Exploring User Reactions to Luxury Brand Videos on YouTube: A Comparative Study of Influencers and Brand-Official Channels

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Abstract

This study offers empirical evidence about individual reactions to brand-related videos posted on YouTube in the luxury context. We use methods of text mining and natural language processing to analyze the characteristics of the posts by people commenting on videos provided by influencers versus brands' official YouTube channels. We mined emotions and sentiments and evaluated the complexity and richness of the language. Data on 282 videos and more than 160 thousand comments suggest that users display an impulsive reaction to a brand's official video and a thoughtful reaction to an influencer's video posted. In fact, in the former case, comments are short, simple, and enthusiastic, while in the latter comments are longer, more complex, and more moderate in terms of positive emotions. This study participates to the debate on the efficacy of influencer marketing to engage customers, offers empirical evidence in the online communication arena of luxury brands, and methodologically suggests a new method to accurately capture users' engagement in the discussion spurred by publishing a brand-related video.

Introduction

User generated content has revolutionized the world of advertising (Kozinets et al. 2010; Lin, Bruning, and Swarna 2018), especially for luxury goods. The constant growth of the luxury market (more than US$418 billion by 2028), the 21% of which is made by online sales (Statista 2023a), signals that the ability to engage the digital consumer is an essential driver of luxury brand consumption (Kumar et al., 2022). In particular, fashion luxury brands gained the biggest share of the market (31%) with an expected growth of 3% in 2023 (Statista 2023a), with Prada and Gucci above all using films embodying their collections broadcasting online (Rees-Roberts 2020). As well, luxury cars continue to grow, registering a CAGR of 6.9% from 2023 to 2030 (Statista 2023a), with the presence of iconic brands such as Ferrari, Porsche, and Lamborghini.

Contemporary production of moving content for the web is now part of luxury brands' image-sharing culture, in an attempt to engage customers, especially on video-sharing platforms including Instagram, TikTok, and YouTube (e.g., Rees-Roberts 2020). In this context, YouTube stands out with 72 billion visits from global users on mobile and 8 billion users accesses from desktop, accounting for 90% of the total (Statista 2023b). Compared to traditional ads and the use of other social media platforms, YouTube allows to reduce costs, overcome time and content restrictions, reach new users who may voluntarily watch the ad, and pretest a video before placing it on traditional TV channels (Tellis et al. 2019). Overall, brands on YouTube struggle to influence viewers' behavior and persuade them with the ultimate goal of inducing purchases or sharing, creating awareness, and soliciting feedback (Chen, Yan, and Smith 2023; Kumar et al. 2022; Siepmann, Holthoff, and Kowalczuk 2021; Tellis et al. 2019).

Not only company-generated content is relevant for luxury brands in the digital arena, but video influencers have a fundamental role in shifting luxury companies' attention from the traditional cinema narrative and drama of fashion films to the "marketing of data" (Rees-Roberts 2020). Thus, the activity of video influencers is central to affecting followers' purchases (Chen, Yan, and Smith 2023; Hughes, Swaminathan, and Brooks 2019; Leung, Gu, and Palmatier 2022). So far, the literature has analyzed video production on social media mostly from the company's perspective, with the exception of Lee and Watkins' (2016) study on user-generated video content in the luxury context. Very few and recent studies consider post characteristics (e.g., Cascio Rizzo, Berger, and Villarroel 2023; Togawa and Sugitani 2021) and to the best of our knowledge no study compared company-generated versus user-generated vblogging.

Against this background, we investigate how the textual characteristics of comments posted to videos signal a different level of engagement depending on whether the video is posted by an influencer or a brand. We focus on social media conversations about luxury brands and compare company- versus user-generated videos on YouTube in their ability to stimulate social media user engagement online. To do so, we compare the characteristics of the conversation (i.e., the users' qualitative and quantitative engagement) spurring from influencers' versus official brand's videos, with a focus on qualitative and quantitative characteristics of the discussion going beyond the insights coming from traditional metrics, such as clicks, impressions, and likes.

From a marketing perspective, videos are more effective in promoting the experiential characteristics of products, not only highlighting the sponsored products' features but also increasing audiences' evaluation of the endorsed products (Chen, Yan, and Smith 2023; Ladhari, Massa, and Skandrani 2020). We maintain that not the simple reaction to a campaign, whether a like or a share, but the more elaborate one in terms of complexity, sentiment, and richness of language can provide real-time inputs to brands on customer engagement. In other words, when texts commenting on a video are short, simple, and enthusiastic, they may signal an impulsive reaction similar to simply putting a like below the post. Conversely, when a comment is longer, more complex, and moderate in terms of positive emotions, it could reflect a more thoughtful reaction as a result of a stronger engagement in the conversation solicited by the post.

Using a real-world study setting, we derive practical results that enable brand managers to design effective influencer marketing campaigns that could lead to improved user engagement and enriched discussion in response to brand-related videos. In this sense, in addition to offering theoretical insights and corroborating empirical evidence to the growing research on influencer marketing, we provide recommendations for how brands can develop campaigns that generate more effective consumer responses.

The paper is organized as follows: first, we discuss the theoretical framework and focus on five textual metrics (namely, word count, lexical diversity, language richness, number of long words, and sentiment); then, we explain data collection and methodology. We finally present the findings and the discussion with implications and directions for further research.

Theoretical background

Posting videos on YouTube: company- and user-generated content

Online company-generated content may lead users to take action, namely click and purchase (Wang, Xiong, and Yang 2019). Previous literature (e.g., Kumar et al. 2022; Tellis et al. 2019; Wang, Xiong, and Yang 2019) has analyzed different elements such as the content characteristics, the brand prominence, the serial position effect, and the ability to engage users. At the same time, user-generated content, shared on social media by influencers, is perceived as more reliable, authentic, and congruent with their audience's tastes (De Veirman and Hudders 2020; Fink et al. 2020; Müller and Christandl 2019). Among users posting content on social media, online influencers are social actors on the web who have a significant social influence on their network of followers, since they are considered opinion leaders (Kim 2022; Leung, Gu, and Palmatier 2022). In fact, different from conventional celebrities, online influencers are ordinary people who have accumulated followers through their posting activity (McQuarrie, Miller, and Phillips 2013). For this reason, they can create a distinct personal brand that attracts followers whose identity resonates with them (Lee and Eastin 2020; Leung, Gu, and Palmatier 2022).

Credibility, storytelling, consistency, content quality and fit with the platform are relevant drivers for influencers to reach notoriety and opinion leadership on social media (Al-Emadi and Ben Yahia 2020; Cascio Rizzo, Berger, and Villarroel 2023). Consequently, online influencers are perceived as close to their specific audience, trustworthy (Lou and Yuan 2019) and credible (Sokolova and Kefi 2019). A recent but compelling literature on influencers includes studies on brands' active engagement of influencers, known as Online Influencer Marketing (see Leung, Gu, and Palmatier 2022 for a review), which may also take the form of Video Influencer Marketing (see Chen, Yan, and Smith 2023 for a review). By doing so, brands may be encapsulated into an influencer's personal narrative that makes an ad more authentic and credible compared to official brands' ads (De Veirman, Cauberghe, and Hudders 2017). Therefore, brands can leverage the influencers' followers to easily reach and impact their target consumers (Campbell and Farrell 2020; Chen, Yan, and Smith 2023).

When integrating products in their personal lives by using videos on YouTube, influencers (in this case also known as “vloggers”) represent a powerful marketing tool for luxury companies to reach customers (Lee and Watkins 2016; Teona, Ko, and Kim 2020).

Scholars have used different theoretical perspectives to analyze the link between the influencer activities in commercial settings and the subsequent reactions of online users. From para-social interaction and social comparison theories (e.g., Lee and Watkins 2016; Rasmussen 2018) to appraisal theory (e.g., Hamby and Jones 2021), from Elaboration Likelihood (e.g., Huges, Swaminathan, and Brooks 2019; Teona, Ko, and Kim 2020) to motivation (e.g., Kumar et al. 2022; Tellis et al. 2019), without converging on a prevailing theoretical perspective. However, recently the linguistic approach has received a wider attention in order to explain all the potential online reactions highlighting authenticity and the type of language used (e.g., Packard and Berger 2024; Togawa and Sugitani 2021).

So far, academic literature and practice have focused on how to select and engage influencers and integrate them into their marketing communication plan (e.g., Lou and Yuan 2019; Sundermann and Raabe 2019; Ye et al. 2021). “Influencer marketing research focuses on source effects and content strategies” (Kim 2022, p. 417). However, not only the persuasiveness of influencer marketing (e.g., Breves et al. 2019; De Veirman and Hudders 2020; Schouten, Janssen, and Verspaget 2020), but also how to balance such a strategy into the whole strategic communication process (e.g., Lin, Bruning, and Swarna 2018; Sundermann and Raabe 2019) have received much research attention. However, like in traditional communication, online media content – e.g., a video – may have no influence on the audience unless it becomes the subject of conversation (Katz 2015). Indeed, clickbait may be good for attracting views but not for sustaining long-term value (Du et al. 2021; Fossen and Schweidel 2019). Overall, the literature on online customer engagement suffers from inconsistency between the conceptualization and the operationalization of the construct (Liu, Shin, and Burns 2021), and, to the best of our knowledge, very few papers (Chen, Yan, and Smith 2023; Leung, Gu, and Palmatier 2022) have investigated the engagement in terms of verbal reaction to the influencers’ post. Interestingly, from the parasocial interaction theory perspective (Rasmussen 2018), a compelling literature suggests that not only celebrities play a relevant role in marketing strategies, but also online influencers may serve as actor models who motivate their followers to take action toward the products featured in their posts (e.g., Kim 2022; Lu et al. 2023; Jin, Ryu, and Muqaddam 2021).

Analyzing engagement in discussions around a video

Users' responses to social media content have been measured in different ways in terms of behavioral actions over cognitive or affective responses (Gavilanes, Flatten and Brettel 2018; Moran, Muzellec and Johnson 2020; Munaro et al. 2021). In particular, informative online content positively affects brand attitudes and purchase intentions (Lou and Yuan 2019), while hedonic content stimulates greater arousal and deeper customer engagement (Hughes, Swaminathan, and Brooks 2019). The active interaction with the influencers' posts can be used to prove the loyalty of their audience to potential advertisers (van Driel and Dumitrica 2021). Different levels of engagement have been measured ranging from a minimum level (i.e., reading and watching brand posts or following a brand) to a medium (i.e., liking, sharing, and commenting on brand posts) or high level of engagement (i.e., creating user-generated content such as posts, reviews, or articles related to the brand) (Dhaoui 2014; Liu, Shin, and Burns 2021).

The combination of likes, comments, and shares (i.e., the digital engagement formula) gives a comprehensive evaluation of influencer marketing campaigns; "likes" reflect viewers' positive attitudes towards the posted content, "comments" refer to viewers' discussions regarding the posted content, and "shares" indicate viewers' recommendations of the content in their social networks (Cheng et al. 2021). Against this background, it is important to understand how social media users communicate, which is a less investigated domain (Berger, Rocklage, and Packard 2022). The language used in online posts provides a long-term measurement of engagement (e.g., Du et al. 2021; Packard and Berger 2024; Pezzuti, Leonhardt, and Warren 2021). In fact, while the language used reflects an agent's characteristics (Berger et al. 2020), it may impact the attitudes and future purchase intentions of other readers (Packard and Berger, 2017; Packard, Moore, and McFerran 2018). As the linguistic style of a user-generated comment is not usually under conscious control, it can reveal attempts at managing impressions and relationships more accurately than the content of a post (Ludwig et al. 2013; Pennebaker, Mehl, and Niederhoffer 2003).

Marketing scholars have started to investigate the types of user-generated content, focusing on the role of linguistic features in affecting the development of a discussion around an argument (e.g., Aleti et al. 2019; Packard and Berger 2024; Pezzuti, Leonhardt and Warren 2021; Visentin, Tuan, and Di Domenico 2021). In the following paragraph, we provide an account of the linguistic features that best describe the style of comments that could impact users' engagement in the discussion of company- versus user-generated video posts on YouTube.

Word Count: Counting words is a typical approach of lexicon methods to analyze texts when using specific dictionaries to detect writing styles (e.g., Berger et al. 2020; Humphreys and Wang 2018) and the raw number of words in a text may reflect the psychological characteristics of the writer (Koutsoumpis et al. 2022). Following Melumad et al. (2019) brief contents may encourage people to use an emotional language, given the focus on the gist of the experience expressed by the text, against the expectation that cutting the number of words would signal parsimoniousness in the description along with the reduction of emotionality (Chen, Baird, and Straub, 2020). In this line, word count signals engagement (Cascio Rizzo, Berger, and Villarroel 2023) as well as fake texts (Humphreys and Wang, 2018) and content virality (Nanath and Joy 2023). Consequently, short comments (e.g., "Like it!") may inhibit further comments from other users and represent just a signal of first-impression appreciation of the content. Thus, as influencers aim to engage their followers in the discussions, we expect average longer comments to their posts than to official company (video) posts.

Lexical Diversity: The lexical diversity of a user-generated comment is given by the ratio of unique words to the total number of words used (Aswani, Kar, and Vigneswara Ilavarasan 2018). It measures the heterogeneity of the words used in a text, as an indicator of the lexical sophistication of the language (Kyle, Crossley, and Jarvis 2021; Jarvis 2013). Lexical diversity affects readers' ability to grasp the meaning of a text (Leroy, Kauchak, and Mouradi 2013). High lexical diversity is associated with greater vocabulary variation and generally relates to texts that are more difficult to read (Kyle, Crossley, and Berger 2018). On social media, low lexical diversity is associated with topics considered more accessible (e.g., fashion) versus more specialized or advanced topics (e.g., business or health) (Antypas et al. 2022). Therefore, we expect that an influencer's post should stimulate comments higher in lexical diversity compared to simple appreciations of brand-generated content.

Language Richness: The richness of the language used in a comment shows the originality and the articulation of the text as it introduces rich and new information in the discourse (Toschi, Ughetto, and Fronzetti Colladon 2023). Against measuring richness by using the length of the text (as in Nanath and Joy 2023), different methods may be used to assign a role to different words in a text (see Vermeer 2000 for a review). Recent research suggested to go beyond simple text length measures and consider the richness of a given text as a measure of its originality compared to a corpus (e.g., Toschi, Ughetto, and Fronzetti Colladon 2023). For example, comments to a YouTube video might be long but naïve – e.g., containing many emoticons and many times the word "thanks", but without providing any new information compared to the other comments. Therefore, we follow a Term-Frequency Inverse-Document-Frequency (TF-IDF) logic (Roelleke and Wang 2008), which prioritizes those words that frequently appear in a small subset of documents, as they signal something new being introduced to the conversation. Consequently, we acknowledge that a comment is richer when it introduces terms/concepts that are not common in the majority of the other comments and expect that this could be the case of a discussion that develops around an influencer's video posted on YouTube, compared to videos posted on official company channels.

Long words: The number of long words (i.e., more than six letters) is often used as a measure of language complexity and proved to be related to individual characteristics such as education and social class (see Tausczik and Pennebaker 2010 for a review). As noticed by Pancer et al. (2018), long words are not necessarily more difficult than short words. Similarly, Arguello et al. (2006) found that messages with longer words are less likely to receive comments in the context of social media. Overall, we may expect that comments in a discussion around a user-generated video on YouTube would be characterized by a smaller quota of long words compared to the case of a company-generated video.

Arousing emotions: positive and negative sentiments

Audiences are more receptive to messages arousing affective states; highly arousing content is likely to be shared more frequently and widely (Aleti et al. 2019; Xu and Zhang 2018). Highly arousing content is also more likely to circulate and can be used instrumentally for social sharing (Akpinar and Berger 2017). Although different methods have been highlighted to calculate the sentiment of the text, to the best of our knowledge no research exists about a direct association between the sentiment of the post and the ability of user-generated content to stimulate engagement in a discussion. When considering YouTube videos, we should expect less extreme emotions (negative or positive) in a thoughtful discussion triggered by an influencer's post, compared to more enthusiastic reactions to a company-generated video designed to obtain likes and impressions.

Methodology

Data collection

In order to analyze how social media users express their opinions on YouTube and how much their comments could increase the ability of a brand-related communication to hold the attention and engage online users, we selected 282 YouTube videos across two industries (Automotive vs. Fashion) and coming from two sources (Official brand channel vs. Influencer channel). Among different video platforms, we selected YouTube since its content is publicly accessible and the platform has billions of monthly active users, being one of the most visited websites in the world. Indeed, the number of YouTube monthly active users has been constantly increasing since its launch, reaching over 2.6 billion in 2022 (Statista 2023b). Additionally, YouTube is the second largest search engine behind its parent company Google (Davies 2024).

We considered luxury brands (i.e., Ferrari and Porsche in the automotive industry and Gucci, Louis Vuitton, and Prada within the fashion system) that have embraced online communities to build customer relationships through online conversation (Dhaoui 2014). These brands are listed in the "100 Best Global Brands" (Interbrand.com) and have had an official YouTube channel and sufficient user-generated content since 2017. Consequently, they offer a unique opportunity to test how different online communication strategies (namely, relying on influencers versus direct broadcasting videos) have different effects on the audience's engagement (Mazzoli et al. 2019). Videos related to each brand were randomly selected in the official and influencer channels. In particular, we randomly selected videos from the official channels of brands that posted at least 25 videos in one year. After manually selecting those related to the brands in our sample, we followed the same procedure for videos posted on influencer channels. Our selection process was also based on a minimum level of user engagement; therefore, selected videos had at least one comment, 1000 views (with an average of 943,499.93 views), and at least 5 likes (with an average of 8136.32 likes).

Overall, we gathered 246,296 video comments (all those available for the selected videos at the time of the data collection). We considered only the comments in English, thus resulting in 162,177 comments posted by users between 2017-06-14 and 2022-12-20. Table 1 reports a pivot table with the summary statistics of videos per category. Overall, the videos published by influencers were able to stimulate more comments than those provided by the companies.

Table 1: Summary statistics of videos

		Automotive			Fashion				Total
		Ferrari	**Porsche**	**Total**	**Gucci**	**Louis Vuitton**	**Prada**	**Total**	
Influencer	Videos	22	25	47	19	21	19	59	106
	Views	19100351	9829126	28929477	12543382	4570062	3425282	20538726	49468203
	Likes	190737	200332	391069	353882	241747	258822	854451	1245520
	Comments	20117	22447	42564	62450	9291	5337	77078	119642
Official	Videos	28	26	54	39	35	48	122	176
	Views	11450050	53409347	64859397	41696192	68525430	41517759	151739381	216598778
	Likes	250460	294542	545002	280277	53061	170582	503920	1048922
	Comments	14170	13233	27403	9392	1635	4105	15132	42535
Total	Videos	50	51	101	58	56	67	181	282
	Views	30550401	63238473	93788874	54239574	73095492	44943041	172278107	266066981
	Likes	441197	494874	936071	634159	294808	429404	1358371	2294442
	Comments	34287	35680	69967	71842	10926	9442	92210	162177

Text Preprocessing and Study Variables

Automated text analysis, carried out using the SBS BI web app (Fronzetti Colladon and Grippa 2020), provided a set of indicators of the individual comments. Prior to calculating indexes, the text was preprocessed by removing punctuation, links, special characters (e.g., icons), and stop-words (Perkins 2014). To assess whether a video posted by an influencer could stimulate more engagement compared to a video posted by a brand's official channel, we focused our analysis on various measures.

Word count. We calculated the length of the comments using the word count, which is the number of words (tokens) appearing in a YouTube comment after text pre-processing (i.e., the removal of links, emoticons, stop-words, etc.).

Lexical Diversity. We calculated the Type-Token Ratio (TTR; Jarvis 2013; 2002), which measures the ratio of unique words (types) to the total number of words (tokens) in a text. A higher TTR indicates a higher lexical diversity.

Language richness. We calculated the language richness of a comment according to the following formula:

$$Language\ richness = \sum_{w \in V} f_w \log \frac{N}{n_w}$$

where N is the total number of comments in the corpus and V is the set of words appearing in the comment; f_w is the frequency of word w, and n_w is the number of comments where the word w appears.

For example, the following comment shows high lexical diversity and language richness:

"@mrelmostudios certainly not. Manufacturers cannot simply slap a different transmission into a car and sell it. The entire exact drivetrain must be legally certified for emissions and fuel consumption in every country it is to be sold in not to mention the engineering (both just fitting it in there and reliability- and safety testing) and product-support required. The cost of all of this is astronomical which is why there are fewer and fewer drivetrain choices for any given model in the marketplace. Manuals are going away because younger drivers aren't familiar with them as you said not having grown up with them as in prior generations but even experienced drivers mostly just don't want them as they're a pita to drive in modern driving conditions. Also good autoboxes are superior to manuals in every performance metric and if you really care about performance they are the obvious choice despite some peoples' romantic notions."

Conversely, the following comment is full of repetitions and does not add much to the discussion:

"st✫ what are you doing here in the talent market for the question of how to get the best of the best of the best of the best of the best of the best of the world series of events in a moment of love for us and our friends for the first time in our lives and we have coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee and coffee"

Indeed, the former has a higher TTR ratio (i.e., fewer repeated words) and is much more informative than the latter.

Long Words. We counted the number of words with more than six letters in a comment and divided it by the total number of words (to account for comment length).

Sentiment. We calculated two variables measuring positive and negative language sentiment by using a frequency-based approach – i.e., considering the valence of words appearing in the text. In particular, we used the well-known NRC lexicon (Mohammad and Turney 2013), which has two lists of words that indicate positive and negative sentiments. We calculated the proportion of positive and negative words in each comment by counting the number of occurrences of each type of word and dividing that by the total number of words in the comment. We then multiplied this proportion by 100 to obtain a score for each comment. This way, we obtained scores between 0 and 100. Accordingly, the comment *"I am living their past now with a different model - 911 turbo 991 but the same level of love"* would mostly represent positive emotions, while negative ones prevail in the comments *"so ugly"* or *"fool crazy company car"*.

Results

Word count

An ANOVA provides a significant effect on the word count of the source, of the industry, and their interaction. Comments to influencer videos do not differ in length between industries ($m_{Automotive}$=18.099, $m_{Fashion}$=18.123; Cohen's d=-9.38e-04). Instead, in the case of the official brand channels, comments are significantly longer for the automotive industry than for the fashion industry ($m_{Automotive}$=13.219, $m_{Fashion}$=9.584; Cohen's d=.223). Interestingly, comments to influencer videos are significantly longer than comments to official brand videos, both in the case of automotive ($m_{Influencer}$=18.099, $m_{Official}$=13.219; Cohen's d=.214) and fashion ($m_{Influencer}$=18.123, $m_{Official}$=9.584; Cohen's d=.435). The interaction plot of Figure 1.A graphically represents these data.

Lexical Diversity

An ANOVA provides a significant effect of the source, the industry, and their interaction. Lexical diversity of comments to influencer videos differs between industries ($m_{Automotive}$=.947, $m_{Fashion}$=.941; Cohen's d=.06) as well as comments to official brand videos ($m_{Automotive}$=.96, $m_{Fashion}$=.971, Cohen's d=-.149). Comments to influencer videos are significantly less lexically diverse than comments to official brand videos, both in the case of automotive ($m_{Influencer}$=.947, $m_{Official}$=.96, Cohen's d=-.162) and fashion ($m_{Influencer}$=.941, $m_{Official}$=.971; Cohen's d=-364). The interaction plot of Figure 1.B graphically represents these data.

Language Richness

An ANOVA provides a significant effect of the source, the industry, and their interaction. The language richness of the comments to influencer videos differs between industries ($m_{Automotive}$=70.406, $m_{Fashion}$=63.906; Cohen's d=.068) as well as comments to official brand videos ($m_{Automotive}$=52.329, $m_{Fashion}$=39.13; Cohen's d=.193). Comments to influencer videos are significantly richer than comments to official brand video both in the case of automotive ($m_{Influencer}$=70.406, $m_{Official}$=52.329; Cohen's d=.197) and fashion ($m_{Influencer}$=63.906, $m_{Official}$=39.127; Cohen's d=.334). The interaction plot of Figure 1.C graphically represents these data.

Long words percentage

An ANOVA provides a significant effect of the source and the industry, with no interaction effects. The percentage of long words in comments to influencer videos differs between industries ($m_{Automotive}$=.253, $m_{Fashion}$=.231; Cohen's d=.111) as well as comments to official brand videos ($m_{Automotive}$=.275, $m_{Fashion}$=.255; Cohen's d=.089). Interestingly, comments to influencer videos include a significantly larger percentage of long words than comments to official brand videos, both in the case of automotive ($m_{Influencer}$=.253, $m_{Official}$=.275; Cohen's d=-.108) and fashion

($m_{Influencer}$=.231, $m_{Official}$=.255; Cohen’s d=-.108). The interaction plot of Figure 1.D graphically represents these data.

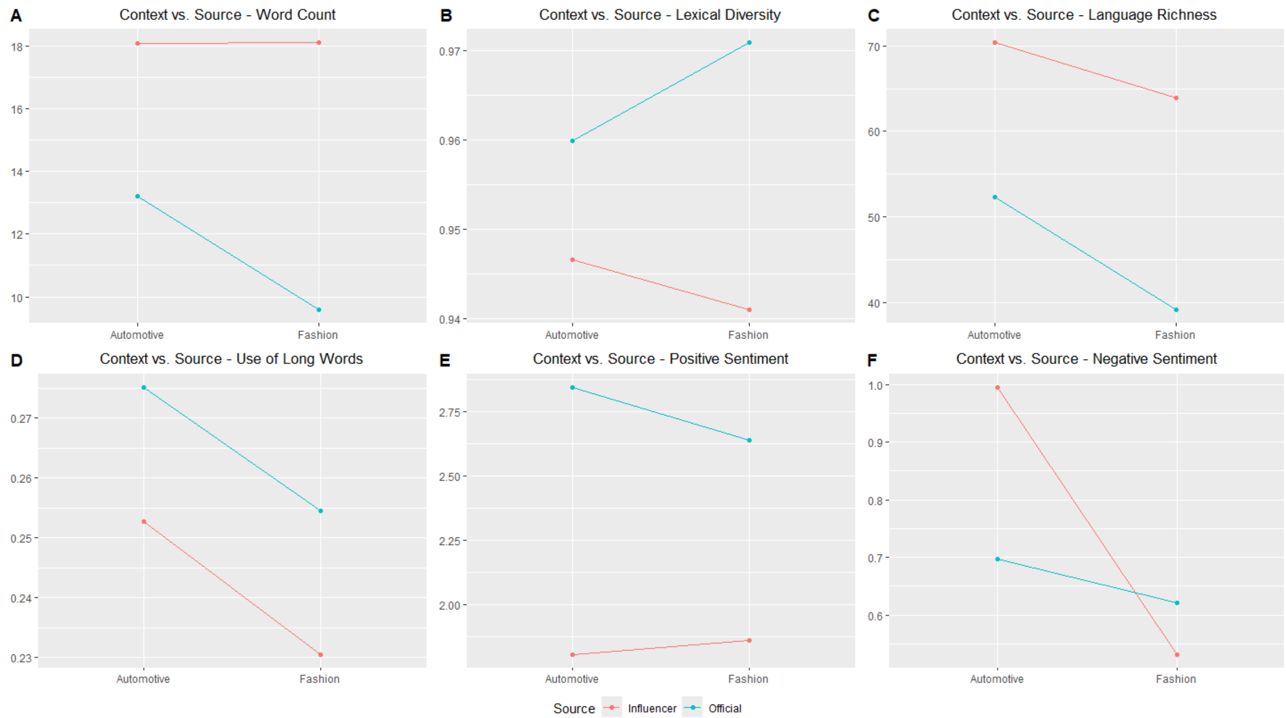
Sentiment

An ANOVA provides a significant effect of the source and the industry on positive and negative sentiment. No interaction effect was found in the case of positive sentiment, while it resulted as significant in the case of negative sentiment.

The positive sentiment of comments to influencer videos differs between industries ($m_{Automotive}$=6.046, $m_{Fashion}$=8.082; Cohen’sd = -.188) as well as for official brand videos ($m_{Automotive}$=7.435, $m_{Fashion}$=9.351; Cohen’s d = -.124). Similarly, the negative sentiment of video comments differs across industries, both in the case of influencer videos ($m_{Automotive}$=3.97, $m_{Fashion}$=2.59; Cohen’s d=.164) and in the case of official brand videos ($m_{Automotive}$=2.959, $m_{Fashion}$=3.654; Cohen’s d=-.076).

When coming to differences related to the video source, official brand channels stimulated more enthusiastic comments compared to influencer, both in the case of automotive (positive sentiment: $m_{Influencer}$=6.046, $m_{Official}$=7.435; Cohen’s d=-.111; negative sentiment: $m_{Influencer}$=.3.97, $m_{Official}$=.2.959; Cohen’s d=.114) and fashion (positive sentiment: $m_{Influencer}$=8.082, $m_{Official}$=9.351; Cohen’s d=-.09; negative sentiment: $m_{Influencer}$=2.591, $m_{Official}$=3.654; Cohen’s d=-.122). The interaction plots of Figure 1.E and 1.F graphically represent these data.

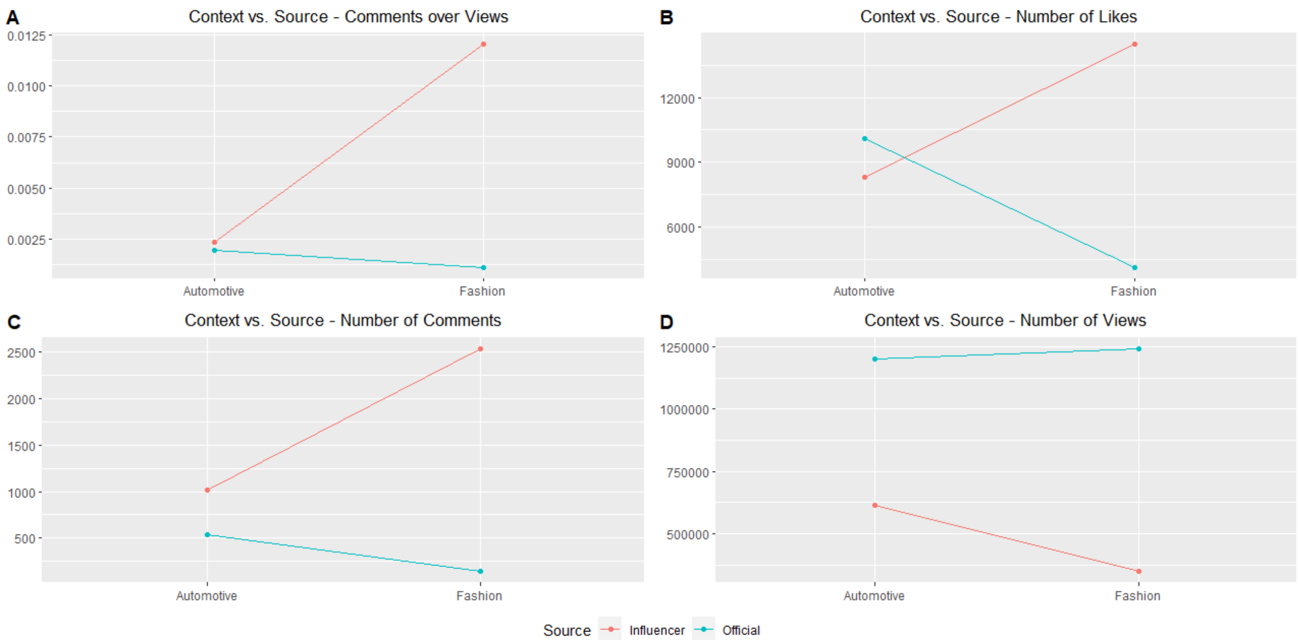
Figure 1: Interaction plots for comments' characteristics.



Analysis of feedback

To analyze the aggregated feedback of individuals, we focused on traditional metrics (namely, the number of comments, likes, views, and comments per view). First, an ANOVA indicates that the ratio of comments per view does not differ between industries (automotive vs. fashion), but it does between sources (influencer vs. official; the interaction effect is barely significant with a p-value=.073). The same result is found for the number of likes, with a significant interaction effect. Consistent with the previous analyses, the number of comments is affected only by the source, and no interaction effect is supported. The same pattern is observed for the number of views. The corresponding interaction plots are graphically represented in Figure 2.

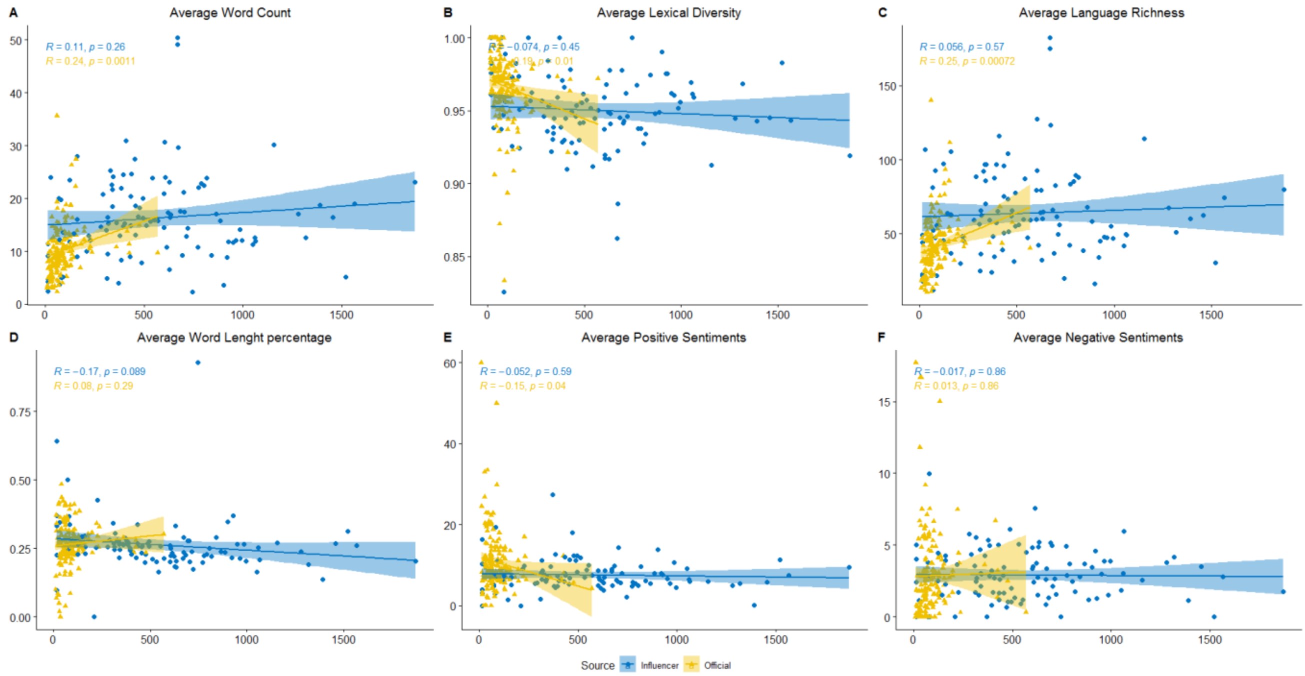
Figure 2: Interaction plots for the feedback to videos.



Interestingly, a negative binomial on the number of comments (AIC: 3867.3; null deviance: 499.86, df=281; residual deviance: 365.04, df=278) displays a significant effect of the length of the video (b=.002), a negative effect of the fashion context (b=-.516) and a negative effect of posting on an official brand's channel (b=-1.026). Differently, the number of views appears to be affected only by the source (AIC: 7927.5; null deviance: 400.90; df=281; residual deviance: 379.88, df=278) being sustained by the official brand's channel (b=1.202).

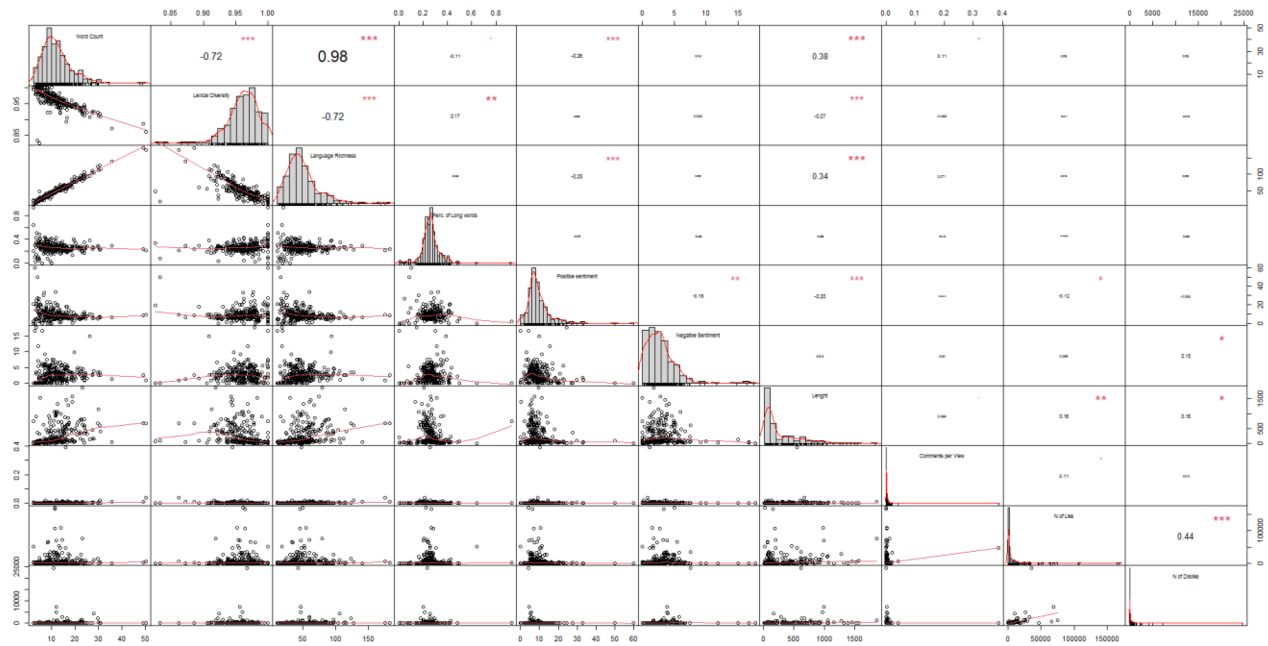
Irrespective of source and context, we analyzed the relationship between the feedback to videos (number of likes and dislikes, number of views, number of comments, ratio of comments per view) and the video length. An ANOVA displays that the average number of words in the comments to a video is affected by its length, as well as the average lexical diversity and average richness. The average percentage of long words is not affected by any video characteristics. Finally, positive sentiment is associated with the video length, but the same does not happens for negative sentiment. Positive comments are related to the number of likes and, consistently, negative sentiment is linked to the number of dislikes. Figure 3 graphically reports the scatterplots of the comments' average characteristics against the length of the corresponding video.

Figure 3: The effect of the length of the video on comments average characteristics.



Finally, Figure 4 graphically reports correlations and scatterplots between pairwise variables.

Figure 4: Pairwise variables correlations and scatterplots.



In line with the previous analyses on the disaggregated data, the source of the video (influencer vs. official) and the industry (automotive vs. fashion) have effect on the comments' features of the– in the case of word count (linear models, R^2=.25; $b_{Source:Official}$=-7.03; $b_{Industry:Fashion}$=-2.32) and text complexity (linear model, R^2=.25 $b_{Source:Official}$=-2.66; $b_{Industry:Fashion}$=-1.06). Only the industry has an effect on lexical diversity (linear model, R^2=.14; $b_{Source:Official}$=.016), and only the industry has an effect on the positive sentiment (linear model, R^2=.08; $b_{Industry:Fashion}$=2.59) and on the percentage of long words used (linear model, R^2=.04; $b_{Industry:Fashion}$=-3.51). No effect was observed in the case of negative sentiment.

Topic Modeling

In addition, we explored the content of the comments to the videos published on official vs. influencer YouTube channels, in the two industries (fashion and automotive). We used a network approach and the SBS BI software (Fronzetti Colladon and Grippa 2020) to model the main topics emerging from the online discourse. The software served to the construction of semantic networks, where nodes represented discourse terms. These nodes were linked based on their co-occurrence, with the strength of the links determined by the frequency of co-occurrence (Danowski, 2009; Diesner, 2013). Building upon previous research (e.g., Lancichinetti et al., 2015), we employed a network topic modeling approach and relied on the Louvain algorithm (Blondel et al., 2008) to identify the most significant semantic clusters, also known as discourse topics. To describe these topics, we considered their most relevant words, as determined by the importance measure proposed by Fronzetti Colladon and Grippa (2020). This measure identifies nodes with strong connections within their cluster and weak connections to nodes outside the cluster. The main results of this analysis are presented in Table 2.

Table 2: Topic modeling

Main Topics	Relevance (%)	Top Keywords	Category
Like for ads	39.0%	**car, Porsche, video, make, love, best, beautiful, commercial, ad, good, great, well, amazing, watch**	**Automotive Official**
Branding & design	23.7%	**looks, Ferrari, like, Aston Martin, design, front, new, corvette, McLaren, Lamborghini, rear, lights, back, suv, Jaguar**	
Intention to buy	12.4%	**buy, get, people, want, know, money, rich, right, trying, wait, take, give, dollar**	
Electric mobility	9.8%	**Tesla, years, model, roadster, time, charge, stations, price, range, supercharger, battery, chargers, production, miles**	
Product performance	5.9%	**km, circuits, flick, speed, automobile, code, traction, slide, traffic, tail, part, test**	
Promotions	5.4%	**inbox, giveaway, picked, today, fan, monoposto, Mercedes, cabriolet, cultish**	
Product Placement	3.9%	**furious, James Bond, fast, song, movie, trailer, theme, music, name, cutscene, story, Goldfinger**	
Intention to buy	31.2%	**car, Porsche, buy, get, years, money, price, want, cost, afford, reliable, expensive, repair, pay, million, value**	**Automotive Influencer**
Like for content	20.8%	**video, love, watch, great, thanks, make, good, Jeremy, review, channel, see, congratulations, comment, nice, YouTube**	
Product features	13.8%	**water, engine, injection, front, system, weight, seat, rear, wheel, intercooler, spray, plastic, cool, tank, oil, windows, holders**	
Branding & design	10.3%	**like, look, Ferrari, sound, better, pipe, straight, convertible, Lamborghini, McLaren, pretty, Aston, beetle**	
Rational reactions	9.9%	**know, people, think, say, really, never, German, try, mean, opinion, talking, words, care, bad, understand**	
Product performance	8.4%	**drive, track, speed, time, lane, road, go, fast, limited, autobahn, top, gear, Germany, highway, pass, faster, live**	
Sport ambassadors	2.7%	**Vettel, Hamilton, win, dominant, Mercedes, season, race, championship, driver, team, Alonso, unlucky, Verstappen, crash**	
Like for content	21.8%	**like, people, know, famous, make, dance, years, girl, think, old, time, hate, tiktok, feel, user, person, way**	**Fashion Official**
Food connection	14.3%	**chicken, fish, chips, shop, left, walking, eating, leave, fried, holding, thought, street, food, store**	
Like for product	12.6%	**new, Prada, classy, collection, absolutely, splendid, dashing, brand, win, choosing, stunning, invited, fit**	
Music connection	8.3%	**park, best, proud, hope, producer, happiest, dream, model, bless, friends, life, Korean, musician, singer, Vuitton, dancer, multitalented**	
Emotional reactions	8.2%	**love, unconditional, appreciate, sensational, entertainment, consistent, inspired, support, grateful, forever, country, show, unlimited, watching**	
Intention to buy	7.9%	**Gucci, fashion, buy, reinventing, wearing, modern, clothes, progressive, money, good, high, innovative, influential, art, price, afford**	
Video ambience	7.8%	**song, name, music, link, video, swag, cover, background, massive, campaign, film, tea**	
Movie Ambassador	5.8%	**Emma Stone, beautiful, flower, ad, Emilia Clarke, perfume, seen, woman, funny, heroine, building, floor, advertisement, swimming, incredible**	

Product placement	2.7%	**killers, natural, born, references, sky, sailor, moon, movie, dynamic, cycle, moonlight, red, crop, starlight,**	
Vintage Style	2.1%	**YSL, vintage style, Balenciaga, vintage shopping, Portugal vetements, Chanel, Paris, vintage fashion, Dior, velvet, furs, underground, pump, sauvage, bleu**	
Like for content	39.5%	**love, video, inspiration, million, congrats, watching, happy, deserve, amazing, subscribers, thank, person, proud, life, vlog, YouTube**	**Fashion Influencer**
Intention to buy	34.0%	**like, Gucci, look, people, buy, think, money, feel, good, say, wear, shirt, need, brand**	
Promotions	23.4%	**bag, win, email, want, first, use, designer, afford, always, mom, luxury, work, Vuitton, give, yahoo**	
Sport Ambassadors	1.2%	**homme, Jeyhun, Ronaldo, Prada, user, Messi, headphone, fragrance, intense, ambassador, social, media, handsome**	

Note. Relevance is calculated with respect to the overall discourse.

The analysis shows a wider variety of topics for the official videos in the fashion industry compared to the influencer videos and the automotive industry. This suggests that the conversation around the brand communication is less focused, while influencers drive the conversation around their content and persons. While some topics are recurrent (e.g., intention to buy, product placement, product features, etc.), some others are exclusive of the industry (e.g., Emotional vs. Rational reactions, respectively Fashion vs. Automotive) and of the source of the video (e.g., Sport ambassadors vs. Product placement, respectively Influencer vs. Official Company).

The appreciation (i.e., liking), for both product and content, is relevant for both sources and industries, which confirms the importance of the YouTube platform as a means to communicate with the target market.

Discussion

Our results contribute to the debate around the efficacy of influencer marketing to engage customers by offering empirical evidence in the case of individual reactions to videos posted on YouTube by influencers in luxury contexts. First, in line with previous studies (e.g., Evans et al. 2017; Sokolova and Kefi 2019), the present paper supports that influencer marketing appeals to customers better than traditional advertising, since it gives consumers a sense of close relationships and fit with their favorite influencers. Second, the results on the characteristics of the language used by people commenting on videos suggest that YouTube users display an impulsive reaction to a brand's official video and a thoughtful reaction to an influencer's video posted. We find that texts commenting on official brand videos are short, simple, and enthusiastic, while texts commenting on influencer videos are longer, more complex, and more moderate in terms of positive emotions.

This paper provides two main theoretical contributions. First, we propose measures to capture whether online media sources are able to hold their audiences' attention. To do so, we challenge the current assumption about considering views, clicks, shares, and likes as indicators of engagement and propose that, in line with recent literature (e.g., Cascio Rizzo, Berger, and Villarroel 2023; Packard and Berger 2024) the language used the text and its characteristics (richness above all) offer a more interesting view of user reaction to brand-related messages. In this vein, we see customer engagement as not limited to a quantitative account of viewers' actions (possibly determined by automatism, distraction, or unreflected reactions); we maintain that it can be assessed through a combination of textual characteristics of the comments left on a video on YouTube. In fact, our findings corroborate the idea that the comments are the result of a less immediate reaction verbalized through thoughtful words and sentences. In a nutshell, writing a long, articulated, and thoughtful comment requires much more reflection and effort compared to distractedly (or too enthusiastically) clicking a like. Although psychological literature focused on impulsive behavior or personality (e.g., Reynolds 2006) and marketing literature has long analyzed impulsive buying (Muruganantham and Bhakat 2013), to the best of our knowledge no literature in textual analysis indicates those characteristics of text signaling an impulsive vs. reflexive reaction to an online content. As a consequence, providing a set of textual features that may be used as proxy for these two reactions, as we did in the present study, is relevant per se. Noteworthy, our results should stimulate further research on this topic.

Second, we contribute to the debate on the untheorized changing socio-technological conditions that question the adequacy of the classical two-step flow model of communication proposed some decades ago in a pure offline society (Park 2019). To do so, we offer robust empirical evidence that corroborates the assumption about the ability of influencers to act as opinion leaders. Scholars have challenged the two-step flow hypothesis, acknowledging a change in the way individuals receive and process information due to technological changes (e.g., Bennett and Iyengar 2008; Leung, Gu, and Palmatier 2022). While opinion leaders may be more attuned to the media than the individuals they influence (Katz 2015), “many video influencers have emerged and become key opinion leaders in their respective domains of interest” (Chen, Yan, and Smith 2023 p. 215). To the best of our knowledge, only a few recent marketing papers have analyzed this topic (Chen, Yan, and Smith 2023; Leung, Gu, and Palmatier 2022), calling for further research and empirical evidence. Recent literature gradually provides empirical evidence that not only celebrities (e.g., Aw and Labrecque 2020), but also social media influencers may play a relevant role in stimulating their followers to purchase the products featured in their posts (e.g., Jin, Ryu, and Muqaddam 2021; Kim 2022; Lu et al. 2023). In this vein, we offer a robust empirical assessment of the superiority of the ability of influencers versus official brand channels to galvanize thoughtful discussions around the videos they post on YouTube. This evidence is supported both when analyzing textual characteristics at the single comment level and when controlling for some video objective metrics at an aggregate level. Moreover, we offer empirical evidence in an understudied context, namely luxury.

The topic modeling confirms the results from the quantitative analyses; the conversation around the influencer videos is different from the conversation around the company official videos. The language is a “window” on the user thoughts. As suggested by very recent papers (e.g., Packard and Berger 2024), the way with which the users write their comments to the videos differs depending on the sources (influencer vs. company) and the industry (fashion vs. automotive).

In line with previous literature in marketing (e.g., Chen, Yan, and Smith 2023; Hughes, Swaminathan, and Brooks 2019; Leung, Gu, and Palmatier 2022), the behavioral responses (i.e., intention to buy) are more prevalent when the video is made by an influencer, which confirms the importance of the human connection and peer influence. The literature focusing on parasocial relationships within a network of celebrity vs. influencer followers (Aw and Labreque 2020; Jin, Ryu, and Muqaddam 2021; Kim 2022; Lu et al. 2023), focuses on the mediating role of the ability of the online actor, in our case the influencer, to stimulate parasocial relationships with the community of followers. Our paper contributes to this literature unveiling the textual characteristics of the posts' reaction that are more likely to signal the engagement with the influencer. This also provides indications on how to communicate with different targets of followers, as they are potential customers.

From a managerial perspective, companies should consider the explanatory power of language for achieving a strong level of user engagement because brand-related content produced by consumers in response to an advertising campaign can significantly shape the opinions and choices of other readers. Brands can leverage more authentic influencer marketing campaigns with influencers who already embrace the image or views of their target. Particular attention should be paid to the selection of influencers by identifying ex ante different market segments' position regarding the appeal (or lack) of the influencers. Luxury companies can capitalize on the social and hedonic dimension of influencers campaigns by highlighting the social and symbolic values of their brands in their communication efforts. By doing so, the online engagement of consumers will be stimulated, bringing benefits to companies which can strengthen their relationship with costumers and their brand attachment. Consequently, managers should ensure that influencers produce and upload sponsored posts of high hedonic value.

Limitations and future directions

This paper is exploratory in nature and thus has some limitations. First, the analyses presented do not account for the time sequence of commenting behavior. Future studies should consider the effects related to commenting after other comments, eventually including text features to investigate the ability of a discussion to hold customer engagement. A recent research attempted to analyze what encourages individuals to keep on reading an article (Berger, Moe, and Schweidel 2023), but unfortunately, no research has analyzed the textual characteristics of existing discussions stimulating new individuals to contribute to the discussion around a brand-related message.

Moreover, we did not include any information about the development rate or speed of the discussion and its decline. Possible further research questions to investigate are: What determines the amplitude of the time window of a discussion around a brand-related communication? What about the rate of commenting in the raising of the curve? And what determines the time after which the discussion can be considered concluded? What about overlapping discussions about the same brand?

Furthermore, beyond the richness of the textual information extracted from individual comments, no user-related data have been included. In this regard, it could be of interest to control the frequency of comments by user, or analyze sub-threads indicating separate discussions, the status of commenters in the online community, or their connections inside and outside the social media, among other characteristics.

Lastly, we did not account for possible exogenous events that may possibly influence the flow of comments. Future research might investigate the role of off-line press, social or environmental shocks, and other effects in mitigating versus stimulating the online discussion.

References

Akpinar, E., and J. Berger. 2017. Valuable virality. Journal of Marketing Research 54 (2): 318–30.

Al-Emadi, F. A., and I. Ben Yahia. 2020. Ordinary celebrities related criteria to harvest fame and influence on social media. Journal of Research in Interactive Marketing 14 (2): 195–213.

Aleti, T., J. I. Pallant, A. Tuan, and T. van Laer. 2019. Tweeting with the stars: automated text analysis of the effect of celebrity social media communications on consumer word of mouth. Journal of Interactive Marketing 48: 17–32.

Antypas, D., A. Ushio, J. Camacho-Collados, L. Neves, V. Silva, and F. Barbieri. 2022. Twitter topic classification. arXiv preprint arXiv:2209.09824.

Arguello, J., B. S. Butler, E. Joyce, R. Kraut, K. S. Ling, C. Rosé, and X. Wang. 2006. Talk to me: foundations for successful individual-group interactions in online communities. In Proceedings of the SIGCHI conference on Human Factors in computing systems (pp. 959-68).

Aswani, R., A. K. Kar, and P. Vigneswara Ilavarasan. 2018. Detection of spammers in twitter marketing: a hybrid approach using social media analytics and bio inspired computing. Information Systems Frontiers 20: 515-30.

Aw, E. C. X., and L. I. Labrecque. 2020. Celebrity endorsement in social media contexts: understanding the role of parasocial interactions and the need to belong. Journal of Consumer Marketing, 37(7): 895–908.

Bennett, W. L., and S. Iyengar. 2008. A New Era of Minimal Effects? The Changing Foundations of Political Communication. Journal of Communication 58: 707-31.

Berger, J., A. Humphreys, S. Ludwig, W. Moe, O. Netzer and D. Schweidel. 2020. Uniting the Tribes: Using Text for Marketing Insight. Journal of Marketing Research 84(1): 1-25.

Berger, J., M. D. Rocklage, and G. Packard. 2022. Expression Modalities: How Speaking Versus Writing Shapes Word of Mouth. Journal of Consumer Research 49(3): 389-408.

Berger, J., W. W. Moe, and D. A. Schweidel. 2023. What Holds Attention? Linguistic Drivers of Engagement. Journal of Marketing 0(ja). https://doi.org/10.1177/00222429231152880

Blondel, V. D., J.-L. Guillaume, R. Lambiotte, and E. Lefebvre. 2008. Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment 10: 10008.

Breves, P. L., N. Liebers, M. Abt, and A. Kunze. 2019. The perceived fit between Instagram influencers and the endorsed brand: How influencer-brand fit affects source credibility and persuasive effectiveness. Journal of Advertising Research 59(4): 440–54.

Campbell, C., and J. R. Farrell. 2020. More than meets the eye: The functional components underlying influencer marketing. Business Horizons 63(4): 469–79.

Cascio Rizzo, G. L., J. Berger, and F. Villarroel. 2023. What Drives Virtual Influencer's Impact?. arXiv preprint arXiv:2301.09874.

Chen, L., A. Baird, and D. Straub. 2020. A linguistic signaling model of social support exchange in online health communities. Decision Support Systems 130: 113233.

Chen, L., Y. Yan, and A. N. Smith. 2023. What drives digital engagement with sponsored videos? An investigation of video influencers' authenticity management strategies. Journal of the Academy of Marketing Science 51: 198–221.

Cheng, M., J. Liu, J. Qi, and F. Wan. 2021. Differential effects of firm generated content on consumer digital engagement and firm performance: An outside-in perspective. Industrial Marketing Management, 98, 41–58.

Danowski, J. A. 2009. Inferences from word networks in messages. The Content Analysis Reader: 421-29.

Davies, D. 2024. Meet The 7 Most Popular Search Engines In The World. February 11. https://www.searchenginejournal.com/seo/meet-search-engines/.

De Veirman, M., and L. Hudders. 2020. Disclosing sponsored Instagram posts: The role of material connection with the brand and message-sidedness when disclosing covert advertising. International Journal of Advertising 39(1): 94–130.

De Veirman, M., V. Cauberghe, and L. Hudders. 2017. Marketing through Instagram influencers: The impact of number of followers and product divergence on brand attitude. International Journal of Advertising 36(5): 798–828.

Dhaoui, C. 2014. An empirical study of luxury brand marketing effectiveness and its impact on consumer engagement on Facebook. Journal of Global Fashion Marketing 5(3): 209-22.

Diesner, J. 2013. From Texts to Networks: Detecting and Managing the Impact of Methodological Choices for Extracting Network Data from Text Data. KI - Künstliche Intelligenz 27(1): 75–8.

Du, R. Y., O. Netzer, D. A. Schweidel, and D. Mitra. 2021. Capturing Marketing Information to Fuel Growth. Journal of Marketing 85 (1): 163–83.

Evans, N. J., J. Phua, J. Lim, and H. Jun. 2017. Disclosing Instagram influencer advertising: The effects of disclosure language on advertising recognition, attitudes, and behavioral intent. Journal of Interactive Advertising 17(2): 138–49.

Fink, M., M. Koller, J. Gartner, A. Floh, and R. Harms. 2020. Effective entrepreneurial marketing on Facebook – A longitudinal study. Journal of Business Research 113: 149-57.

Fossen, B. L., and D. A. Schweidel. 2019. Social TV, advertising, and sales: Are social shows good for advertisers?. Marketing Science 38(2): 274-95.

Fronzetti Colladon, A., and F. Grippa. 2020. Brand Intelligence Analytics. In Digital Transformation of Collaboration, ed. A. Przegalinska, F. Grippa, and P.A. Gloor, 125–41. Cham: Springer Nature Switzerland.

Gavilanes, J. M., T. C. Flatten, and M. Brettel. 2018. Content strategies for digital consumer engagement in social networks: Why advertising is an antecedent of engagement. Journal of Advertising 47(1): 4–23.

Hamby, A., and N. Jones. 2022. The effect of affect: An appraisal theory perspective on emotional engagement in narrative persuasion. Journal of Advertising 51(1): 116-31.

Hughes, C., V. Swaminathan, and G. Brooks. 2019. Driving brand engagement through online social influencers: An empirical investigation of sponsored blogging campaigns. Journal of Marketing 83(5): 78–96.

Humphreys, A., and R. J.-H. Wang. 2018. Automated Text Analysis for Consumer Research. Journal of Consumer Research 44: 1274-306.

Jarvis, S. 2013. Capturing the Diversity in Lexical Diversity. Language Learning 63: 87–106.

Jin, S. V., E. Ryu, and A. Muqaddam. 2021. I trust what she's# endorsing on Instagram: moderating effects of parasocial interaction and social presence in fashion influencer marketing. Journal of Fashion Marketing and Management: An International Journal, 25(4): 665–81.

Katz, E. 2015. Where Are Opinion Leaders Leading Us?. International Journal of Communication, 9: 1023-28.

Kim, H. 2022. Keeping up with influencers: exploring the impact of social presence and parasocial interactions on Instagram. International Journal of Advertising, 41(3): 414–34 .

Koutsoumpis, A., J. K. Oostrom, D. Holtrop, W. Van Breda, S. Ghassemi, and R. E. de Vries. 2022. The kernel of truth in text-based personality assessment: A meta-analysis of the relations between the Big Five and the Linguistic Inquiry and Word Count (LIWC). Psychological Bulletin 148(11-12): 843.

Kozinets, R. V., K. De Valck, A. C. Wojnicki, and S. J. S. Wilner. 2010. Networked narratives: Understanding word-of-mouth marketing in online communities. Journal of Marketing 74(2): 71–89.

Kumar, V., I. Khan, M. Fatma, and A. Singh. 2022. Engaging luxury brand consumers on social media. Journal of Consumer Marketing 39(1): 121-32.

Kyle, K., S. Crossley, and C. Berger. 2018. The tool for the automatic analysis of lexical sophistication (TAALES): version 2.0. Behavior research methods 50: 1030-46.

Kyle, K., S. A.Crossley, and S. Jarvis. 2021. Assessing the validity of lexical diversity indices using direct judgements. Language Assessment Quarterly 18(2): 154-70.

Ladhari, R., E. Massa, and H. Skandrani. 2020. YouTube vloggers’ popularity and influence: The roles of homophily, emotional attachment, and expertise. Journal of Retailing and Consumer Services 54: 102027. doi:10.1016/j. jretconser.2019.102027

Lancichinetti, A., M. I. Sirer, J. X. Wang, D. Acuna, K. Körding, and L. A. N. Amaral. 2015. High-Reproducibility and High-Accuracy Method for Automated Topic Classification. Physical Review X 5(1): 011007.

Lee, J. A., and M. S. Eastin. 2020. I like what she’s #endorsing: The impact of female social media influencers’ perceived sincerity, consumer envy, and product type. Journal of Interactive Advertising 20(1): 76–91.

Lee, J. E., and B. Watkins. 2016. YouTube vloggers' influence on consumer luxury brand perceptions and intentions. Journal of Business Research 69(12): 5753-60.

Leroy, G., D. Kauchak, and O. Mouradi. 2013. A user-study measuring the effects of lexical simplification and coherence enhancement on perceived and actual text difficulty. International Journal of Medical Informatics 82(8): 717-30.

Leung, F. F., F. F. Gu, and R. W. Palmatier. 2022. Online influencer marketing. Journal of the Academy of Marketing Science. 50: 226–51.

Lin, H.-C., P. F. Bruning, and H. Swarna. 2018. Using online opinion leaders to promote the hedonic and utilitarian value of products and services. Business Horizons 61 (3): 431–42.

Liu, X., H. Shin, and A. C. Burns. 2021. Examining the impact of luxury brand’s social media marketing on customer engagement: Using big data analytics and natural language processing. Journal of Business Research 125: 815-26.

Lou, C., and S. Yuan. 2019. Influencer marketing: How message value and credibility affect consumer trust of branded content on social media. Journal of Interactive Advertising 19(1): 58–73.

Lu, Y., X. Liu, Y. Hu, and C. Zhu. 2023. Influence of livestreamers' intimate self-disclosure on tourist responses: The lens of parasocial interaction theory. Journal of Hospitality and Tourism Management, 57: 170–78.

Ludwig, S., K. de Ruyter, M. Friedman, E. C. Brüggen, M. Wetzels, and G. Pfann. 2013. More than words: the influence of affective content and linguistic style matches in online reviews on conversion rates. Journal of Marketing 77: 87–103.

Mazzoli, V., L. Grazzini, R. Donvito, and G. Aiello. 2019. Luxury and Twitter: An issue of the right words. Qualitative Market Research: An International Journal 22 (1): 33–49.

McQuarrie, E. F., J. Miller, and B. J. Phillips. 2013. The megaphone effect: Taste and audience in fashion blogging. Journal of Consumer Research 40(1): 136-58.

Melumad, S., J. J. Inman, and M. T. Pham. 2019. Selectively Emotional: How Smartphone Use Changes User Generated Content. Journal of Marketing Research 56(2): 259-75.

Mohammad, S.M., and P.D. Turney. 2013. Crowdsourcing a Word-Emotion Association Lexicon. Computational Intelligence 29(3): 436–65.

Moran, G., L. Muzellec, and D. Johnson. 2020. Message content features and social media engagement: evidence from the media industry. Journal of Product & Brand Management 29(5): 533–45.

Müller J., and F. Christandl. 2019. Content is king – But who is the king of kings? The effect of content marketing, sponsored content & user-generated content on brand responses. Computers in Human Behavior 96: 46–55.

Munaro, A. C., R. Hübner Barcelos, E. C. F. Maffezzolli, J. P. Santos Rodrigues, and E. Cabrera Paraiso. 2021. To engage or not engage? The features of video content on YouTube affecting digital consumer engagement. Journal of Consumer Behaviour 20(5): 1336–52.

Muruganantham, G., and R. S. Bhakat. 2013. A review of impulse buying behavior. International Journal of Marketing Studies, 5(3): 149–60.

Nanath, K., and G. Joy. 2023. Leveraging Twitter data to analyze the virality of Covid-19 tweets: a text mining approach. Behaviour & Information Technology 42(2): 196-214.

Pancer, E., V. Chandler, M. Poole, and T.J. Noseworthy. 2019. How readability shapes social media engagement. Journal of Consumer Psychology 29 (2): 262-70.

Packard, G., and J. Berger. 2024. The Emergence and Evolution of Consumer Language Research. Journal of Consumer Research ucad013, https://doi.org/10.1093/jcr/ucad013

Packard, G., and J. Berger. 2017. How Language Shapes Word of Mouth's Impact. Journal of Marketing Research 54(4): 572-88.

Packard, G., S. Moore, and B. McFerran. 2018. (I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer-Firm Interactions. Journal of Marketing Research 55(4): 541-55.

Park, C. S. 2019. Revisiting the two-step flow model on Twitter: Interconnection of self-identified South Korean Twitter opinion leadership, news consumption, news links, and news curation. Electronic News 13(2): 63-77.

Pennebaker, J. W., M. R. Mehl, and K. G. Niederhoffer. 2003. Psychological aspects of natural language use: Our words, our selves. Annual Review of Psychology 54(1): 547–77.

Perkins, J. 2014. Python 3 Text Processing with NLTK 3 Cookbook. Birmingham: Packt Publishing.

Pezzuti, T., J. M. Leonhardt, and C. Warren. 2021. Certainty in language increases consumer engagement on social media. Journal of Interactive Marketing 53: 32-46.

Rasmussen, L. 2018. Parasocial interaction in the digital age: An examination of relationship building and the effectiveness of YouTube celebrities. The Journal of Social Media in Society 7(1): 280–94.

Rees-Roberts, N. 2020. After fashion film: social video and brand content in the influencer economy. Journal of Visual Culture 19(3): 405–21.

Reynolds, B., A. Ortengren, J. B. Richards, and H. De Wit. 2006. Dimensions of impulsive behavior: Personality and behavioral measures. Personality and Individual Differences 40(2): 305–15.

Schouten, A. P., L. Janssen, and M. Verspaget. 2020. Celebrity vs. Influencer endorsements in advertising: The role of identification, credibility, and Product- Endorser fit. International Journal of Advertising 39(2): 258–81.

Siepmann, C., L. C. Holthoff, and P. Kowalczuk. 2022. Conspicuous consumption of luxury experiences: an experimental investigation of status perceptions on social media. Journal of Product & Brand Management 31(3): 454-68.

Sokolova, K., and H. Kefi. 2019. Instagram and YouTube bloggers promote it, why should I buy? How credibility and parasocial interaction influence purchase intentions. Journal of Retailing and Consumer Services 49: 86–101.

Statista. 2023a. Luxury Goods – Worldwide. https://www.statista.com/outlook/cmo/luxury-goods/worldwide

Statista. 2023b. Global social networks. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/, accessed on June 15, 2023

Sundermann, G., and T. Raabe. 2019. Strategic communication through social media influencers: Current state of research and desiderata. International Journal of Strategic Communication 13 (4): 278–300.

Tausczik, Y. R., and J. W. Pennebaker. 2010. The psychological meaning of words: LIWC and computerized text analysis methods. Journal of Language and Social Psychology 29(1): 24-54.

Tellis, G. J., D. J. MacInnis, S. Tirunillai, and Y. Zhang. 2019. What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence. Journal of Marketing 83(4): 1-20.

Teona, G., E. Ko, and S. J. Kim. 2020. Environmental claims in online video advertising: effects for fast-fashion and luxury brands. International Journal of Advertising 39(6): 858-87.

Togawa, T., and Y. Sugitani. 2022. Looks far beyond my reach: The zoom effect in product videos influences luxury perception and purchase intention. Journal of Consumer Psychology 32(4): 687-98.

Toschi, L., E. Ughetto, and A. Fronzetti Colladon. 2023. The identity of social impact venture capitalists: exploring social linguistic positioning and linguistic distinctiveness through text mining. Small Business Economics, 60: 1249–80.

van Driel, L., and D. Dumitrica. 2021. Selling brands while staying “Authentic”: The professionalization of instagram influencers. Convergence 27(1): 66–84.

Vermeer, A. 2000. Coming to grips with lexical richness in spontaneous speech data. Language testing 17(1): 65-83.

Visentin, M., A. Tuan, and G. Di Domenico. 2021. Words matter: How privacy concerns and conspiracy theories spread on Twitter. Psychology & Marketing 38: 1828–46.

Wang, P., G. Xiong, and J. Yang. 2019. Serial position effects on native advertising effectiveness: Differential results across publisher and advertiser metrics. Journal of Marketing 83(2): 82-97.

Xu, W. W., and C. Zhang. 2018. Sentiment, richness, authority, and relevance model of information sharing during social Crises—the case of# MH370 tweets. Computers in Human Behavior 89: 199–206.

Ye, G., L. Hudders, S. De Jans, and M. De Veirman. 2021. The Value of Influencer Marketing for Business: A Bibliometric Analysis and Managerial Implications. Journal of Advertising 50(2): 160-78.