*Clío América*/ Vol. 14, No. 28 - 2020 / 543 – 560
http://dx.doi.org/10.21676/23897848.4146

# Analysis of content and message characteristics in Twitter: the case study of luxury make-up

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

**Cindy Paola Pinzón-Ríos[1], Ignacio Osuna-Soto[2] & Ernesto Barrera-Duque[3]**

[1]INALDE Business School, Universidad de La Sabana, Colombia. ***Email***: cindy.pinzon@inalde.edu.co
[2]INALDE Business School, Universidad de La Sabana, Colombia. ***Email:*** ignacio.osuna@inalde.edu.co
[3]INALDE Business School, Universidad de La Sabana, Colombia. ***Email:*** ernesto.barrera@inalde.edu.co



**To cite this article:** Pinzón, R. C., Osuna, S. I. & Barrera, D. E. (2020). Analysis of content and message characteristics in twitter: the case study of luxury make-up. *Clío América, 14*(28), 543-560. http://dx.doi.org/10.21676/23897848.4146

Recibido: 26 junio de 2020
Aceptado: 19 de octubre de 2020
Publicado en línea: noviembre 20 de 2020

## ABSTRACT

This paper seeks to understand the impact of social media users interactions reported in luxury makeup brands strategy. We used a mix of methodologies: the qualitative methodology was useful to analyze a content analysis that was performed through Twitter during two months of 2016. In the quantitative methodology we applied a Zero Inflated Poisson Regression Model to determine tweet characteristics related with response and a large volume of interaction. This study reveals that in the consumer journey, the user report was predominant in relation to pre-purchase and post-purchase, but the some interaction is predominant at the extremes of the journey. Also, tweet interaction is increased with hedonistic values, specifically beauty, but surprisingly links and videos within the tweet content undermine its interaction. In an applied way, marketers in luxury makeup brands can use these findings to improve marketing strategies and explore new opportunities in the consumer journey.

**Keywords:** social media; consumer behavior; content analysis; consumer journey; luxury makeup.

## RESUMEN

Este artículo busca comprender el impacto reportado por los usuarios de las redes sociales sobre las estrategias de las marcas de maquillaje de lujo. Para lo cual se utiliza una combinación de metodologías: cualitativa para realizar un análisis de contenido mediante twitter, durante dos meses de 2016. En la metodología cuantitativa se aplicó el Modelo de Regresión de Poisson Inflado Cero (Zero Inflated Poisson Regression Model ) 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, en el reporte del usuario predomina la precompra y poscompra, pero la interacción es mayor en los extremos del recorrido. Además, la interacción de los tweets incrementa con valores hedonistas, específicamente como la belleza, pero sorprendentemente los enlaces y videos dentro del contenido del tweet desmejoran su interacción. De manera aplicada, los especialistas en marketing en marcas de maquillaje de lujo pueden utilizar estos hallazgos para mejorar las estrategias de marketing y explorar nuevas oportunidades en el recorrido del consumidor.

**Palabras clave:** redes sociales; comportamiento del consumidor; análisis de contenido; viaje del consumidor; maquillaje de lujo.

**JEL:** C00; R11.

## INTRODUCTION

The reason for this research is to understand the impact social media users interactions in 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 luxury products are linked to self-image and are an extension of the user's personality (Kulsiri 2012; Wiedmann, et al, 2009; Parguel, *et al*, 2016). This is why luxury brands have reconsidered their marketing and communication strategies since the appearance of the Web 2.0, in order to reach the target audience by the creation of fan pages, applications, blogs, exclusive events and fashion shows (Boero, 2015 ). For them, social networks are marketing communications tools and services that help to 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, in addition to an initial vision based on utilitarian values such as personalization and aesthetic vision of the product, luxury brands also develop hedonic effects (McCormick & Livett, 2012), thus having an impact on the value perceived 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 the *Think with Google* report (2013), 67 % of the "C-Gene" population is made up of social networks and digital technology lovers, who enjoy publishing photos and sharing information on social networks. These behaviors are relevant if one takes into account 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 behavior patterns of luxury make-up users on Twitter, identifying the main challenges and opportunities for associated brands. We focus on Twitter since the messages published in this social network affect the brand's image and awareness (Jansen, *et al*, 2009) and, consequently, Twitter is a useful tool to identify the users emotions during important events (Gul, *et al*, 2016), which could be associated with the consumer journey, facilitating the understanding of the consumer's 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), as well as by Riff, et al (2014), on which other research on the Twitter social network is based, (that is Vidal , *et al*, 2015, Hosch, et al, 2016, Vidal, *et al*, 2016, Gul, *et al*., 2016), since this social network enables us to learn about the users' expectations and experiences in real time (Gul, *et al*, 2016). Also, this research deepens in the influence of the messages characteristics on the volume of interaction, as well as no reaction at all, using the Zero Inflated Poisson Regression Model (ZIP henceforth) (Lambert, 1992).

We found that in the case of luxury brands hedonic values present divergent results. On the one hand, beauty in tweet's content increase interaction, but social values undermine such interaction. Also, from the consumer journey perspective, a predominance of pre-purchase in awareness and post-purchase in loyalty followed by advocacy were identified in the report, but the post-purchase phase is predominant in the volume of interaction. Likewise, in the message characteristics category evidence that links and videos within the tweet content undermine its interaction. These results show a disarticulation between the proposed online and offline marketing strategies, where the use of social networks like Twitter is perceived to make the brands known, thus being exposed to lose potential clients that are sensitive to the purchase of a product. This paper keeps moving forward knowledge because there are no papers with this type of analysis and focus on luxury brands, which allows understanding the consumer journey in social media (Twitter).

In this manner, the recognition of the behavioral report associated with the consumer's journey, the context of use, attitude, the values associated with the luxury makeup brands in the Twitter social network and the message characteristics, are sought through the content analysis of tweets on luxury makeup. Also, the recognition of which are the characteristics of the messages that influence the users to have a large volume of interaction or no reaction at all is relevant from a managerial perspective. This analysis will enable to learn about the method of election, the experience and the journey of the luxury make-up consumer, and the message characteristics, allowing to explore the form of consumption and its behavior having an impact on the industry and on the way in which 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 finally, we finish up with a discussion and conclusions of our work.

**Identification of behavioral patterns in social networks**

Social networks allow the knowledge of users from an angle, which is not easily noticeable in an offline environment. In Twitter it is possible to gain visibility and acquire a symbolic power in social movements (Wang, *et al*, 2016). Research in this social network considers it as a useful tool for the identification of emotions during important social events and on multiple topics (Gul, *et al*, 2016). Messages published in Twitter affect image and brand awareness, being a good means to monitor perception from the discussions of communities (Jansen, *et al*, 2009). Consequently, it is possible to identify the attitude of a user towards a brand, determining if it is positive, negative, or aspirational, or if the aim is to have an influence on it (Khan, *et al*, 2014; Balazs & Velásquez, 2016). Also, it enables the identification of values associated with brands (either hedonic or utilitarian) and the context of use (Annie, 2012; McCormick & Livett, 2012).

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

Social networks allow us to recognize the type of user by classifying them as average users, influencers, or as brands (Hutter, *et al*, 2013; Gul, *et al*., 2016). In this manner, it is possible to identify leading opinion users with a greater influence on the audience. Influencers are users who recommend, talk about and carry out assessments on brands, products and services, achieving an effect on the others (Neves, *et al*, 2015).

The level of influence in social networks is associated with the number of followers, being a method that allows for an assessment of the impact and relevance in an audience (Freberg, *et al*, 2011; Li, *et al*, 2013; Neves, *et al*, 2015). And although there is no specific way to identify if a user is an influencer, there are certain aspects that are taken into account, such as the structure of the social network, the dissemination of messages (Cha, et al, 2010; Reilly, *et al*, 2014); the number of messages, mentions and favorites (Li, *et al*, 2013, Gul, *et al*, 2016); and the associated responses (Neves, *et al*, 2015). But, in addition to the author of the tweet (type of user), the message characteristics are also important for the influence on other users. Herein, the presence and characteristics of images, videos, as well as the redirection to other sites using links (Bello, *et al*., 2017). This is how videos are used by both users and brands to promote products and tell their stories (Smith, *et al*., 2011). In the case of images, the colors present are a relevant aspect to analyze, in view of the fact that previous studies such as that of (Demattè, *et al*., 2007) have identified that the black color, cold tones and tints allusive to darkness are associated with upmarket or high-end and fine or elegant products.

Likewise, the analysis of the images content at the semiotic and symbolic levels has enabled the identification of the users' and brands' rhetoric, from the communication of needs, social status and expectations (Oswald & Oswald, 2012). In this manner, users' images on social networks allow them to learn about personality features, emotions and associated expressions, being a reflection of the user's identity (Feng & O'Halloran, 2012; Rokka, 2015). Also, the presence of links redirecting to social networks 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 determinant, since each tweet generates the sensation of a "face-to-face" communication (Steinmann, *et al*., 2015) framed in the consumer journey.

**The consumer journey**

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

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

The Twitter social network 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 the type of Starbucks interactions and established that 80 % of users expressed opinions and experiences about products or brands, as well as asked questions and shared information. Also, the use of emoticons as a mechanism to express or emphasize emotions associated with an experience has been studied (Vidal, et al., 2016). Finally, influencers are users who recommend, talk and assess 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, but at the same time positively or negatively influencing the others' first phase of the journey. This is why customer experience, from the perspective of the consumer journey, is dynamic (Lemon & Verhoef, 2016).

## METHODOLOGY

Studies carried out by Vidal, *et al*., (2015), Hosch, *et al*, (2016), Vidal, *et al*., (2016), and Gul *et al*., (2016), among others, have identified consumer behavioral patterns as from the content analysis on Twitter. This social network is the one 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). This public network allows to get 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 the months of October and November 2016, since during this time of the year there is a 56 % increase in the searches for makeup, due to the 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).

The search on the Twitter system resulted in 1 154 recovered tweets, of which 479 were rejected because although they contained the search keywords "luxury makeup", they did not correspond to a segment or to a luxury brand1. The remaining 675 tweets corresponded to the true meaning of luxury makeup and these tweets were the object of our analysis.

A manual content analysis was performed to the data collected (that is, tweets on luxury makeup) (Krippendorff, 2012). From this analysis, large amounts of social media texts could be converted into small summaries, allowing the understanding of how decisions were made, permitting the identification of insights in the reports that were shared (Gandomi & Haider, 2015). In this manner, the content found in the tweets were quantified through the creation of themes and subtopics or features (Krippendorff, 2012), identifying the frequency in which the latter appeared (Hsieh & Shannon, 2005). A numerical value was assigned to their presence, in order to systematize and quantify the descriptions present in the tweets (Riff, et al, 2014), being the analyzed characteristics of the subjects inclusive values , that is, a tweet could belong to several features. The topics and features were defined in the light of the findings of the theoretical review, namely: Type of user, message characteristics, and behavioral report.

Once we had classified each tweet on such topics and features, a ZIP model was performed. The most common outcome of a tweet is a no reaction at all, so according to Lambert (1992), a finite mixture models of two distributions combining an indicator distribution for the zero case (no reaction) and a standard count distribution

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

(Mullahy, 1986) for the interaction, reflecting this reality. ZIP assumes that with probability p the unique observation (tweet) is 0, and with probability 1-p is the observed volume of interaction (responses + likes + retweets) that follows a Poisson distribution represented with 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 in 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 presence of a predominant color including cold, neutral and warm tones. (2) Also, we amplified the presence of a human being specifying woman. (3) Furthermore, the figure was specified as a product. (4) In message characteristics, we amplify links determining where they were directed: video, marketplace, blog or news, other social networks an even broken link. Finally, (5) in the customer journey we separate the pre-purchase phase in awareness and consideration and the post-purchase phase in loyalty and advocacy.

Social networks such as Facebook and Twitter increase social mobilization and enable the identification of information that is 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 networks (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 networks enable us to learn about behavioral and attitudinal patterns, in order to predict the users' behavior and their 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 that exists between consumers and brands (Smith, *et al*, 2012), this is the main reason why the paper analysis focuses on Twitter rather than Facebook

The interconnection of users in social networks also allows the establishment of the link of influence between them, as proposed by Christakis & Fowler (2013), compared to the scale of three people of influence, where messages with negative connotations tend to be more viral than positive (Stieglitz & Dang-Xuan 2013). Therefore, the analysis of hashtags enables the classification of users by means of the type of information that interests them from what they share (Wang, *et al*, 2016).

## RESULTS

**Content analysis**

The content analysis performed to the 675 tweets collected between October and November, object of the present study, was carried out covering three main subjects: Type of user, message characteristics, and behavioral report.

**Type of Users**

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

**Message characteristics**

The way in which the information or the opinion is presented, or a tweet is written, can influence the behavior of other users, therefore the identification of the message's main characteristics allows to learn about the form of interaction and communication, as well as to have an overall understanding of the user's report. In this manner, there are five features that 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 also (v) the interaction of the tweet, as presented in Table 1 (message characteristics). A managerial implication is that by identifying which are the key axes in a tweet, these can be used in brand communication to influence users and therefore generate greater interaction.

There was text in 100 % of the tweets, 51.4 % of which were accompanied directly by an image. Also, were links in 85.78 % of the tweets, 40.76 % redirected to a news or blogs portal, 20.55 % took to a shopping portal.

In the case of the presence of images in the tweet and the redirection to a social network with images, these were characterized by neutral tones (47.1 %) or warm tones

(46.9 %). Images showed mostly products (58.4 %); 32.4 % of them had a female presence; and only 3.3 % of them had texts with phrases allusive to luxury.

Most of the tweets with videos recommended the use of products (71.8 %), while 22.7 % were tutorials and 3.6 % reflected luxury lifestyle models. Finally, 53.18 % of the tweets had no interaction, 62.59 % had "like (s)", 30.95 % had been retweeted, and 6.47 % had a response.

**Table 1.** Type of user and Message Characteristics

| Theme | Features | Percentage (%) | Frequency |
|---|---|---|---|
| I. Type of user | 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 Portal (link) | 20.5 | 119 |
| | Broken link | 8.9 | 52 |
| | Redirecting links from others social | 14.7 | 85 |
| | Redirecting links from news or blog | 40.7 | 236 |
| If, have 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, have video | | | |
| | Recommend use | 71.8 | 79 |
| | Tutorial | 22.7 | 25 |
| | Lifestyle | 3.6 | 4 |
| Social media interaction | Answer | 6.5 | 28 |
| | Retweet | 30.9 | 134 |
| | Like | 62.6 | 271 |
| | Neither | 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. In this manner, the following were analyzed in the features: the user's attitude; the values associated with luxury make-up; the moment in the consumer journey; and the context of use. The results are shown in Table 2 (behavior report).

**Table 2.** Behavior report

| Theme | Features | Percentage (%) | Frequency | Exemplar tweets |
|---|---|---|---|---|
| III.I Attitude | Positive | 17.4 | 118 | "Kardashian Ben Nye Banana Luxuary Powder 3oz 85g Bottle Luxury Face Makeup sdfg dlvr.it/MklDX6 - Ebay" (To influence Example) |
| | Negative | 0.4 | 3 | |
| | To influence | 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 #bbloggers #bblogger #makeup #luxury #fashion #fbloggers #style"(Beauty example) |
| | Lifestyle | 17.4 | 266 | |
| | Beauty | 38.0 | 582 | |
| Utilitarian values | Problem resolution | 5.4 | 83 | "Ben Nye Powder Banana Luxury Powder Makeup / Foundation Cosmetics Visage Poudre ln.is/thainessinfo…" (Characteristics of product example) |
| | Meet needs | 8.6 | 132 | |
| | Characteristics of product | 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/(…)" (awareness example) |
| | 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/(…)" (purchase example) |
| Post-purchase | | 22.1 | 150 | "The opulent sparkle of @nuxe_us nuxefrance #fur #luxury #skin #glisten #makeup #body instagram.com/(…)" (loyalty example) |
| | Experience | 4.1 | 28 | |
| | Repurchase | 0.4 | 3 | |
| | Return 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" (Merchandising and news example) |
| | 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 that was most frequently observed was the influence having a commercial intention, or the promotion of a positive attitude in users towards a brand, or a product (79.6 %), followed by a positive attitude (17.4 %), where users emphasized experiences with the use and preference for some product or brand.

It was observed that a tweet could have values associated with hedonism and utilitarianism, being hedonistic values predominant in 60 %. Specifically, the use of luxury make-up was associated with beauty as an end or a means in 38.0 %, followed by a lifestyle in 17.4 %, evidencing not only the use of luxury make-up but also its extension to other luxury lines, as well as social relations (4.2 %), where the status was emphasized. The utilitarian values, for their part, accounted for 40 % of the tweets, highlighting the characteristics of a product in 26.5 % (that is benefits, references, or the presence of a brand ambassador). Also, 8.6 % of the tweets expressed the satisfaction of needs like the search for some product or the intention of use.

It was observed that the most frequent phase in the consumer journey was the pre-purchase phase (76.3 %), followed by the post-purchase phase (22.1 %) and 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.

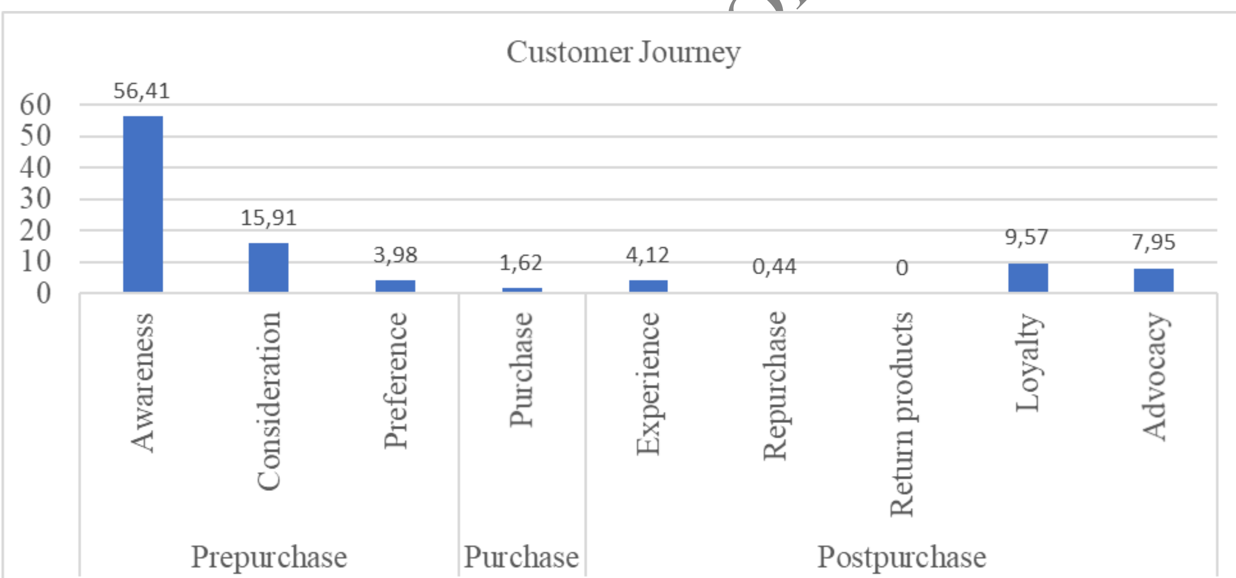


**Figure 1.** Customer Journey

**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, being 73.94 % of the tweets the space where a product or brand was announced with a marked commercial intention, and that also 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 the advocacy report (8.0 %). This last stage was characterized by users who expressed a commitment to the brand by making recommendations to other users regarding specific products or brands based on their own experience.

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

**Zero Inflated Poisson Regression Model**

Also, the ZIP model performed to the 675 tweets, object of the present study, analyzed the influence of the messages characteristics in the volume of interaction or no reaction from a tweet. The results are shown in Table 3

**Table 3.** Zero Inflated Poisson Regression Model *(p-value ***<0.01; **<0.05; *<0.10)*

| 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 |

**Source:** own elaboration



As mentioned early, a message without reaction is present in 53.18 % of tweets. For this subset of the data we found that the likelihood of a no response decreases if the tweet has an image (-2.39; p<0.01) the image has a figure (-0.89; p<0.10) and 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 it references to social hedonic values (-1.76; p<0.05). This shows that a greater reaction is influenced by aspects that move the desire and aspiration for the brand, such as social hedonic values and the presence of a link, because it generates a sense of connection with the brand. We also found that the tweet increases its likelihood of no response if the image has some predominant color (2.16; p<0.01) and when the tweet refers to commercial utilitarian values (1.22; p<0.01).

In the degree of interaction, it is observed, in the type of user category, that it is greater when it is an influencer (0.44; p<0.01), as well as if it is a brand (1.55; p<0.01). From the message characteristics perspective, the interaction increases when the tweet has an image of a woman (3.48; p<0.01) and a figure of the product (1.32: p<0.01), while the degree of interaction decreases when the tweet has the presence of the name of the brand within the text (-0.20; p<0.10), the image has predominant colors such cold tones (i.e. blue, green) ((-0.90; p<0.01), neutral tones (i.e. black, white, gray) (-0.76; p<0.01) or even warm tones (i.e. red, yellow) (((-0.90; p<0.01). Accounting for the fact that the presence of a woman increases tweet's interaction, the presence of other human beings (i.e. man, girl) diminishes interaction (-2.12; p<0.10). Same phenomena happens with other figures 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 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.** Volume of interaction *(p-value ***<0.01; **<0.05; *<0.10)*

| **Category** | **Sub-Category** | **Variable** | **Coefficient** | **Z** |
|---|---|---|---|---|
| **VOLUME OF INTERACTION** | | | | |
| Type of User | User | Influencer | 0.4373*** | 5.01 |
| | | Brand | 1.5494*** | 10.96 |
| Message Characteristics | Text | Presence of 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 |
| | | Figure | -0.9012*** | -3.15 |
| | | Figure - Product | 1.3205*** | 4.51 |
| | | Text as Image | -0.1585 | -0.72 |
| | Video | Presence of a video | -0.5327 | -0.73 |
| | | Video about use recomendations | 0.085 | 0.14 |
| | Links redirecting to… | Video | -0.535 | -0.6 |
| | | Marketplace pr shopping portal | -2.3939*** | -16.78 |
| | | Blog or news | -1.6569*** | -16.21 |
| | | Other Social Network | -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 solution | 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 Phase | -1.2625*** | -4.94 |
| | Post-Purchase Phase | Loyalty | -0.6564*** | -5.04 |
| | | Advocacy | -0.1044 | -0.72 |
| Intercept | | | 0.7342*** | 4.33 |

**Source:** own elaboration

In the behavioral reporting category, tweets have greater interaction if they are associated with hedonic values of lifestyle (1.13;p<0.01) and beauty (0.73;p<0.01), while those associated with social aspects generate less interaction (-0.59; $p<0.01$), as well as those that are related with a non-habitual context of use (-0.31; $p<0.05$). Also, if the tweet has the utility value of meeting needs the interaction will be greater (1.34; $p<0.01$). Likewise, the 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. This allows us to see that the customer journey must be framed in extremes (awareness or advocacy) to not impact negatively on the volume of interaction.

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

## DISCUSSION

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

The results show the predominance of an average type of user and the absence of interactions. This result is as expected, considering that the lifestyle associated with luxury brands is not massive and that followers -being high impact influencers only- interact with celebrities (this is artists, bloggers, etc.). The latter can adjust the flow of information in the audience and allow for the establishment of links between them, as well as to identify the type of interaction (Bello, *et al*., 2017; Wang, *et al*., 2016; Christakis & Fowler, 2013).

In line with Bello, *et al*, (2016), we identified that the tweets were characterized by having the presence of texts accompanied by images or links that led to blogs or to the news, as well as links that led to shopping portals, thus inviting to the purchase or knowledge of products. Likewise, the images that showed both products and women, which according to Janse, *et al*., (2009) affect brand perception and awareness, show personal user characteristics as evidenced by Kosinski, *et al*., (2013). The images with the presence of women and the product are the ones that have the greatest influence on the interaction. Having thus greater interaction the images with predominance in cold and neutral colors that are sensor-associated with luxury (Demattè, *et al*., 2007).

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

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

As a consequence of the reported behavior, the use of Twitter in luxury brands is related to the opposite ends of the consumer journey: to brand knowledge in the pre-purchase phase and to loyalty and recommendation in the post-purchase phase, thus showing the type of interaction among users and between company and client (Richardson, 2010). In the light of what Powers *et al*., (2012) have expressed, the fact of having a greater report in the opposite ends of the consumer journey shows that the role of Twitter is knowledge for the current purchase, as well as knowledge and influence for the next purchases (Lemon & Verhoef, 2016; Houghton *et al*., 2013 and Vidal, *et al*., 2015). In this way, in online marketing strategy for positive impact in the volume of interaction must be emphasized.in customer journey in awareness and/or advocacy. Porque son en esas sub-fases en las que se tendrán mayor interacción, para esto se pueden identificar usuarios que estén en estas sub-fases y funcionen como "abanderados" de la marca para mover a más usuarios y apalancar las estrategias de marketing en ellos.

## CONCLUSION

In practice, the results of this research have an impact on the luxury make-up industry in the development of complementary marketing strategies between what is done online and what is done offline, due to a lack of coordination with digital marketing strategies and in the perception that one has towards luxury make-up brands. The challenge of mobilizing purchases, overcoming the knowledge stage, as well as the opportunity to influence potential customers of this or of other segments can be developed to the extent that a clear use of values associated with the brand is exercised in each communications opportunity that arises, as well as in the characteristics of the message and in the author of such message.

Finally, the reports also identified one trend linked to luxury make-up: is a preference and search for vegan products, that are natural, and free from animal abuse. For future research, other luxury products could be analyzed (e.g. food, clothes), and also make comparisons between such products. Likewise, other sectors could be analyzed.

**Conflict of interest statement**

The authors of the present paper state that during the realization of the same there was no conflict of interest and that the content and appreciations of it, do not compromise the institutions for which they work.

## REFERENCIAS BIBLIOGRÁFICAS


Amatulli, C., Guido, G. & Nataraajan, R. (2015). Luxury purchasing among older consumers: exploring inferences about cognitive Age, status, and style motivations. *Journal of Business Research*, *68*(9), 1945-1952. https://www.sciencedirect.com/science/article/pii/S01482963150 00053?casa_token=xVrpaL7cGAkAAAAA:cOerwIZw19SYmBJp0kbRqc30udpH9cad30hzZscCcNUW09YUBQvUVF1e-2-f657gJb7ezHbe9w

Annie, S. (2012). The potential of social media for luxury brand management. *Marketing Intelligence & Planning*, *30*(7), 687-699. https://www.emerald.com/insight/content/doi/10.1108/0263 4501211273805/full/html?casa_token=avH6_gkNtJYAAAAA:Yoahzh_n6CONaFNKWONqGPfGiRvkL9kQ0OFHLtq2_xwjWYSSlmmm0-YjUWFkgOIFQx6ROwczIMl3xWuWIcojWV17zvsQzJFXSSn8YvkdemGvGKWlMmk

Balazs, J. A. & Velásquez, J. D. (2016). Opinion mining and information fusion: a survey. *Information Fusion*, *27*, 95-110. https://www.sciencedirect.com/science/article/pii/S15662535150005 36?casa_token=u5X28txOn1cAAAAA:7eEeoOqnTLFTpJIlWFu9FhABEXvodnu6-tO3ojHaNTAnE0tWuTxvOfZTRGv6NSQc04_M0RqSHA

Bello, G., Hernandez J. & Camacho, D. (2017). Detecting discussion communities on vaccination in twitter. *Future Generation Computer Systems*, *66*, 125-136. https://www.sciencedirect.com/science/article/pii/S0167739X16302175?casa_token=wyUyhWBMREAAAAAA:n2nibQ1mGzl3Yjg1j305aEzSLmEOLSLAc7fri

UxdmW2S2TLlAXan-p8SFYIZMV7178umHkjRjw

Bello, G., Jung, J. & Camacho, D. (2016). Social big data: Recent achievements and new challenges. *Information Fusion*, *28*, 45-59. https://www.sciencedirect.com/science/article/pii/S 1566253515000780?casa_token=emJ3kf4ZtfYAAAAA:QpNKs3J-R9PN94JFoTdy0hZ3ffxywr2-DqIjy2OjRPV6D1aB_9CWWF5h1Fv5t9ks8bNJzq-T9A

Bennett, W. & Segerberg, A. (2012). The logic of connective action: Digital media and the personalization of contentious politics. *Information, Communication & Society*, *15*(5), 739-768. https://doi.org/10.1080/1369118X.2012.670661

Boero, M. (2015). The language of fashion in postmodern society: A social semiotic perspective. *Semiotica*, *2015*(207), 303-325. 10.1515/sem-2015-0037

Brant, A. (2016) Using an Algorithm to Figure Out What Luxury Customers Really Want. Harvard Business Review. 1 – 4. https://hbr.org/2016/07/using-an-algorithm-to-figure-out-what-luxury-customers-really-want

Cha, M., Haddadi, H., Benevenuto, F. & Gummadi, P. K. (2010). Measuring user influence in twitter: The million follower fallacy. *Icwsm*, *10*(10-17), 30. https://ojs.aaai.org/index.php/ICWSM/article/view/14033

Christakis, N. & Fowler, J (2013). Social contagion theory: examining dynamic social networks and human behavior. Statistics in medicine, *32*(4), 556-577. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3830455/

Deloitte. (2014). *Global Power of Luxury Goods: in the hands of the consumer*. https://www2.deloitte.com/tr/en/pages/consumer-business/articles/global-powers-of-luxury-goods-2014.html

Demattè, M., Sanabria, D. & Spence, C. (2007). Olfactory–tactile compatibility effects demonstrated using a variation of the Implicit Association Test. *Acta psychologica*, *124*(3), 332-343. https://www.sciencedirect.com/science/article/pii/S0001691806000527?casa_token=3vDxnLV92U8AAAAA:c46jSRY6cRYOlOKWLHQBhnSUdst8dLDX0LeELxfKB7G7N2kaLZE-E7Ne_Nc7btY5ReD-dsGMRg

Feng, D. & O'Halloran, K. (2012). Representing emotive meaning in visual images: A social semiotic approach. *Journal of Pragmatics*, *44*(14), 2067-2084. https://www.sciencedirect.com/science/article/pii/S0378216612002603?casa_token=z_0slUTzduEAAAAA:E8JnPMA64QcoLEgVDWXbQU2XkQzQ-CARs0eDOn5aUvz8lmt-wKpUTyhQEAjt26ztVEITU97gDQ

Freberg, K., Graham, K., McGaughey, K. & Freberg, L. (2011). Who are the social media influencers? A study of public perceptions of personality. *Public Relations Review*, *37*(1), 90-92. https://www.sciencedirect.com/science/article/pii/S0363811110001207?casa_token=wwaMvBq2GvUAAAAA:ZWwjz00gDBNdrV04v9TMGnCJ5yAdzSQjeMRleVlI57YWzWtRC3tcakWyRoLLoQ8QC2ZhqzquOQ

Gandomi, A. & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137-144. https://www.sciencedirect.com/science/article/pii/S0268401214001066

Gul, S., Mahajan, I., Nisa, N., Tariq, S., Jan, A. & Ahmad, S. (2016). Tweets speak louder than leaders and masses: An analysis of tweets about the Jammu and Kashmir elections 2014. *Online Information Review*, *40*(7), 900-912. https://doi.org/10.1108/OIR-10-2015-0330

Hachaj, T. & Ogiela, M. (2017). Clustering of trending topics in microblogging posts: A graph-based approach. *Future Generation Computer Systems*, *67*, 297-304. https://doi.org/10.1016/j.future.2016.04.009

Hoe, D., & Sian, C. (2011). An analysis of tweets in response to the death of Michael Jackson. In *Aslib Proceedings*. Emerald Group Publishing Limited 63, (5), 432-444. https://doi.org/10.1108/00012531111164941

Hosch, B., Amrit, C., Aarts, K. & Dassen, A. (2016). How do online citizens persuade fellow voters? Using Twitter during the 2012 Dutch parliamentary election campaign. *Social science computer review*, *34*(2), 135-152. https://doi.org/10.1177/0894439314558200

Houghton, D., Joinson, A., Caldwell, N. & Marder, B. (2013). Tagger's delight? Disclosure and liking in Facebook: the effects of sharing photographs amongst multiple known social circles. Birmingham Business School: Discussion Paper Series. https://www.econstor.eu/handle/10419/202647

Hutter, K., Hautz, J., Dennhardt, S. & Füller, J. (2013). The impact of user interactions in social media on brand awareness and purchase intention: the case of MINI on Facebook. *Journal of Product & Brand Management*, *22*(5/6), 342-351. https://doi.org/10.1108/JPBM-05-2013-0299

Hsieh, H. F. & Shannon, S. E. (2005). Three approaches to qualitative content analysis. *Qualitative health research*, *15*(9), 1277-1288. https://doi.org/10.1177/1049732305276687

Jansen, B., Zhang, M., Sobel, K. & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American society for information science and technology*, *60*(11), 2169-2188. https://doi.org/10.1002/asi.21149

Khan, F., Bashir, S. & Qamar, U. (2014). TOM: Twitter opinion mining framework using hybrid classification scheme. *Decision Support Systems*, *57*, 245-257. https://doi.org/10.1016/j.dss.2013.09.004

Kosinski, M., Stillwell, D. & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, *110*(15), 5802-5805. https://doi.org/10.1073/pnas.1218772110

Krippendorff, K. (2012). Content analysis: An introduction to its methodology. Sage Publications. https://books.google.com.co/books?hl=es&lr=&id=s_yqFXnGgjQC&oi=fnd&pg=PP1&ots=b3ZS-UolyV&sig=hCMQSPTxzl-dUxoH5AxMfwPeHgs&redir_esc=y#v=onepage&q&f=false

Kulsiri, P. (2012). Self-Concept, Locus of Control, Media Exposure, And Behavior Of Youth Toward Luxury Products Purchase. *Journal of Business & Economics Research (Online)*, *10*(1), 11. https://www.clutejournals.com/index.php/JBER/article/view/6729

Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics*, *34*(1), 1-14. https://www.tandfonline.com/doi/abs/10.1080/00401706.1992.10485228

Lemon, K. & Verhoef, P. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69-96. https://doi.org/10.1509/jm.15.0420

Li, J., Peng, W., Li, T. & Sun, T. (Abril, 2013). *Social network user influence dynamics prediction*. Asia-Pacific Web Conference. 2013. *Springer, Berlin, Heidelberg. https://link.springer.com/chapter/10.1007/978-3-642-37401-2_32*

McCormick, H. & Livett, C. (2012). Analysing the influence of the presentation of fashion garments on young consumers' online behaviour. Journal of Fashion Marketing and Management: An International Journal, *16*(1), 21-41. https://doi.org/10.1108/13612021211203014

Mullahy, J. (1986). Specification and testing of some modified count data models. *Journal of econometrics*, *33*(3), 341-365. https://doi.org/10.1016/0304-4076(86)90002-3

Neves, A., Vieira, R., Mourão, F. & Rocha, L. (2015). Quantifying Complementarity among Strategies for Influencers' Detection on Twitter. *Procedia Computer Science*, *51*, 2435-2444. https://doi.org/10.1016/j.procs.2015.05.428

Osuna, I. & Pinzón, C. (2017). Comportamiento y experiencia de consumo desde la interconexión e interactividad de la World Wide Web: un recorrido teórico. *I+ D REVISTA DE INVESTIGACIONES*, *8*(2) 35-45. https://doi.org/10.33304/revinv.v08n2-2016004.

Oswald, L. & Oswald, L. (2012). *Marketing semiotics: Signs, strategies, and brand value*. Oxford University Press. https://books.google.com.co/books?hl=es&lr=&id=42IQnidxP8IC&oi=fnd&pg=PP1&dq=Marketing+semiotics:+Signs,+strategies,+and+brand+value&ots=N88xPpCCpD&sig=aBmkv0KjE0c78DY8m5kWSyT2ENY&redir_esc=y#v=onepage&q=Marketing%20semiotics%3A%20Signs%2C%20strategies%2C%20and%20brand%20value&f=false

Parguel, B., Delécolle, T. & Valette-Florence, P. (2016). How price display influences consumer luxury perceptions. *Journal of Business Research*, *69*(1), 341-348. https://doi.org/10.1016/j.jbusres.2015.08.006

Pinzón, C., Osuna, I. & Jaramillo, L. (2018). Digital Marketing Strategies for Luxury

Cosmetics Brands: Latin America's Case–Colombia. In Ozuem, W. & Azemi, Y. *Digital Marketing Strategies for Fashion and Luxury Brands*. (1Ed, pp. 126-144). IGI Global. https://books.google.com.co/books?hl=es&lr=&id=z-Y7DwAAQBAJ&oi=fnd&pg=PR1&dq=Digital+Marketing+Strategies+for+Fashion+and+Luxury+Brands&ots=gDKmBD5L5E&sig=TqTDBqac2ebNkDbDlQA2_OYGqzQ&redir_esc=y#v=onepage&q=Digital%20Marketing%20Strategies%20for%20Fashion%20and%20Luxury%20Brands&f=false

Powers, T., Advincula, D., Austin, M., Graiko, S. & Snyder, J. (2012). Digital and social media in the purchase decision process. *Journal of advertising research*, *52*(4), 479-489. 10.2501/JAR-52-4-479-489

Reilly, C., Salinas, D. & De Leon, D. (10-13 March 2014). *Ranking users based on influence in a directional social network*. Computational Science and Computational Intelligence (CSCI), 2014 International Conference. Las Vegas, *USA*. 10.1109/CSCI.2014.127

Richardson, A. (2010). Using customer journey maps to improve customer experience. *Harvard Business Review*, *15*(1). http://www.iimagineservicedesign.com/wp-content/uploads/2015/09/Using-Customer-Journey-Maps-to-Improve-Customer-Experience.pdf

Riff, D., Lacy, S. & Fico, F. (2014). *Analyzing media messages: Using quantitative content analysis in research*. Routledge. https://doi.org/10.4324/9780429464287

Rokka, J. (2015). Self-Transformation and Performativity of Social Media Images. *NA-Advances in Consumer Research*. *43*. https://www.acrwebsite.org/volumes/1019697/volumes/v43/NA-43

Smith, A., Fischer, E. & Yongjian, C. (2012). How does brand-related user-generated content differ across YouTube, Facebook, and Twitter? Journal of Interactive Marketing, 26(2), 102-113. https://doi.org/10.1016/j.intmar.2012.01.002

Smith, A., Fischer, E. & Yongjian, C. (2011). Differences in brand-related user-generated content across three social media sites: An inductive content analysis. *NA-Advances in Consumer Research* *39*, 766.

https://www.acrwebsite.org/volumes/1009529/volumes/v39/NA-39

Steinmann, S., Mau, G. & Schramm-Klein, H. (2015). Brand communication success in online consumption communities: An experimental analysis of the effects of communication style and brand pictorial representation. *Psychology & Marketing*, *32*(3), 356-371. https://doi.org/10.1002/mar.20784

Stieglitz, S. & Dang-Xuan, L. (2013). Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. Journal of Management Information Systems, 29(4), 217-248. https://doi.org/10.2753/MIS0742-1222290408

Think With Google. (2013). *Introducing Gen C: The YouTube Generation.* https://ssl.gstatic.com/think/docs/introducing-gen-c-the-youtube-generation_research-studies.pdf

Twitter. (2016) *Privacy policy*. https://twitter.com/privacy?lang=es

Vidal, L., Ares, G. & Jaeger, S. (2016). Use of emoticon and emoji in tweets for food-related emotional expression. *Food Quality and Preference*, *49*, 119-128. https://doi.org/10.1016/j.foodqual.2015.12.002

Vidal, L., Ares, G., Machín, L. & Jaeger, S. (2015). Using Twitter data for food-related consumer research: A case study on "what people say when tweeting about different eating situations". *Food Quality and Preference*, *45*, 58-69. https://doi.org/10.1016/j.foodqual.2015.05.006

Wiedmann, K., Hennigs, N. & Siebels, A. (2009). Value-based segmentation of luxury consumption behavior. *Psychology & Marketing*, *26*(7), 625-651. https://doi.org/10.1002/mar.20292

Zhang, J. & Mao, E. (2016). From online motivations to ad clicks and to behavioral intentions: An empirical study of consumer response to social media advertising. *Psychology & Marketing*, *33*(3), 155-164. https://doi.org/10.1002/mar.20862