a mix of methodologies. The qualitative method was useful for content analysis on Twitter for two months of 2016. The quantitative method applied a zero-inflated Poisson regression model to determine tweet characteristics related to replies and an extensive interaction volume. This study reveals that the user report was predominant in the consumer journey concerning pre-purchase and post-purchase, but interaction prevails at the extremes of the journey. Also, tweet interaction increases with hedonistic values, specifically beauty, but surprisingly, links and videos within the tweet content undermine interaction. Pragmatically, luxury makeup brand marketers can use these findings to improve marketing strategies and explore new opportunities for the consumer journey.

Keywords: social media; consumer behavior; content analysis; consumer journey; high-end makeup.

RESUMEN

En este artículo, se busca comprender el impacto reportado por los usuarios de las redes sociales sobre las estrategias de las marcas de maquillaje de lujo. Para esto, se utiliza una combinación de metodologías: cualitativa para realizar un análisis de contenido mediante Twitter, durante dos meses de 2016 y cuantitativa, en la cual se aplicó el modelo de regresión Poisson inflado con ceros para determinar las características del tweet, relacionadas con la respuesta y un gran volumen de interacción. Este estudio revela que, en el viaje del consumidor, predomina la precompra y poscompra en el reporte del usuario, pero la interacción es mayor en los extremos del recorrido. Además, la interacción de los tweets incrementa con valores hedonistas, específicamente la belleza, pero sorprendentemente los enlaces y videos dentro del contenido del tweet desmejoran su interacción. De manera aplicada, los especialistas en marketing de marcas de maquillaje de lujo pueden utilizar estos hallazgos para mejorar las estrategias de marketing y explorar nuevas oportunidades en el viaje del consumidor.
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Palabras clave: redes sociales; comportamiento del consumidor; análisis de contenido; viaje del consumidor; maquillaje de lujo.

JEL: C00; R11.

INTRODUCTION

This research aims to understand the impact of social media user interactions on luxury makeup brands' strategy, being an area with little exploration and knowledge. Luxury brands are associated with exclusivity and visibility (Parguel *et al*., 2016), given that high-end products are linked to self-image and are an extension of the user's personality (Kulsiri, 2012; Parguel *et al*., 2016; Wiedmann *et al*., 2009). Therefore, luxury brands have reconsidered their marketing and communication strategies since the appearance of Web 2.0 to reach their target audience by creating fan pages, applications, blogs, exclusive events, and fashion shows (Boero, 2015). For them, social media are marketing communication tools and services that help understand the dichotomy of hedonic and utilitarian values associated with luxury (Annie, 2012). The understanding of this dichotomy is relevant since, for example, in online shopping, besides an initial vision based on utilitarian values such as personalization and aesthetics, luxury brands produce hedonic effects (McCormick & Livett, 2012), thus impacting the perceived value and experience throughout the consumer journey (Lemon & Verhoef, 2016).

The analysis of digital platforms enables a better understanding of the consumer (Brant, 2016), and this understanding should turn into specific strategies for different customer segments and better results. According to Think with Google (2013), 67 % of the Gen C population comprises social media and digital technology lovers who enjoy posting photos and sharing information online. These behaviors are relevant if one considers that the market is expected to grow 25 % by 2025 (Deloitte, 2014) and that future patterns in offline purchasing can be identified from online behavior (Houghton *et al*., 2013).

This research explains and assesses the behavioral patterns of luxury makeup users on Twitter, identifying the main challenges and opportunities for associated brands. We focus on Twitter since the messages posted on this social media affect the brand's image and awareness (Jansen *et al*., 2009). Consequently, Twitter is a valuable tool to identify user emotions during important events (Gul *et al*., 2016), which could be associated with the consumer journey and facilitate the understanding of consumer behavior.

This research intends to identify the users' behavioral patterns using the content analysis methodology proposed by authors such as Krippendorff (2012), Hsieh & Shannon (2005), and Riff et al. (2014), on which other Twitter research is based (Gul *et al*., 2016; Hosch et al., 2016; Vidal *et al*., 2015, Vidal, *et al*., 2016,). This social network enables us to learn about the users' expectations and experiences in real time (Gul *et al*., 2016). Also, this research delves into the influence of the message characteristics on the interaction volume and the absence of reaction using the zero-inflated Poisson regression model (ZIP) (Lambert, 1992).

We found that in the case of luxury brands, hedonic values produce divergent results. On the one hand, beauty in tweet content increase interaction, but social values undermine it. From the consumer journey perspective, the predominance of awareness during pre-purchase and loyalty during post-purchase, followed by advocacy, was identified in the report named Twitter findings "What users post", but the post-purchase phase takes precedence in interaction volume. Likewise, the message characteristics category reveals that links and videos within the tweet content weaken interaction. These results show a lack of coordination between the proposed online and offline marketing strategies, where social media such as Twitter make brands known, thus being exposed to the loss of potential customers that are sensitive to the purchase of a product. This paper advances knowledge on the subject because there are no papers with this type of analysis and focus on luxury brands that allow understanding the consumer journey in social media (Twitter).

Recognizing the behavioral report associated with the consumer journey based on psychological terms, the context of use, attitude, the values associated with luxury makeup brands in Twitter, and the message characteristics is sought through the content analysis of tweets on luxury makeup. Also, identifying the characteristics of the messages that influence users to have a large volume of interaction or no reaction is relevant from a managerial perspective. This analysis will enable us to learn about the method of election, the experience and journey of the high-end makeup consumer, and the message characteristics and explore the impact of the form of consumption and its behavior on the industry and how the strategies of digital marketing are presented.

The remainder of this paper is organized as follows. In the next section, we describe the methodology and the data used in our study. Subsequently, we present the conceptual background for the analysis. In the fourth section, we describe the results and finish with a discussion and the conclusions of our work.

Identification of behavioral patterns in social media

Social media provides knowledge of users from an angle that is not easily noticeable in an offline environment. On Twitter, it is possible to gain visibility and acquire symbolic power in social movements (Wang, 2016). Research on this social network is considered helpful for identifying emotions during important social events and towards multiple topics (Gul *et al*., 2016). Messages published on Twitter affect image and brand awareness, being a suitable means to monitor perception from communities' discussions (Jansen *et al*., 2009). Consequently, we can determine whether a user's attitude towards a brand is positive, negative, or aspirational or whether the aim is to influence it (Balazs & Velásquez, 2016; Khan *et al*., 2014). Those messages also enable the identification of values associated with brands (either hedonic or utilitarian) and the context of use (Annie, 2012; McCormick & Livett, 2012).

There is ample evidence of content analysis of social media in the literature available, specifically Twitter. For example, there are studies on the users' reactions to phenomena such as Michael Jackson's death, with analysis of the existence of web links and their origin (Hoe & Sian, 2011). Vidal *et al.* (2015) have identified consumption patterns and possible future consumer situations from what , where, when, and with whom the user eats . Moreover, personal characteristics have been inferred from the likes analyzed, such as an individual's IQ, political party, sexual orientation, marital status of parents, and beliefs (Kosinski *et al*., 2013). Even the intentionality of messages has been established; Hosch *et al*. (2016) determined that 60 % of the messages during election campaigns in the Netherlands were persuasive. The latter allows companies and brands to adjust their value proposals to the preferences and behaviors identified on social media.

Social media reveals the user type by classifying them as average users, influencers, or brands (Gul *et al*., 2016; Hutter *et al*., 2013). In this manner, we can detect opinion leaders with a more significant influence on the audience. Their level of influence on social media is associated with their number of followers, which allows assessing the impact on and relevance to an audience (Freberg *et al*., 2011; Li *et al*., 2013; Neves *et al*., 2015). Although there is no specific way to identify if a user is an influencer, there are certain aspects that are considered, such as the structure of the social media, the dissemination of messages (Cha *et al*., 2010; Reilly *et al*., 2014), the number of messages, mentions, and favorites (Gul, *et al*., 2016; Li *et al*., 2013), and the associated replies (Neves *et al*., 2015).

Nevertheless, in addition to the tweet author (user type), the message characteristics are also crucial to the influence on other users. Here, the presence and characteristics of images, videos, and redirection to other sites using links (Bello *et al*., 2017) show how both users and brands use videos. In the case of images, colors are relevant to the analysis because previous studies such as that of Demattè *et al*. (2007) have identified that black color, cold tones, and tints allusive to darkness are associated with upmarket or high-end and refined or elegant products.

Likewise, the semiotic and symbolic analysis of the image content has enabled the identification of users' and brands' rhetoric from the communication of needs, social status, and expectations (Oswald & Oswald, 2012). In this manner, users' images on social media help them learn about personality features, emotions, and associated expressions, reflecting the user's identity (Feng & O'Halloran, 2012; Rokka, 2015). Links redirecting to social media or different web portals complement the message shared by the user, thus facilitating a complete understanding of the communicative intention (Hoe & Sian, 2011). The level of tweeting interaction is also a determining factor since each tweet generates "face-to-face" communication (Steinmann *et al*., 2015) within the consumer journey.

The consumer journey

Customer's experience with a brand conditions purchase decision. Therefore, it is critical to identify the route that the consumer takes and observe interactions between company and customers, focusing on the customer's point of view (Richardson, 2010), which is possible through social media such as Twitter. For the correct management of customer experience, Lemon and Verhoef's (2016) proposal is a holistic understanding based on the customer journey. They identify three main phases in the consumer journey, namely: pre-purchase (that is, awareness, consideration, and preference), purchase (that is, purchase and payment), and post-purchase (that is, experience, repurchase, loyalty, and advocacy). From this perspective, the web presence challenges brands to adapt to a change of language in order to promote brand identity, seeking to reduce the steps in purchase decision (Boero, 2015).

It is acknowledged that social media such as Twitter influence decision-making in the first two phases (pre-purchase and purchase). In a study carried out with users of different brands such as Motorola, General Motors, among others, Powers et al. (2012) established the role of social media in the purchase decision. They also analyzed the behavior of users and the sales cycle, identifying that 21 % of users look for information on social media to confirm purchase intention. Social media introduce new products and facilitate the relationship between emotions and logic in shopping. The favorable or unfavorable perception of an item directly affects the intention to buy a product or acquire a service (Zhang & Mao, 2016).

Twitter may also have a role in the third phase of the consumer journey: post-purchase. Jansen et al. (2009) conducted a Twitter content analysis study on Starbucks' type of interaction and established that 80 % of users expressed opinions and experiences about products or brands, asked questions, and shared information. The use of emoticons as a mechanism to express or emphasize emotions associated with an experience has also been studied (Vidal et al., 2016). Finally, influencers are users who recommend, talk about, and review brands, products, and services, achieving an effect on others (Neves et al., 2015). They are brand promoters or detractors, clearly manifesting their perception and experience at the end of their journey and positively or negatively influencing the others' first phase of the journey. Thus, customer experience is dynamic from the consumer journey perspective (Lemon & Verhoef, 2016).

METHODOLOGY

Studies carried out by Gul et al. (2016), Hosch et al. (2016), Vidal et al. (2015), Vidal et al. (2016), among others, have identified consumer behavioral patterns from the content analysis of Twitter. This social network is preferred for this type of analysis since it has no restrictions and has the prior consent of users as a requirement to be part of the platform (Twitter, 2016). It allows getting acquainted with users in real time (Hoe & Lee, 2011), given that they share their opinions, experiences, expectations, and points of view (Gul *et al*., 2016).

Twitter data collection took place in October and November 2016. During this time of the year, there is a 56 % increase in the searches for makeup due to celebrations and dance seasons (Think with Google, 2014). The search for tweets was carried out using the keywords "luxury makeup" in the Twitter search system (search.twitter.com - esTwitter). Luxury makeup was defined according to three types of users: high-luxury, luxury, and semi-luxury (Pinzón *et al*., 2018).This search resulted in 1,154 retrieved tweets, of which 479 were excluded because although they contained the search keywords "luxury makeup," they did not correspond to a segment or a luxury brand[1]. The remaining 675 tweets were compatible with the true meaning of luxury makeup and became the subject matter of our analysis.

We performed a manual content analysis on the data collected (tweets on luxury makeup) (Krippendorff, 2012). From this analysis, large amounts of social media texts could be converted into small summaries to understand how decisions were made, permitting the identification of insights in the shared reports (Gandomi & Haider, 2015). Then, we quantified the content found in the tweets by creating themes and subtopics or features (Krippendorff, 2012), identifying the frequency with which they appeared (Hsieh & Shannon, 2005). A numerical value was assigned to their presence to systematize and quantify the descriptions in the tweets (Riff *et al*., 2014), being the subjects' analyzed characteristics inclusive values; that is, a tweet could belong to several features. We defined the themes and features in light of the theoretical review findings: user type, message characteristics, and behavioral report.

After classifying each tweet on such themes and features, a ZIP model was applied. The most common outcome of a tweet is no reaction at all; so, according to Lambert (1992), a finite mixture model of two distributions combines an indicator distribution for zero cases (no reaction) and a standard count distribution (Mullahy, 1986) for the interaction, reflecting this reality. ZIP assumes that probability p, the unique observation (tweet), is 0, and 1-p is the observed interaction volume (replies + likes + retweets) that follows a Poisson distribution represented by λ as a random variable. Therefore,

$$\mathrm{pr}(Y_j = 0 \mid x_j, z_j) = F_j + (1 - F_j)\exp(-\lambda_j) \qquad (1)$$

$$\mathrm{pr}(Y_j = n \mid x_j, z_j) = (1 - F_j)\exp(-\lambda_j)\frac{\lambda_j^n}{n!} \text{ for n=1,2,...} \qquad (2)$$

For the second equation, to better deepen the analysis, some of the variables were amplified to finetune the insights generated. For instance, (1) in the characteristics of the image, we amplified the predominant color, including cold, neutral, and warm tones. (2) Also, we amplified the presence of women. (3) Furthermore, the

[1] For example, they were makeup artists who did not use luxury products or who only talked about beauty, makeup, or events not related to luxury products. Likewise, tweets that were in a language other than English or that referred to job searches were rejected.

figure 1 was specified as a product. (4) In message characteristics, we amplified links to determine where they directed: video, marketplace, blog or news, other social media, and even broken links. Finally, (5) for the customer journey, we divided the pre-purchase phase into awareness and consideration and the post-purchase phase into loyalty and advocacy.

Social media such as Facebook and Twitter increase social mobilization and enable the identification of information shared by the users (Bennett & Segerberg, 2012), making it very convenient for content analysis and viral marketing of messages. Moreover, it is possible to identify communities and market segments in these social media (Hachaj & Ogiela, 2017), which is not a superficial matter in the case of luxury brands since the meaning of brands and consumer preferences may change depending on the consumers' cognitive age (Amatulli *et al*., 2015). Likewise, user reports on social media enable us to learn about behavioral and attitudinal patterns to predict users' behavior and preferences (Osuna & Pinzón, 2017). Specifically, Twitter is associated with the immediacy of communication with users, from which it is possible to learn about experiences and the link between consumers and brands (Smith *et al*., 2012). This is the main reason the paper analysis focuses on Twitter rather than Facebook.

The interconnection of users in social media also establishes links of influence between them, as proposed by Christakis & Fowler (2013), compared to the three degrees of influence, where messages with negative connotations tend to be more viral than positive ones (Stieglitz & Dang-Xuan 2013). Therefore, the analysis of hashtags enables user classification by the information that they share (Wang *et al*., 2016).

RESULTS

Content analysis

The content analysis performed on the 675 tweets collected between October and November, the subject matter of the present study, was carried out covering three main topics: user type, message characteristics, and behavioral report.

Type of user

Following Freberg *et al*. (2011), Li *et al*. (2013), and Neves *et al*. (2015), we identified that 44.8 % of users were influencers, given their large number of tweets and that their number of followers was higher than the followings, thus having an impact on other users. Besides, 48.2 % were average users because their number of followers did not show an effect on users, and 7 % were brands, of which 57.4 % were beauty brands and 42.5 % were product distributors, as presented in Table 1 (user type).

Message characteristics

How the information or the opinion is presented or a tweet is written can influence the behavior of other users. Therefore, identifying the main message characteristics provides data about the form of interaction and communication and an overall understanding of the user's report. Five features are analyzed: (i) the message characteristics; (ii) the tones, in case the message has an image; (iii) the content of the image; (iv) if there is a video, the type of video; and (v) the interaction of the tweet, as shown in Table 1 (message characteristics). A managerial implication is that by identifying the core ideas in a tweet, they can be used in brand communication to influence users and promote more significant interaction.
There was text in 100 % of the tweets, 51.4 % of which were accompanied by an image. Also, there were links in 85.78 % of the tweets, 40.76 % redirected to a news or blogs portal and 20.55 % to a shopping website.

In the case of images in the tweet and redirection to a social network with images, they were characterized by neutral (47.1 %) or warm tones (46.9 %). Images showed mostly products (58.4 %); 32.4 % of them had a female, and only 3.3 % had texts with sentences allusive to luxury.

Most of the tweets with videos recommended products (71.8 %), while 22.7 % were tutorials and 3.6 % reflected luxury lifestyles. Finally, 53.18 % of the tweets had no interaction, 62.59 % had likes, 30.95 % had been retweeted, and 6.47 % had replies.

Table 1. User type and message characteristics

Theme	Features	Percentage	Frequency
I. User type	Influencer	44.8	300
	Brand	7	47
	Average user	48.2	323
II. Message characteristics	Text	100	675
	Image	51.4	347

	Video (link)	15	87
	Shopping website (link)	20.5	119
	Broken link	8.9	52
	Links redirecting to other social media	14.7	85
	Links redirecting to news or blog	40.7	236
If tweet has an image			
Image tones	Cool	6.6	28
	Neutral	47.1	199
	Warm	46.9	198
Types of images	Product	58.4	339
	Store	0.5	3
	Nature	0.2	1
	Social	3.1	18
	Text	3.3	19
	Man	1.7	10
	Girl	0.3	2
	Woman	32.4	188
If tweet has a video			
	Recommended use	71.8	79
	Tutorial	22.7	25
	Lifestyle	3.6	4
Social media interaction	Reply	6.5	28
	Retweet	30.9	134
	Like	62.6	271
	None	53.2	359

Source: own elaboration

Behavioral report

Tweets report user behavior that could be a past behavior at the time or an intention (future behavior), allowing for a better understanding of their needs, experiences of use, and recognition of market opportunities. The following aspects were analyzed in the features: user's attitude, values associated with high-end makeup, the phase in the consumer journey; and the context of use. The results are shown in Table 2 (behavioral report).

Table 2. Behavior report

Theme	Features	Percentage	Frequency	Sample tweets
III.I Attitude	Positive	17.4	118	"Kardashian Ben Nye Banana Luxury Powder 3oz 85g Bottle Luxury Face Makeup sdfg dlvr.it/MklDX6 - eBay" (example of influential)
	Negative	0.4	3	
	Influential	79.6	538	
	Aspirational	2.5	17	
III.II Associated values				
Hedonic values	Social	4.2	64	"The best mornings start with GORGEOUS treats from the Armani team #beauty

	Lifestyle	17.4	266	#bbloggers #bblogger #makeup #luxury #fashion #fbloggers #style" (example of beauty)
	Beauty	38.0	582	
Utilitarian values	Problem-solving	5.4	83	"Ben Nye Powder Banana Luxury Powder Makeup / Foundation Cosmetics Visage Poudre ln.is/thainessinfo…" (example of product characteristics)
	Meeting needs	8.6	132	
	Product characteristics	26.5	406	
III.III Consumer journey	Pre-purchase	76.3	518	"Ben Nye Luxury Banana Powder 1.5 oz Bottle Face Makeup Kim Kardashian $9.99 bonanza.com/ (…)" (example of awareness)
	Awareness	56.4	383	
	Consideration	15.9	108	
	Preference	4.0	27	
Purchase	Purchase	1.6	11	"Recebidos @sephora #princess #makeupaddict #makeup #makeupclass #metalic #sephora #luxury… instagram.com/(…)" (example of purchase)
Post-purchase		22.1	150	"The opulent sparkle of @nuxe_us nuxefrance #fur #luxury #skin #glisten #makeup #body instagram.com/ (…)" (example of loyalty)
	Experience	4.1	28	
	Repurchase	0.4	3	
	Returned products	0.0	0	
	Loyalty	9.6	65	
	Advocacy	8.0	54	
III.IV Context of use	Social event	2.4	18	"Get a makeover at #Bengaluru's new @Sephora_India store. Details here: toi.in/o6n2iZ #luxury #makeup #beauty" (example of merchandising and news)
	Fashion show	2.5	19	
	Habit	21.2	158	
	Gift	3.4	25	
	Search	2.5	19	
	Merchandising and news	68.0	507	

Source: own elaboration

In the tweets, the attitude most frequently observed was influential with a commercial intention, or the promotion of a positive attitude among users towards a brand or a product (79.6 %), followed by a positive attitude where users emphasized experiences with the use of and preference for some product or brand (17.4 %).

We observed that a tweet could have values associated with hedonism and utilitarianism, being hedonistic values predominant in 60 %. Specifically, the use of luxury makeup was associated with beauty as an end or a means in 38 %, followed by lifestyle in 17.4 %, showing not only the use of luxury makeup but also its extension to other luxury lines, and social relations (4.2 %), emphasizing status. The utilitarian values, for their part, accounted for 40 % of the tweets, highlighting the characteristics of a product in 26.5 % (benefits, references, or a brand ambassador). Also, 8.6 % of the tweets expressed the satisfaction of needs such as searching for some product or the intention to use.

The most frequent phase in the consumer journey was the pre-purchase phase (76.3 %), followed by the post-purchase phase (22.1 %). Only 1.6 % of the tweets were associated with the purchase phase (distribution between phases and their stages in Figure 1). From the consumer journey perspective, stages are selective for content analysis.

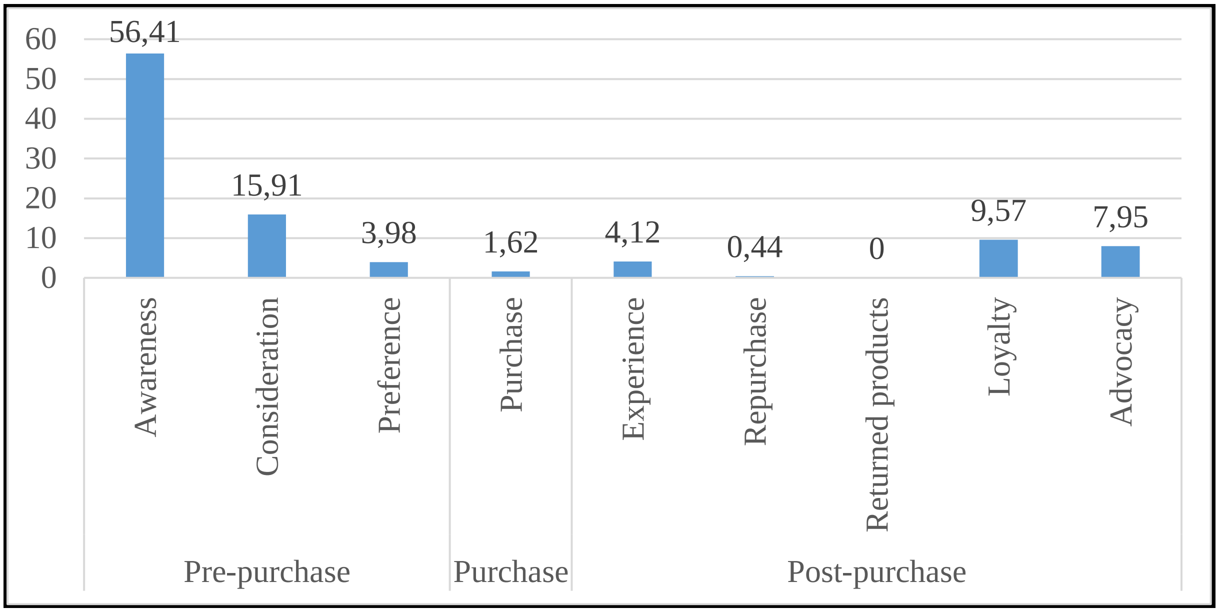

Figure 1. Customer Journey

Source: own elaboration based on Lemon & Verhoef (2016) model.

In the pre-purchase phase, 56.4 % of the total tweets were classified as awareness-raising, 73.94 % of which mentioned a product or brand with a marked commercial intention and showed a lifestyle associated with luxury. In the purchase phase, 1.62 % of the tweets reported the specific moment of purchase and receipt of a product. However, 83.45 % of all the tweets reported an intent to purchase or sought to influence the purchase.

The third phase of the consumer journey grouped 9.6 % of the total tweets, where the loyalty stage was the majority (43.3 %), followed by advocacy (8 %). This last stage was characterized by users who expressed a commitment to the brand by recommending specific products or brands to other users based on their own experience.

Finally, the most frequent context of use was associated with merchandising and news (68 %), followed by the luxury makeup consumption habit (21.2 %).

Zero-inflated Poisson regression model

The ZIP model performed on the 675 tweets analyzed the influence of the message characteristics on the volume of interaction or absence of reaction. The results are shown in Table 3.

Table 3. Zero-inflated Poisson regression model

Category	Sub-Category	Variable	Coefficient	Z
NO REACTION AT ALL…				
Type of User		Influencer	-0.2294	-0.75
		Brand	-0.3606	-0.72
Message Characteristics	Text	Presence of a brand within the text	0.6955	1.32
	Image	Presence of an Image	-2.3990***	-4.33
	Image - Colors	Presence of a predominant color	2.1576***	2.86
	Image - Content	Human Being	0.612	1.37

		A Figure	-0.8924	-1.7*
		Text as Image	-3.0859***	-2.57
	Video	Presence of a video	-0.2033	-0.38
	Links	Presence of a redirecting link	-1.2070***	-2.67
Behavioral Report	Hedonic Values	Social	-1.7580**	-2.21
		Lifestyle	0.1224	0.37
		Beauty	-0.0446	-0.1
	Utilitarian Values	Problem solution	0.0333	0.09
		Meeting needs	1.2238***	3.52
	Context of use	No Habit	-0.135	-0.25
	Attitude	Positive	0.4102	0.38
		Aspirational	-2.416	-0.92
		To influence or Commercial	0.306	0.29
Customer Journey	Pre-purchase Phase	Pre-purchase	2.4105*	1.92
	Post-purchase Phase	Post-purchase	1.028	0.87
Intercept			-2.6495	-1.58

Note**:** *p*-value: ***< 0.01; **< 0.05; *< 0.10

Source: own elaboration

As mentioned early, a message without reaction occurs in 53.18 % of tweets. For this subset of the data, we found that the likelihood of no reply decreases if the tweet has an image (-2.39; $p < 0.01$), a figure (-0.89; $p < 0.10$), or a text (-3.08; $p < 0.01$). It also decreases if the tweet has a link redirecting the user (-1.21; $p < 0.01$) or references social hedonic values (-1.76; $p < 0.05$), proving that the number of reactions is influenced by aspects that move the desire and aspiration for the brand, such as social hedonic values and or links, because they create a sense of connection with the brand. We also found that the tweet increases its likelihood of no reply if the image has some predominant color (2.16; $p < 0.01$) or refers to commercial utilitarian values (1.22; $p < 0.01$).

Regarding the user type category, interaction volume is more considerable when it is an influencer (0.44; $p < 0.01$) or a brand (1.55; $p < 0.01$). From the message characteristics perspective, the interaction increases when the tweet has the image of a woman (3.48; $p < 0.01$) or a figure of the product (1.32; $p < 0.01$), while the degree of interaction decreases when the tweet has the name of the brand within the text (-0.20; $p < 0.10$) or the image has predominant colors such as cold (i.e., blue, green) (-0.90; $p < 0.01$), neutral (i.e., black, white, gray) (-0.76; $p < 0.01$) or even warm tones (i.e., red, yellow) (-0.90; $p < 0.01$). Considering that the presence of a woman increases tweet interaction, the image of other human beings (i.e., man, girl) diminishes it (-2.12; $p < 0.10$). The same phenomenon happens with other pictures different than the product itself (-0.90; $p < 0.05$).

An interesting result about the role of links is found. While links decrease the likelihood of having no replies, they also undermine the interaction volume (Table 4), especially links redirecting the user to a marketplace (-2.39; $p < 0.01$), a blog or news (-1.66; $p < 0.01$), or other social media (-1.27; $p < 0.01$). Broken links (links that do not work) also have a negative impact (-1.94; $p < 0.01$). Thus, links do not promote interaction, but reduce it. Surprisingly, we could not find any relationship between a video in the tweet and replies.

An interesting result about the role of links is found. While links decrease the likelihood of having no responses, they also undermine the volume of interaction (table 4), especially links related with redirecting the user to a marketplace (-2.39; $p<0.01$), a blog or news (-1.66; $p<0.01$), to other social networks (-1.27; $p<0.01$). We also found that broken links (links that does not work) also have a negative impact (-1.94; $p<0.01$). By these general means, it was identified that the links do not provide interaction. in fact, they reduce it. Surprisingly, we could not find any relationship between the presence of a video in the tweet with the response.

Table 4. Interaction volume

Category	Sub-Category	Variable	Coefficient	*Z*
INTERACTION VOLUME				
User type	User	Influencer	0.4373***	5.01
		Brand	1.5494***	10.96
Message characteristics	Text	A brand within the text	-0.2027*	-1.92
	Image - Predominant color	Cold tones	-0.9031***	-4.16
		Neutral tones	-0.7567***	-4.25
		Warm tones	-0.8980***	-5.19
	Image - Content	Human Being	-2.1237*	-1.9
		Human Being - Woman	3.4836***	3.12
		Picture	-0.9012***	-3.15
		Picture - Product	1.3205***	4.51
		Text as image	-0.1585	-0.72
	Video	A video	-0.5327	-0.73
		Video about use recommendations	0.085	0.14
	Links redirecting to…	Video	-0.535	-0.6
		Marketplace or shopping website	-2.3939***	-16.78
		Blog or news	-1.6569***	-16.21
		Other social media	-1.2723***	-9.37
		Broken (not working)	-1.9420***	-11.09
Behavioral report	Hedonic values	Social	-0.5938***	-5.94
		Lifestyle	1.1347***	13.62
		Beauty	0.7313***	5.95
	Utilitarian values	Problem-solving	0.1078	0.97
		Meeting needs	1.3436***	15.28
	Context of use	No habit	-0.3111**	-2.42
Customer Journey	Pre-purchase phase	Awareness	-0.0979	-0.77
		Consideration	-1.2917***	-7.94
	Purchase phase	Purchase	-1.2625***	-4.94
	Post-purchase phase	Loyalty	-0.6564***	-5.04
		Advocacy	-0.1044	-0.72
Intercept			0.7342***	4.33

Note: *p*-value: ***< 0.01; **< 0.05; *< 0.10

Source: own elaboration

In the behavioral reporting category, tweets have more significant interaction if they are associated with hedonic values of lifestyle (1.13; $p < 0.01$) and beauty (0.73; $p < 0.01$), while those related to social aspects (-0.59; $p < 0.01$)or a non-habitual context of use (-0.31; $p < 0.05$) generate less interaction. Besides, if the tweet has the utility value of meeting needs, the interaction will be higher (1.34; $p < 0.01$). A tweet will have less interaction if reference is made to the pre-purchase stage of consideration (-1.29; $p < 0.01$), the purchase phase (-1.26; $p < 0.01$), and the post-purchase stage of loyalty (-0.65; $p < 0.01$) in the customer journey category. Therefore, the customer journey must be focused on the extremes (awareness or advocacy) not to impact the interaction volume negatively.

This study reveals that the user report was predominant in the consumer journey concerning pre-purchase and post-purchase, but some interaction is predominant at the extremes of the journey. Also, tweet interaction increases with hedonistic values, specifically beauty, but surprisingly links and videos within the tweet content undermine interaction.

DISCUSSION

The purpose of this research is to explain the behavior patterns of luxury makeup users, based on their reports on Twitter, recognizing market opportunities and brand challenges. Research results evidence that Twitter is a social network that helps identify consumer behavior patterns from the content analysis of its publications.

The findings show the predominance of an average user type and the absence of interactions, as expected, considering that the lifestyle associated with luxury brands is not massive and that followers —being high impact influencers only— interact with celebrities (artists, bloggers). The latter can adjust the flow of information towards the audience, establish links between them, and identify the type of interaction (Bello *et al*., 2017; Christakis & Fowler, 2013; Wang *et al*., 2016).

In line with Bello *et al*. (2016), we identified that the tweets were characterized by texts accompanied by images or links directing to blogs or news and shopping websites, thus inviting to purchasing or knowing products. Likewise, according to Jansen *et al*. (2009), the images that showed both products and women affect brand perception and awareness and reveal personal user characteristics, as noted by Kosinski *et al*. (2013). The images with women and the product or predominant cold and neutral colors associated with luxury (Demattè *et al*., 2007) have the most significant influence on interaction.

The characteristics of the tweets were recognized from the behavior reports, where users referred to hedonic values allusive to beauty and utilitarian values in which the product characteristics predominate. This phenomenon confirms the dichotomy of luxury products in social media raised by Annie (2012), who states that this hedonic-utilitarian dichotomy does not permit an adequate use of these platforms. It can be caused by the presence of multiple customer segments (Annie, 2012), where luxury makeup users are expected to link brands with their self-image as an extension of their personality (Kulsiri, 2012; Parguel *et al*., 2016; Wiedmann *et al*., 2009), communicating primarily hedonic values. However, to make the message effective in terms of their interaction, it must appeal to hedonic values, such as lifestyle associated with luxury and beauty, and utilitarian values to meet a need.

Likewise, the users' behavior is identified in the journey by merchandising and news, followed by consumption habits and the use of makeup, as strategies for brand awareness, influence, and recommendation (blogs, fashion shows, events, among others) (Boero, 2015). In addition, by associating the tweets with positive and influential attitudes more frequently, they seek to arouse interest from other users and affecting their purchase intention (Jansen *et al*., 2009; Zhang & Mao, 2016).

Because of the reported behavior, the use of Twitter by luxury brands is related to the opposite ends of the consumer journey: brand knowledge in the pre-purchase phase and loyalty and recommendation in the post-purchase phase, thus suggesting the type of interaction among users and between company and customer (Richardson, 2010). In light of what Powers *et al*. (2012) have expressed, having greater report in the opposite ends of the consumer journey demonstrates that the role of Twitter is providing knowledge for the current purchase, as well as knowledge and influence for subsequent purchases (Houghton *et al*., 2013; Lemon & Verhoef, 2016; Vidal, *et al*., 2015). In this way, any online marketing strategy must emphasize awareness or advocacy within the customer journey for positive impact on the interaction volume. In this way, any online marketing strategy must emphasize in awareness or advocacy within the customer journey for positive impact on the interaction volume, because there will be more interaction in those sub-phases. For this reason, the marketers can identify users who are in these sub-phases and function as "influencers" for the brand to influence more users and leverage marketing strategies.

CONCLUSION

In practice, the results of this research have an impact on the development of complementary marketing strategies in the luxury makeup industry as it helps improve coordination with digital marketing strategies and the perception that one has towards luxury makeup brands. The challenge of mobilizing purchases, overcoming the knowledge stage, and influencing potential customers of this or other segments can be faced to the extent that values associated with the brand are explicitly used in each communications opportunity that arises and in the characteristics of the message and its author.

Finally, the reports also pointed to one trend linked to luxury makeup: a preference and search for vegan, natural and cruelty-free products. Other high-end products could be analyzed (e.g., food, clothes) and compared in future research. Likewise, other sectors could be explored.

Conflict of interest statement

The authors state no conflict of interest in the preparation of this paper and that the content and opinions in it do not compromise the institutions for which they work.

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