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To engage or not engage? The features of video content on YouTube affecting digital consumer engagement

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Abstract

Popularity on YouTube is an important metric for influencers and brands. It is linked to video relevance, content, and features that attract audience attention and interest. We present and test a model of YouTube video popularity drivers that trigger several engagement actions (i.e., number of views, likes, dislikes, and comments). These drivers include characteristics—such as language elements, linguistic style, subjectivity, emotion valence, and video category—that influence online video popularity on YouTube. An analysis of a database comprising more than 11,000 videos from 150 digital influencers shows that several factors help to boost the number of views, likes/dislikes, and comments. We find that medium-length and long videos posted during non-business hours and weekdays and those using a subjective language style, less-active events, and temporal indications are more likely to receive views, likes, and comments. Moreover, the use of negative or low-arousal emotion helps to promote a general interest in a YouTube video.

1 | INTRODUCTION

Social media have become an essential part of digital marketing strategies (Arora et al., 2019). Among social media platforms, YouTube has emerged as a leader in video sharing (Aggrawal et al., 2018). YouTube has over two billion monthly logged-in users over 100 countries around the world, who watch more than one billion hours of video every day, and more than 500 hours of content are uploaded to YouTube every minute (YouTube, 2020). Advertisers are predicted to invest 11.76 billion U.S. dollars in the platform in 2020 (Statista, 2019).

Digital marketers are interested in knowing what kinds of video content drive different forms of online customer engagement. The literature has focused on the contents of posts on Facebook pages (Banerjee & Chua, 2019; Hughes et al., 2019; Sabate et al., 2014) and Twitter pages (Francalanci & Hussain, 2017). However, engagement in video-sharing platforms may have characteristics different from engagement in other social media. Moreover, while YouTube shares some engagement measures with other platforms such as likes and comments, it also includes views and dislikes, which have not been considered in previous studies.

These social media metrics show not only how effective a content/influencer is (Balabanis & Chatzopoulou, 2019) but also serve as a heuristic clue for new adopters. Moreover, different metrics of engagement must be analyzed separately in marketing campaigns, primarily because they do not all respond to the same influences. For instance, some studies show that the factors responsible for increasing the number of likes for a post do not necessarily increase the number of comments (De Vries et al., 2012; Sabate et al., 2014).

In this sense, message content can be a powerful tool for promoting digital engagement and diffusion. However, few studies have sought to determine which content elements affect popularity and how they influence audience engagement (Ladhari et al., 2020). Therefore, the relationship between content conception factors on social media and their popularity constitutes a theoretically meaningful research gap (Banerjee & Chua, 2019). Our study investigates which video features drive popularity on YouTube. To elucidate this relationship, our study employs the elaboration likelihood model

(ELM; Petty & Cacioppo, 1986; Petty & Briñol, 2012). ELM is an appropriate model to predict attitude and behavior because it provides scholars and marketers with a conceptual framework for mapping out critical factors in affecting consumer behavior (Teng et al., 2015). ELM has also provided practical guidelines for developing effective communications on a wide variety of topics (Hughes et al., 2019; Kulkarni et al., 2020).

To this end, we present and empirically test a conceptual model to determine how elements such as a video's linguistic style, category, and length influence various consumer engagement metrics, such as views, likes, dislikes, and comments. For this purpose, we analyze transcriptions of the contents of more than 11,000 videos from 150 digital influencers on YouTube across several categories.

This study aims to contribute to research on social influencer marketing and online advertising by providing managers with concrete insights into how to develop videos able to attract customer attention and promote online engagement. Specifically, it offers novel insights into when certain metrics of consumer digital engagement might be elicited over others. Finally, we also provide guidelines on how to choose the most appropriate channels for sponsorship and advertisements.

The structure of this paper is as follows. First, we briefly review the literature on digital consumer engagement and the drivers of online video popularity on social media, including linguistics attributes, content categories and some date of posting, in the light of the main cognitive dual-process model used to explain consumers' attitudes. Then, we develop our research hypotheses and describe our model and methods. Finally, we present the results of the statistical model and a discussion of findings. We conclude the paper with a discussion of results, implications for theory and practice, as well as limitations and suggestions for future research.

2 | CONTEXTUAL FRAMEWORK

2.1 | Digital consumer engagement

Digital consumer engagement (DCE) refers to consumers' interactions with a brand in a digital environment; it strengthens their investment in the brand at different levels and phases to produce traceable reactions such as clicks, likes, comments, and shares (Gavilanes et al., 2018).

Gavilanes et al. (2018) postulate a model that includes a continuum of steps for conceptualizing DCE in social networks. At the beginning of the continuum (i.e., a weak form of DCE), consumers click on posts merely to consume content, which requires little investment from them. In this weak form of DCE, consumers tend to incline toward low levels of involvement since the content is reviewed mostly for personal and entertainment purposes (Swani et al., 2017).

Clicking on the "like" button represents a moderate level of DCE and a more emotional investment from consumers, which is associated with a positive attitude toward the content (Banerjee & Chua, 2019; Gavilanes et al., 2018). The action of liking a message is more intuitive, reflexive, and less cognitive (Labrecque et al., 2020; Swani et al., 2017). A high number of likes may thus indicate that a post's content is of interest, increasing its capacity to disseminate its message (Sabate et al., 2014). The same is presumably true of the "dislike" button, except it signals a negative reaction to the video and an attitude of denial.

Writing a comment requires more time and cognitive resources, which are used to form a position and formulate a contribution. Therefore, this form of response is considered a stronger DCE (Gavilanes et al., 2018; Labrecque et al., 2020; Yoon et al., 2018). Writing a comment involves more emotions and feelings, as people usually comment when the content is really meaningful for them (Sabate et al., 2014).

Though these digital actions can be conceptually regarded as consumer engagement, they reflect qualitatively different types of digital engagement (Yoon et al., 2018). We may expect different reactions to different content types, considering the effects of video content characteristics (such as the emotions, content category, and linguistic elements) on the main engagement-related marketing outcomes. For this reason, a coherent understanding of digital engagement with YouTube video posts depends on several factors, such as the emotional, content category, and linguistic elements that elicit the most consumer engagement.

2.2 | Drivers of online video popularity

The numbers of views, likes, dislikes, comments and shares serve as usual metrics of YouTube video popularity, as well as consumer engagement behavior (Oh et al., 2017). They can strongly affect how the public perceives a YouTube post (Hong & Cameron, 2018). These online measures indicate viewers' satisfaction with post content and may suggest whether the product/service featured is going to be a hit in the market (Aggrawal et al., 2018). For instance, given that, on average, one unit of view for a particular video for U.S. movies is related to $2.00 gross revenue (Oh et al., 2017), managers should allocate more resources on social media content and strategies that will generate personal consumer engagement.

Likes are indicative of the followership of social media influencers and are highly influential on consumer responses (Kay et al., 2020). Expressing a like or dislike of a video and commenting on or judging it all increase social resonance and video popularity (Ladhari et al., 2020). It is generally easier to convince users to like a publication than to share it (Banerjee & Chua, 2019). As cognitive misers, people prefer to read comments that other readers have "liked". The number of views and likes can become a heuristic cue, shaping online consumers' initial impressions of content (Hong & Cameron, 2018). Also, by liking the content/brand, users are able to associate themselves with it and feel a positive impact on their personal self-esteem and self-worth (Oh et al., 2017).

On the other hand, YouTube permits users to "dislike" videos (Oh et al., 2017), generating a negative popularity in the content created. Individuals might share disliked content if they believe that this content might help others (altruistic motivation), burnish their reputation (self-serving motivation), or help to connect them with others (social motivation; Tellis et al., 2019). Thus, it is important to understand the impact of "dislikes" among users and the factors that can boost this negative metric of engagement.

Oh et al. (2017) showed that commenting/sharing content is a heightened form of engagement, encouraging a deeper relationship with consumers. In this sense, comments represent a higher level of engagement than "viewing" and "liking" (simply interfacing) because posting a comment requires a higher level of attention and involvement with the post than simply "liking" it (De Vries et al., 2012; Devereux et al., 2020). Hence, a high number of comments can represent a metric of success or impact (Sabate et al., 2014).

2.3 | Dual-routes models of information processing

Digital consumer engagement as a continuum can be elucidated in dual-process models of influence in attitude-behavior on social media. The main cognitive dual-process models used to explain consumers' attitudes and online decisions by identifying the process routes of persuasion are ELM (Petty & Cacioppo, 1986) and Chaiken's (1980) heuristic-systematic model (HSM; Teng et al., 2015).

ELM is one of the most frequently mentioned theories in communication and information processing (Le et al., 2020). This theory has been cited as an appropriate theoretical background to examine the effects of two main factors: the message for a central processing route and the source for a peripheral processing route (Hughes et al., 2019; Le et al., 2020; Sokolova & Kefi, 2019; Srivastava & Kalro, 2019). This dual-process theory posits that, in high elaboration likelihood states, when both the motivation and ability to process are high, individuals are likely to engage in thoughtful processing of a message—the central route—and thus be more inclined to be persuaded by argument quality and message characteristics (Petty & Cacioppo, 1986). These can be manifest attributes such as word count, a number of sentences, which are easily observable; or latent factors, which are implied from the text and capture the quality of information embedded within the message, such as writing style, and message valence (Srivastava & Kalro, 2019).

By contrast, those in low elaboration likelihood states (i.e., lacking the ability or motivation to deliberate thoughtfully) are more likely motivated by peripheral cues, which in turn guide attitude formation (Petty & Briñol, 2012; Petty & Cacioppo, 1986). These peripheral cues may include the number of followers and the number of posts (Hughes et al., 2019), as well as reviewer identity (self-disclosure) and reputation/self-presentation variables, which together signal trust and expertise of the reviewers (Srivastava & Kalro, 2019).

Similarly, HSM (Chaiken, 1980) describes cognitive processing as either systematic or heuristic. While systematic processing entails a detailed processing of content and the role of message-based cognitions as judgment-relevant information, heuristic information processing needs minimal cognitive effort to reach conclusions based on the least effort principle, relying on simple rules/heuristics or non-content cues (Chaiken, 1980; Teng et al., 2015).

HSM and ELM shared fundamental similarities (Barcelos et al., 2019; Teng et al., 2015). For instance, both models assume that, when people have high motivation and resources to process detailed information, they follow the central/systematic route, considering and elaborating on all the available information and carefully evaluating all the available attributes. On the other hand, people follow the peripheral/heuristic route of processing when they look for simple cues signaling the value of the object and base their judgments on simple decision rules (Barcelos et al., 2019; Teng et al., 2015).

Considering these dual-routes models of information processing, we posit that consumers assessing views, likes and dislikes should unconsciously devote fewer mental resources to evaluate the message content and follow the "peripheral route," relying more on heuristics, simple inferences, and social cues (Schulze et al., 2014). Thus, the number of likes may signal people's credibility perceptions of the information (Hong & Cameron, 2018).

By contrast, such heuristics may be less relevant when consumers follow the "central route," in which argument quality exerts a greater impact on persuasion, and unconsciously devote more thought to the actual message (Hughes et al., 2019). This high involvement induces a more meticulous processing of the information accessed (Balabanis & Chatzopoulou, 2019); generally associated with behavior such as writing a comment. We adopt this dual process for two drivers of YouTube video popularity: linguistic style and video category.

2.4 | Linguistic style

Language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand (Tausczik & Pennebaker, 2010). Language's role is critical in culturally bound social cognition (Maass et al., 2006). By going beyond the content features of an online review (i.e., what is said), the language style (i.e., how the content is conveyed) significantly affects how the message is received by readers (Liu et al., 2019). This happens because two types of words (content and style/function words) are processed differently in different brain regions (Ireland & Pennebaker, 2010). Moreover, certain linguistic characteristics stimulate the mechanics of content/brand relationship connections and self-presentation during the decoding process (Labrecque et al., 2020).

We, therefore, discuss the linguistic style of YouTube videos in terms of three word-level elements of language—function words, personal pronouns, and verbs—as well as three broader language factors: influencers' analytical thinking, subjectivity, and emotional valence. Based on user-generated content literature, argument quality (represented by these linguistics elements) and message valence are the key latent content factors that determine persuasiveness (Srivastava & Kalro, 2019). In addition, since function words and pronouns consistently vary as a function of psychological state, measuring these words is important in order to get rough proxies of people's psychological worlds (Chung & Pennebaker, 2007). Moreover, many studies have pointed out that emotional appeals have a great influence on consumer engagement by inducing consumer interaction with the brand and driving contents to go viral (Kujur & Singh, 2018).

In linguistic analysis, *function words* have little lexical meaning, but they reflect how people are thinking, speaking, or writing more than what they are thinking about, and have a significant impact on how the communication is received by listeners or readers (Ireland & Pennebaker, 2010; Liu et al., 2019; Pennebaker et al., 2014). Function words provide important psychological cues to thought processes, intentions, and motivations (Chung & Pennebaker, 2007; Tausczik & Pennebaker, 2010). Such as pronouns, they provide the reader with auxiliary information such as who is the creator and intended recipient of the message (Cruz et al., 2017).

Function words are not as explicit as content words, but they are context-dependent (Aleti et al., 2019) and are much more closely linked to measures of people's social worlds (Tausczik & Pennebaker, 2010). Hence, we propose:

H1. The higher (lower) the level of function words of video content, the more (less) popular the video is.

H1a. The higher (lower) the level of function words of video content, the more (less) views the video is.

H1b. The higher (lower) the level of function words of video content, the more (less) likes the video is.

H1c. The higher (lower) the level of function words of video content, the less (more) dislikes the video is.

H1d. The higher (lower) the level of function words of video content, the more (less) comments the video is.

Pronouns used in brand social media posts influence consumer engagement activities (Labrecque et al., 2020). Personal pronouns are useful linguistic elements that can help identify the attentional focus and shows the quality of a close relationship, which in turn can reveal priorities, intentions, and processing (Tausczik & Pennebaker, 2010). Consumer responses differ according to the use of different personal pronouns.

For instance, Labrecque et al. (2020) find that the use of the first-person plural pronoun ("we") on Facebook has a positive effect on the number of comments and shares, the use of the second-person pronoun ("you") has a higher positive effect on comments than likes and shares, and the use of the third-person ("they") increases all three engagement actions. To Cruz et al. (2017), online brand messages that include a second person pronoun can increase consumer involvement and attitude toward the brand as a result of increasing the extent that consumers engage in self-referencing.

According to Pennebaker (2011), people who use "I" at high rates are focusing on themselves, are more insecure, and tend to be more self-focused (Jordan et al., 2019). While those who use "you" and "we" at higher rates are looking at or thinking about their audience. People who use this externally focused style usually have higher status and exert more influence in social interactions (Jordan et al., 2019). This style usually suggests that the author is speaking from a perspective of high expertise and confidence (Hughes et al., 2019; Pennebaker et al., 2015), which favors the consumer's engagement and decisions (Aleti et al., 2019; Xu & Zhang, 2018). At the same time, lower-status individuals consistently use first-person singular pronouns and impersonal pronouns. Based on this evidence, we propose:

H2. The higher (lower) the level of social personal pronouns in video content, the more (less) popular the video is.

H2a. The higher (lower) the level of social personal pronouns in video content, the more (less) views the video is.

H2b. The higher (lower) the level of social personal pronouns in video content, the more (less) likes the video is.

H2c. The higher (lower) the level of social personal pronouns in video content, the less (more) dislikes the video is.

H2d. The higher (lower) the level of social personal pronouns in video content, the more (less) comments the video is.

The content of a text refers to the basic information it conveys. At the word level, language content includes *regular verbs* (Ireland & Pennebaker, 2010). Verb phrases generally provide greater information about the social/physical context and/or appear best suited to express the relationship between the acting person and his or her immediate environment/object (Maass et al., 2006). English verbs provide a remarkable amount of information about actions. They hint at whether an action is ongoing, partly completed, or completely finished. Whereas personal pronouns provide information about the subject of attention, verb tense can tell us how people are thinking about time (Pennebaker, 2011). Nouns and regular verbs are "content-heavy" in that they define the primary categories and actions dictated by the speaker or writer. In this sense, to have a conversation, it is important to know what people are talking about (Chung & Pennebaker, 2007).

Information-focused content is verbally rich. It typically deliveries arguments or factual descriptions about products, attributes, people, behaviors, and events. Thus, people with greater cognitive involvement may engage better in such verbal content. However, because of its argumentative or factual focus, information-focused content can be dry and uninteresting for most people with the same cognitive involvement. Rather than being shared, information-focused content may irritate consumers and be avoided (Tellis et al., 2019). Considering these arguments, we propose:

H3. The higher (lower) the level of verbs in video content, the less (more) popular the video is.

H3a. The higher (lower) the level of verbs in video content, the less (more) views the video is.

H3b. The higher (lower) the level of verbs in video content, the less (more) likes the video is.

H3c. The higher (lower) the level of verbs in video content, the more (less) dislikes the video is.

H3d. The higher (lower) the level of verbs in video content, the less (more) comments the video is.

Analytical thinking reflects the degree to which a text contains an analytical (rather than narrative) style (Pennebaker et al., 2015). Analytic thinking is a deliberate mode of thought wherein complex concepts are deconstructed into more manageable components and their interrelations (Jordan et al., 2019). An analytical style is argumentative and presents logical or associative ideas and facts and contains more references to complexly organized objects and concepts (Aleti et al., 2019). In this sense, a study of Pennebaker et al. (2014) shows that the ways prospective college students use an analytic style (more function words) in their admissions essays can even foretell their academic performance for up to 4 years.

Language containing high rates of articles and prepositions is necessarily "analytic" in nature due to the function of such linguistic devices, whereas language with low rates of articles and prepositions is generally more experiential and narrative in nature (i.e., diagnostic of a personable, intuitive way of communicating ideas and actions; Jordan et al., 2019).

A narrative style structures events in time and space as stories, considered the core of human nature (Aleti et al., 2019; Van Laer et al., 2018). Stories increase the attention of consumers; thus, the quality of a post's narrative may determine whether consumers will share or disregard it, because stories are at the core of human nature (Aleti et al., 2019; Van Laer et al., 2018). Moreover, as processing narrative-based messages require limited effort (as they are easier to process; Tellis et al., 2019), consumers on social media, generally in low elaboration, will evaluate these video contents highly. We thus propose:

H4. The lower (higher) the level of analytical thinking in a video post, the more (less) popular the video is.

H4a. The lower (higher) the level of analytical thinking in a video post, the more (less) views the video is.

H4b. The lower (higher) the level of analytical thinking in a video post, the more (less) likes the video is.

H4c. The lower (higher) the level of analytical thinking in a video post, the less (more) dislikes the video is.

H4d. The lower (higher) the level of analytical thinking in a video post, the more (less) comments the video is.

Subjectivity refers to feelings, views, or beliefs, as opposed to objectivity, which reveals factual information about the world (Liu, 2012). The followers of trustworthy influencers who show expertise are more likely to purchase the featured products (Sokolova & Kefi, 2019). In this sense, informative videos with more objective sentences than subjective ones will be more highly evaluated by consumers. Informational content triggers the consumer's central processing route, which requires greater cognitive effort. Kulkarni et al. (2020) examine the use of informational appeal and find that individuals report higher sharing intentions for viral ads.

According to Burgess and Green (2018), the "most viewed" section on YouTube contains mostly informational material from broadcast and mass media sources—particularly news footage, political discussion, and interviews. Moreover, according to a survey with more than 12,000 people worldwide (Google, 2019), the best reasons given by people to watch YouTube include the opportunity to learn something new and to dig deeper into one's interests. Hence, considering this preference for information and troubleshooting videos on YouTube and the arguments above, we propose the following:

H5. The higher (lower) the level of objectivity in a video post, the more (less) popular the video is.

H5a. The higher (lower) the level of objectivity in a video post, the more (less) views the video is.

H5b. The higher (lower) the level of objectivity in a video post, the more (less) likes the video is.

H5c. The higher (lower) the level of objectivity in a video post, the less (more) dislikes the video is.

H5d. The higher (lower) the level of objectivity in a video post, the more (less) comments the video is.

Emotional valence refers to the degree to which people express positive emotion or negative emotion (Chen, 2020; Tausczik & Pennebaker, 2010). The effect of valence is complex and leads to different perceptions depending on the context (Srivastava & Kalro, 2019). Even though the underlying psychological mechanisms of emotional expression influencing attitude formation are not fully understood, Chen (2020) suggests that online content exerts more cognitive effort when the emotions conveyed by the message are negative, compared to when the emotions conveyed are positive. Negative messages tend to include more diagnostic features associated with the product/service, and thus tend to be more informative (Chen, 2020). Besides, negative emotions can evoke an unpleasant state of mind and an emotional imbalance in the receiver, which can be rectified by engaging in the featured (desired) behavior (Kujur & Singh, 2018).

In opposition, contents that evoke positive emotional states (such as amusement, excitement, love, joy, warmth, inspiration and pride) should make the receiver feel a positive attitude toward the sharer, enhancing the sharer's opportunities for self-enhancement in the present and reciprocity by the recipient in the future (Kujur & Singh, 2018; Tellis et al., 2019). Moreover, advertisements that induce positive emotions have been shown to change attitudes toward the advertisements and increase purchase intentions and recall, reduce ad avoidance and affect sales (Kujur & Singh, 2018). In the same way, people usually feel more inclined to socialize with those who make them feel good (Aleti et al., 2019; Tellis et al., 2019). Thus, contents with positive emotional valence should be associated with more sharing (Xu & Zhang, 2018).

Hedonic contents that incite positive emotions are usually effective on low-involvement, high-distraction social media platforms (Hughes et al., 2019). Since people with low involvement levels use peripheral routes to process information (Petty & Cacioppo, 1986), we expect positive emotional content to be more salient to the consumer. We thus propose the following:

H6. The higher (lower) the level of positive emotion in a video post, the more (less) popular the video is.

H6a. The higher (lower) the level of positive emotion in a video post, the more (less) views the video is.

H6b. The higher (lower) the level of positive emotion in a video post, the more (less) likes the video is.

H6c. The higher (lower) the level of positive emotion in a video post, the less (more) dislikes the video is.

H6d. The higher (lower) the level of positive emotion in a video post, the more (less) comments the video is.

2.5 | Video category

How a video is interacted with and commented on is often a result of its content's nature. For instance, the comments for a music video will be quite different from those for a comedy video (Yew & Shamma, 2011). Different video genre categories have different patterns and signatures of contextual interaction surrounding them. By identifying these patterns in the social metadata, it is possible to predict a video's specific genre category based on particular responses of social activity (Yew & Shamma, 2011).

Gavilanes et al. (2018) show that different content categories affect DCE metrics at different levels. Hence, different video categories should be associated with different patterns and interactions. Identifying these patterns in social metadata should enable us to predict a video's specific category based on the responses via social activity (Yew & Shamma, 2011). Hence, we propose the following:

H7. Content categories have differential impacts on the popularity of YouTube videos.

H7a. Content categories have differential impacts on the number of views of YouTube videos.

H7b. Content categories have differential impacts on the number of likes of YouTube videos.

H7c. Content categories have differential impacts on the number of dislikes of YouTube videos.

H7d. Content categories have differential impacts on the number of comments of YouTube videos.

2.6 | Control variables

The *time* and *date of posting* have a significant influence on post popularity (Sabate et al., 2014). For instance, since YouTube is a platform based on audiovisual content, we posit that consumers will prefer to watch videos during non-business hours. Moreover, we investigate if there is a relationship between certain days of the week and higher levels of engagement. We expect that consumers visit channels more often on weekends than on weekdays, which can make videos posted during weekends more popular (De Vries et al., 2012; Hughes et al., 2019).

H8. Posting a video during non-business hours positively affects its popularity.

H8a. Posting a video during non-business hours positively affects the number of views.

H8b. Posting a video during non-business hours positively affects the number of likes.

H8c. Posting a video during non-business hours negatively affects the number of dislikes.

H8d. Posting a video during non-business hours positively affects the number of comments.

H9. Posting a video on weekends positively affects its popularity.

H9a. Posting a video on weekends positively affects the number of views.

H9b. Posting a video on weekends positively affects the number of likes.

H9c. Posting a video on weekends negatively affects the number of dislikes.

H9d. Posting a video on weekends positively affects the number of comments.

Video length can also influence popularity. For instance, Banerjee and Chua (2019) have shown that the length of a Facebook post is negatively correlated to its likelihood of being shared. Though the effects of YouTube video length have not yet been explored, many researchers suggested a relationship between the length of the promotional message and the ability of viewers to learn the information contained in the advertisement, in the sense that longer messages should significantly and positively affect advertising/brand recall (Newell & Henderson, 1998). If the content is too short, it may be insufficient to arouse strong emotions. For this reason, advertisers should manage the length of the ad to both attract and sustain viewers' interest while not exceeding their levels of patience (Tellis et al., 2019). As YouTube users might use the platform mainly to relax and learn new things, we expect long and medium-length videos to be more popular than short videos.

H10. Length positively impacts a video's popularity.

H10a. Length positively impacts the number of views.

H10b. Length positively impacts the number of likes.

H10c. Length negatively impacts the number of dislikes.

H10d. Length positively impacts the number of comments.

Based on the above hypotheses, we propose the conceptual model depicted in Figure 1 for our study's empirical analysis. Even though all dependent variables (views, likes, dislikes, and comments) are shown together in the model, we tested their effects separately in different regressions.

3 | METHODOLOGY

The context of this study is the videos uploaded on YouTube by digital influencers. So far, the literature in influencer marketing has focused mainly on the concept of influencers, while the relationship between content and influence remains rather unexplored (Francalanci & Hussain, 2017). YouTube is a content community founded in 2005 that allows users to post, view, comment on and link to videos on the site. Users can also set up personal profiles that display who they subscribe to, recent activity, comments and favorite videos (Smith et al., 2012). Following the huge success of YouTube since its creation, many companies have found that own-branded channels are an excellent way to boost consumer engagement, reach new audiences and convert website visits into purchases (Ferchaud et al., 2018; Kujur & Singh, 2018).

3.1 | Videos sampling and data collection

We investigated empirically data from about 150 digital influencers channels on YouTube from March 30, 2007, to July 15, 2019. We identified the top digital influencers channels by Forbes[1] list of 2017, which ranks influencers based on their reach, propensity for virality, and engagement to each influencers' area of expertise. Only influencers who made it big by building their fame and creating original content from the internet were included on the list. The influencers belong to 11 different product categories: beauty, entertainment, fashion, fitness, food, gaming, home, kids, parenting, tech and business, and travel.

For each one of the 11,177 video posts in the sample, we gathered the number of likes, dislikes and comments, as well as the valence of the comments and other video post characteristics. We relied on the application programming interfaces (APIs) provided by major social media to extract the data. Data collection was conducted via the Python programming language, and data persistence was performed using a MySQL relational database.

We used the YouTube API (YouTube Data V3[2]) for the extraction process (except for the transcriptions). Additionally, we used an open-source tool from Python API called "YouTube-transcript-API[3]" to extract all available auto-generated captions from videos (the API converts audio data into textual data saved in Json files). The caption text

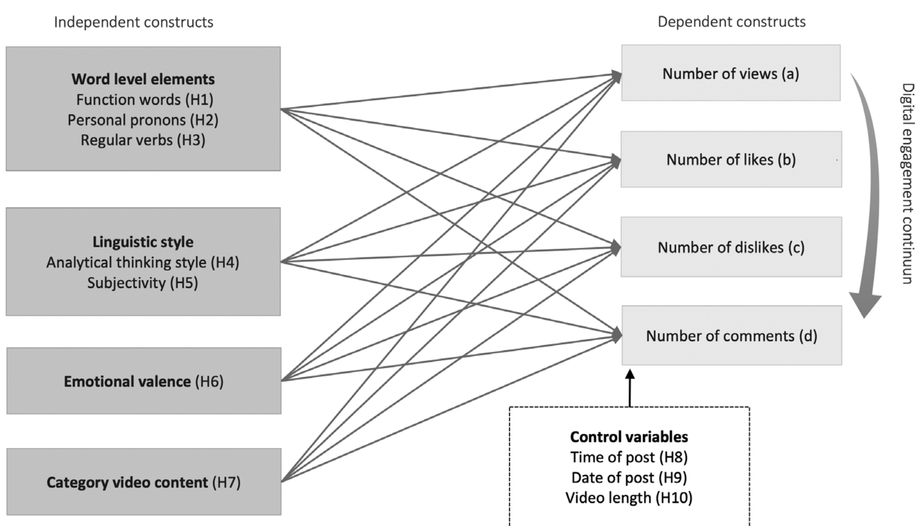

FIGURE 1 Conceptual framework

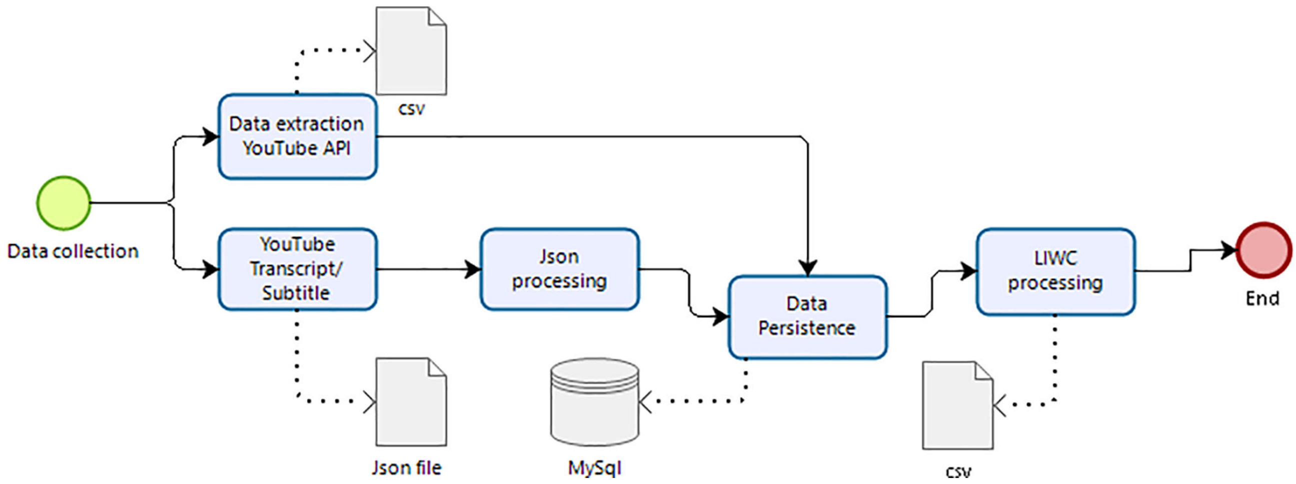

FIGURE 2 Data acquisition from YouTube [Colour figure can be viewed at wileyonlinelibrary.com]

was then processed by a machine-learning model and by the Linguistic Inquiry and Word Count software (LIWC) from Pennebaker et al. (2015) to generate variables for linguistic and emotional style. The default LIWC2015 dictionary is composed of almost 6400 words, word stems, and select emotions (Pennebaker et al., 2015). Figure 2 depicts the whole data-acquisition process.

3.2 | Variable operationalization

We used SPSS 26 software for statistical variables descriptive analysis and regression tests. Table 1 summarizes the information and descriptive statistics for the study's variables. We measured *video popularity* as the number of views, likes, dislikes, and comments, following similar studies (Aggrawal et al., 2018; Arora et al., 2019; De Vries et al., 2012; Hughes et al., 2019). Word-level elements and analytical thinking linguistic style were calculated through automated text analysis using LIWC. The program compares each word in an extract of text against predefined word categories, classified in dictionaries. It then calculates the number of words that match each dictionary (Pennebaker et al., 2015). The outcomes were standardized via conversion to percentiles (0–100) to represent the ratio of words corresponding to each style.

Function words represent the sum of nine different categories (articles, prepositions, personal pronouns, impersonal pronouns, quantifiers, auxiliary verbs, conjunctions, adverbs, negations). A higher percentage of function words indicates more thought processes, emotional states, intentions, and motivations (Tausczik & Pennebaker, 2010). *Personal pronouns* represent the sum of "I, we, you, she/he, they" words. A high number of we-words and social pronouns indicates a more outgoing, social style, while a high number of I-words indicates a more self-oriented, tentative, humble, and even anxious style (Pennebaker et al., 2015; Xu & Zhang, 2018). *Regular verbs* are measured as the percentage of verbs present in each video. A higher percentage of verbs indicates more contextual, informational content shared by the sender (Maass et al., 2006). *Analytical thinking* implies analytical/argumentative video content versus a more narrative style. A high level reflects formal, logical, and hierarchical thinking, while a lower level reflects more informal, personal, and narrative thinking (Pennebaker et al., 2015).

The next two elements, *emotional valence* and *subjectivity*, were obtained through a machine learning model trained to classify the valence and subjectivity of an input text. The model used for this classification employed a Naive Bayes Algorithm, a very common and effective classification method (Liu, 2012), with the open-source TextBlob tool. Python library was then used to process the textual data, based on the Natural Language Toolkit (NLTK). TextBlob uses a movie reviews corpus as labeled training data, which contains 1000 positive and 1000 negative processed reviews with sentiment polarity classification, and 5000 subjective and 5000 objective processed sentences labeled concerning their subjectivity status[4] (see Pang & Lee, 2004).

Positive emotions can be captured by the frequency of words such as happy, excited, and thrilled, whereas negative emotions are related to words such as anxious, tragic, and selfish (Aleti et al., 2019). The output values for valence ranged from −1 to +1, with +1 being an extremely positive text and −1 an extremely negative one. For the analysis model, however, these values were normalized to a scale from 0 to +1 using the MinMaxScaler formula. The output values for subjectivity varied from 0 to +1, with +1 being a very subjective text and 0 a very objective one.

Video's category indicates the YouTube classification of a video based on its content. Similar to Ferchaud et al. (2018), our study sorted videos into 1 of 11 genres: beauty, entertainment, fashion, fitness, food, gaming, home, kids, parenting, tech and business, and travel.

Control variables. Similar to Sabate et al. (2014), we categorized the *time of posting* into business hours (8 am to 6 pm on Monday to Thursday; 8 am to 3 pm on Friday) and non-business hours (any other time). We also presented the *date of video posting* specifying the day of the week, and not simply as a weekday or weekend (see Hughes

TABLE 1 Variable information and descriptive statistics

Continuous variable	Notation	Minimum	Maximum	Mean	*SD*
Number of views	y_{1j}	0.000	290,631,017	3,019,085.27	8,860,648.942
Number of likes	y_{2j}	0.000	8,242,848	71,670.92	193350.981
Number of dislikes	y_{3j}	0.000	591,233	1900.13	9502.193
Number of comments	y_{4j}	0.000	815,963	6697.04	23146.8
Analytic thinking	analytic_j	0.000	99.00	31.972	19.619
Emotional valence	emotion_j	0.000	1.00	0.458	0.061
Subjectivity	subjectivity_j	0.000	1.000	0.514	0.068
Function words	function_j	0.00	71.88	55.356	6.176
I	ppronoun_j	0.000	18.75	5.310	2.632
We		0.000	12.50	1.603	1.264
You		0.000	37.50	3.624	1.937
She/he		0.000	8.97	0.614	0.841
They		0.000	7.50	0.594	0.527
Regular verbs	verb_j	0.00	36.02	19.689	3.514
Categorical variable	**Notation**	**Category**		***N***	**Percent**
Time of video post	post_hour_j	1 (Business hour)		3033	27.10%
		0 (Non-business hour)		8144	72.90%
Video length, min	length_j	Long duration (>20:00 min)		1415	12.70%
		Medium duration (10:00–19:59)		4274	38.20%
		Short duration (0:00–9:59)		5488	49.10%
Date of video post	post_weekd_j	Wednesday		1806	16.2%
		Tuesday		1794	16.1%
		Thursday		1638	14.7%
		Sunday		1412	12.6%
		Saturday		1340	12.0%
		Monday		1678	15.0%
		Friday		1509	13.5%
Video categories	category_j	Travel		755	6.80%
		Tech and Business		914	8.20%
		Parenting		874	7.80%
		Kids		730	6.50%
		Home		906	8.10%
		Gaming		1293	11.60%
		Food		817	7.30%
		Fitness		1129	10.10%
		Fashion		1142	10.20%
		Entertainment		1265	11.30%
		Beauty		1352	12.10%

et al., 2019; Sabate et al., 2014). *Video length* was operationalized through dummy variables representing three video durations: short videos (from 0 to 9:59 min long), medium-length videos (from 10:00 to 19:59 min long), and long-term videos (more than 20:00 min long).

Analysis model. Since many variables were overdispersed, we chose a negative binomial distribution (Hughes et al., 2019; Van Laer et al., 2018) with maximum likelihood estimates (MLE). This distribution allowed a better goodness-of-fit of the model according to the Akaike and the Bayesian information criteria (AIC and BIC) than the Poisson-gamma mixture distribution (NB2) would have provided. The four dependent variables for video post popularity were the number of views, number of likes, number of dislikes, and number of comments per video post *j*. The model for each VD can be expressed as:

TABLE 2 Model results

Variable	Post views	Post likes	Post dislikes	Post comments
Intercept	17.399*** (0.299)	12.661*** (0.299)	11.464*** (0.315)	9.228*** (0.369)
Function words	−0.005 (0.004)	0.003 (0.004)	−0.008** (0.004)	0.014** (0.004)
I	0.001 (0.010)	−0.005 (0.010)	−0.007 (0.011)	0.002 (0.012)
We	0.021 (0.016)	0.001 (0.015)	0.009 (0.017)	0.019 (0.018)
You	−0.008 (0.010)	−0.031** (0.010)	−0.013 (0.011)	−0.025** (0.011)
She/he	−0.026 (0.020)	−0.011 (0.019)	0.064** (0.021)	0.038* (0.023)
They	−0.017 (0.032)	−0.068** (0.031)	−0.101** (0.034)	−0.108** (0.037)
Regular verbs	−0.016** (0.008)	−0.025** (0.007)	−0.045*** (0.008)	−0.035*** (0.008)
Analytic thinking	−0.003* (0.001)	−0.002 (0.001)	−0.006*** (0.002)	−0.002 (0.002)
Subjectivity	0.523** (0.179)	3.199*** (0.206)	−0.324** (0.164)	4.893*** (0.289)
Emotional valence	−3.970*** (0.227)	−5.629*** (0.253)	−4.107*** (0.226)	−6.954*** (0.302)
Category travel	−0.084 (0.083)	−0.232** (0.079)	−0.058 (0.088)	−0.054 (0.094)
Category tech and business	0.025 (0.076)	−0.104 (0.073)	0.012 (0.080)	−0.008 (0.086)
Category parenting	0.024 (0.077)	0.006 (0.075)	−0.096 (0.081)	0.010 (0.088)
Category kids	0.007 (0.085)	−0.157* (0.081)	−0.011 (0.092)	−0.062 (0.093)
Category home	−0.139* (0.074)	−0.169** (0.072)	−0.297*** (0.079)	−0.081 (0.084)
Category gaming	−0.046 (0.069)	−0.051 (0.067)	0.021 (0.073)	0.164** (0.078)
Category food	−0.097 (0.079)	0.040 (0.078)	0.011 (0.083)	0.290** (0.093)
Category fitness	−0.150** (0.073)	−0.217** (0.071)	−0.099 (0.077)	−0.123 (0.083)
Category fashion	−0.213** (0.069)	−0.242*** (0.067)	−0.274*** (0.072)	−0.210** (0.079)
Category entertainment	0.187** (0.069)	0.144** (0.068)	0.114 (0.073)	0.270** (0.080)
Time post	−0.699*** (0.041)	−0.840*** (0.040)	−0.712*** (0.042)	−0.903*** (0.047)
Day of week: Wednesday	−0.084 (0.060)	−0.097 (0.059)	−0.343*** (0.064)	−0.248*** (0.070)
Day of week: Tuesday	−0.032 (0.061)	0.036 (0.060)	−0.222*** (0.064)	0.126* (0.071)
Day of week: Thursday	0.152** (0.062)	0.227*** (0.061)	−0.132** (0.065)	0.089 (0.073)
Day of week: Sunday	−0.292*** (0.063)	−0.202** (0.061)	−0.403*** (0.067)	−0.115 (0.072)
Day of week: Saturday	0.018 (0.064)	−0.006 (0.062)	−0.072 (0.068)	0.187** (0.074)
Day of week: Monday	0.359*** (0.061)	0.356*** (0.059)	0.049 (0.064)	0.167** (0.070)
Video length longer	−0.309*** (0.051)	0.490*** (0.050)	0.323*** (0.055)	0.972*** (0.060)
Video length medium	−0.312*** (0.036)	0.139*** (0.035)	−0.083** (0.037)	0.287*** (0.041)
Overdispersion (α)	2.819 (0.030)	2.672 (0.029)	3.105 (0.034)	3.696 (0.041)
AIC	340,676.254	257,701.377	172,445.854	193,242.871
BIC	340,903.224	257,928.347	172,672.824	193,469.841

Note: For dummy variables, the results were compared with the baseline variables but are not reported in the table. Number of betas (β), standard errors are in parentheses.
Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion.
**p* < .10. ***p* < .05. ****p* < .001.

$$
\begin{aligned}
(\log_{\lambda ij})\gamma_{ij} = \beta_0 &+ \beta_1(\text{function}_j) + \beta_2(\text{ppronoun}_j) + \beta_3(\text{verb}_j) \\
&+ \beta_4(\text{analytic}_j) + \beta_5(\text{emotion}) + \beta_6(\text{subjectivity}_j) \\
&+ \beta_7(\text{post\_weekday}_j) + \beta_8(\text{category}_j) + \beta_9(\text{length}_j) \\
&+ \beta_{10}(\text{post\_hour}_j) \in_{ij}.
\end{aligned}
$$

where $\log_{\lambda ij}$ is the rate of the negative binomial distribution process, and $\in_{ij}$ is the distributed error terms for dependent variables y_{1j}, y_{2j}, y_{3j} and y_{4j}.

4 | RESULTS

Table 2 reports the results of our analysis. To determine effect sizes, we used the incidence rate ratio (IRR) or the factor by which positive scores (>1) would be expected to increase the predictor variable by one standard deviation, ceteris paribus.

Number of views. The effect of function words and personal pronouns was not significant; thus, H1a and H2a were not supported.

However, regular verbs had a negative effect on the number of views (β = −0.016, p = .042, IRR = 0.984); thus, more informative and time-focused content had a negative impact on views. This result supported H3a, that is, information-focused content, rich in number of verbs, can be uninteresting and avoided (Tellis et al., 2019).

The effect of video's analytic thinking was significant and negative (β = −0.003, p = .067, IRR = 0.997), which shows that a more formal and logical style, with hierarchical thinking (i.e., references to complexly organized objects and concepts), reduced the number of views. This result supported H4a. Subjectivity influenced the number of views positively (β = 0.523, p = .003 IRR = 1.688), which means that consumers viewed more subjective content (which relates to personal opinions) as opposed to a more objective content. This result did not support H5a. Emotional valence had a negative effect (β = −3.970, p = .000, IRR = 0.019), which suggests that a very positive language style was not as effective as one expressing more negative emotions. This result rejected H6a.

Concerning the effect of the video category, we compared the 10 categories with "beauty" used as the base dummy variable. The only category positively associated with a higher number of views was "entertainment" (β = 0.187, p = .007, IRR = 1.205), which means that entertainment videos tended to receive more views than others. The categories "home" (β = −0.139, p = .062, IRR = 0.870), "fitness" (β = −0.150, p = .040, IRR = 0.860), and "fashion" (β = −0.213, p = .002, IRR = 0.808) were negatively associated with the number of views relative to the base content, meaning that YouTube videos in these categories did not get as many views as the others. Thus, H7a was partially accepted, as the other categories were not statistically significant.

Regarding posting time, videos posted during business hours received significantly fewer views than those posted during non-business hours (β = −0.699, p = .000, IRR = 0.497). Thus, H8a was supported. Concerning the day of the week on which the video was posted (Friday = base dummy variable), videos posted on Thursday (β = 0.152, p = .015, IRR = 1.164) and Monday (β = 0.359, p = .000, IRR = 1.431) received significantly more views, while videos posted on Sunday (β = −0.292, p = .000, IRR = 0.747) received significantly fewer views. Hence, videos posted during weekdays seem to have had more views, rejecting H9a. Finally, medium-length videos (β = −0.312, p = .000, IRR = 0.732) and long videos (β = −0.309, p = .000, IRR = 0.734) received less views than short ones. Thus, H10a was rejected.

Number of likes. The effect of the video's function words on the number of likes were non-significant, rejecting H1b. The use of the second-person pronoun "you" had a significant and negative effect on likes (β = −0.031, p = .001, IRR = 0.969), as did the use of the third-person pronoun "they" (β = −0.068, p = .030, IRR = 0.934), which suggests that a more tentative, humble, even anxious language style seemed to be more highly appreciated, rejecting H2b.

Regular verbs had a negative effect on the number of likes (β = −0.025, p = .001, IRR = 0.976), suggesting that more informative and action-focused contents tended to receive fewer likes, supporting H3b. The effect of the video's analytic thinking style on the number of likes were non-significant, rejecting H4b. Subjectivity influenced the number of likes positively (β = 3.199, p = .000, IRR = 24.496), which means that viewers enjoyed when influencers expressed their opinions, beliefs, and feelings. Thus, hypothesis H5b was not supported. Emotional valence, on the other hand, had a negative effect (β = −5.629, p = .000, IRR = 0.004), that is, a positive emotion had an impact negative on number of likes, rejecting H6b.

The only category positively associated with a higher number of likes was "entertainment" (β = 0.144, p = .033, IRR = 1.155). The categories "travel" (β = −0.232, p = .004, IRR = 0.793), "kids" (β = −0.157, p = .052, IRR = 0.855), "home" (β = −0.169, p = .019, IRR = 0.844), "fitness" (β = −0.217, p = .002, IRR = 0.805), and "fashion" (β = −0.242, p = .000, IRR = 0.785) were negatively associated with the number of likes relative to the base content, meaning that YouTube videos in these categories did not get as many likes as the others. Thus, H7b was partially supported.

Videos posted during business hours received significantly fewer likes than those posted during non-business hours (β = −0.840, p = .000, IRR = 0.432), supporting H8b. Videos posted on Thursday (β = 0.227, p = .000, IRR = 1.255) and Monday (β = 0.356, p = .000, IRR = 1.427) received significantly more likes, while videos posted on Sunday (β = −0.202, p = .001, IRR = 0.817) received significantly fewer likes, thus rejecting H9b. Finally, medium-length videos were associated with a greater number of likes than short ones (β = 0.139, p = .000, IRR = 1.150), and long videos received even more likes than medium-length and short ones (β = 0.490, p = .000, IRR = 1.632). This result shows that YouTube viewers preferred long videos over short ones, maybe due to the possibility of learning more information. Thus, H10b was supported.

Number of dislikes. The impact of function words was significant and negative (β = −0.008, p = .040, IRR = 0.992), which means this way of expressing thought processes reduced the number of dislikes, supporting H1c. The use of the pronouns "she/he" had a significant and positive effect on dislikes (β = 0.064, p = .003, IRR = 1.066), and the use of the pronoun "they" had a negative effect on dislikes (β = −0.101, p = .003, IRR = 0.904), suggesting that a more social-focused style was more greatly appreciated, supporting H2c.

Regular verbs had a negative effect on the number of dislikes (β = −0.045, p = .000, IRR = 0.956), supporting H3c. The effect of analytical thinking on the number of dislikes was significant and negative (β = −0.006, p = .000, IRR = 0.994); thus, a more formal and logical style attracted a smaller number of dislikes, rejecting H4c. Both subjectivity (β = −0.324, p = .048, IRR = 0.724) and positive emotional valence (β = −4.107, p = .000, IRR = 0.016) were significantly associated with fewer dislikes, supporting H5c and H6c.

Regarding video content category, "home" videos (β = −0.297, p = .000, IRR = 0.743) and "fashion" videos (β = −0.274, p = .000, IRR = 0.760) were negatively associated with a greater number of dislikes; H7c was thus partially accepted. Regarding the post time, videos posted during business hours received fewer dislikes than those posted during non-business hours (β = −0.712, p = .000, IRR = 0.491), rejecting H8c. Videos posted on Wednesday (β = −0.343, p = .000, IRR = 0.710), Tuesday (β = −0.222, p = .000, IRR = 0.801), Thursday (β

= −0.132, p = .043, IRR = 0.876), and Sunday (β = −0.403, p = .000, IRR = 0.669) received fewer dislikes, rejecting H9c. Medium-length videos received fewer dislikes than short ones (β = 0.083, p = .028, IRR = 0.921); however, long videos received more dislikes (β = 0.323, p = .000, IRR = 1.382), perhaps because a long time spent watching the video induced consumers to manifest more discontent. Thus, H10c was partially supported.

Number of comments. The impact of function words were significant and positive (β = 0.014, p = .002, IRR = 1.014), supporting H1d. The use of the pronouns "you" (β = −0.025, p = .030, IRR = 0.976) and "they" (β = −0.108, p = .004, IRR = 0.897) had a significant and negative effect on comments. Meanwhile, using "she/he" increased the number of comments (β = 0.038, p = .095, IRR = 1.039), partially supporting H2d. Regular verbs negatively impacted the number of comments (β = −0.035, p = .000, IRR = 0.966), supporting H3d.

Analytical thinking was not significantly associated with the number of comments, rejecting H4d. Subjectivity was significantly associated with more comments (β = 4.893, p = .000, IRR = 133.302), rejecting H5d. Positive emotional valence was significantly associated with fewer comments (β = −6.954, p = .000, IRR = 0.001), rejecting H6d. Regarding video category, "gaming" (β = 0.164, p = .036, IRR = 1.178), "food" (β = 0.290, p = .002, IRR = 1.337), and "entertainment" (β = 0.270, p = .001, IRR = 1.310) received more comments, while "fashion" (β = −0.210, p = .008, IRR = 0.811) received fewer. Thus, H7d was partially accepted.

Videos posted during business hours received fewer comments than those posted during non-business hours (β = −0.903, p = .000, IRR = 0.405), supporting H8d. Videos posted on Saturdays (β = 0.187, p = .011, IRR = 1.206), Tuesdays (β = 0.126, p = .075, IRR = 1.135), and Mondays (β = 0.167, p = .017, IRR = 1.181) received more comments than those posted on Wednesday (β = −0.248, p = .000, IRR = 0.780), partially supporting H9d. Finally, both medium-length videos (β = 0.287, p = .000, IRR = 1.332) and long videos (β = 0.972, p = .000, IRR = 2.643) received more comments than short ones, supporting H10d.

5 | DISCUSSION

5.1 | Theoretical implications

The results of our study show that not all factors that help to boost the number of views and likes have similar effects on the number of comments or dislikes. Thus, the choice of digital influencers or channel on YouTube should be based not only on the number of views and subscribers but also on how they communicate and engage with users.

Following ELM, this study shows that the specific linguistic style used in social media content elicits different routes of information processing. Using the dual-process model for online consumer behavior as the background and drawing upon information processing, the results help to improve the understanding of different attributes that contribute to the popularity of online content. For instance, marketers can employ the ELM framework to map out possible variables and assess their impact on attitude change (Teng et al., 2015). In this sense, YouTube offers a comparatively rich and long content format for analysis, which helps to highlight information about influencers/brands even if the brands are peripheral to the video's main focus (Smith et al., 2012). The results of our analysis contribute to the understanding and application of ELM theory in social media content research, advancing previous studies that focused mostly on the message and its source only (Le et al., 2020).

Another contribution of our findings is in expanding growing research on the viability of linguistic elements in marketing communication, that is, not only the informational content itself but how it is presented. We tested the effect of several elements of language on DCE variables and, for instance, the use of function words was shown to have a positive impact on comments and a negative one on dislikes. As expected, a greater cognitive processing favored the assessment of these linguistic latent elements of communication. Writing style influenced how readers evaluated the content, corroborating the conclusions of Liu et al. (2019).

The overuse of the pronouns "you" and "they" negatively affected digital engagement via likes and comments, suggesting that content creators should avoid addressing their content directly to "others". This might be explained by the arguments of Cruz et al. (2017), who propose that second-person pronouns do not enhance consumer involvement and brand attitude when directed at consumers that are more (vs. less) collectivistic, as these tend to subordinate their own personal goals to the goals of their in-groups. The result of using "she/he" seems contradictory, as it encouraged dislikes while also having a positive effect on the number of comments. Unlike previous studies (Aleti et al., 2019; Pennebaker et al., 2015; Xu & Zhang, 2018), our results do not suggest that videos using an externally focused style (i.e., we-words, which usually demonstrate a higher confidence and expertise), are less likely to be liked. It is possible that YouTube users experience a greater sense of closeness and identification with influencers who show weaknesses and uncertainties, as suggested by Jordan et al. (2019).

The previous argument is also supported by the finding that subjectivity positively affected DCE variables. Hence, even if the consumer goal on YouTube content is to learn something or help deepen some personal interest, it is important that the video adopts a more personal tone of voice, with informal language, closer to the reality of the consumer. This finding also suggests that self-disclosure may be an effective strategy for encouraging post popularity. This corroborates predictions from ELM, as factors as content creator identity (self-disclosure) and reputation/self-presentation acting as peripheral factors, and thus, are processed through the peripheral route (Srivastava & Kalro, 2019).

Our results also show that viewers react negatively to the use of a large number of verbs, which indicates denser informational content, as well as more actions and temporal events, and demand higher message elaboration. Given that function words and a subjective style are good indicators of the broad ways people connect to others, verbs may also distance the speaker from the behaviors and occurrences described. Pennebaker (2011) also notes that people who use verbs at high rates tend to be more deceptive than people who use fewer verbs. At the same time, they reduce the number of dislikes.

Our findings also show that the most argumentative/informative are less viewed than others, perhaps because of their increased cognitive complexity. Moreover, these videos received fewer dislikes, contradicting the literature on the effectiveness of narrative content on social media (Aleti et al., 2019; Van Laer et al., 2018). This may indicate that people are more focused on problem-solving information when on YouTube than when on other platforms, like Facebook and Instagram.

Regarding emotional valence, our results corroborate those of Labrecque et al. (2020), in the sense that positive emotions impact negatively the number of views, likes and comments. It is possible that extremely positive emotions are considered unrealistic or associated with dishonest behavior. Tellis et al. (2019) also suggested that sharing negative ad content might be consistent with an altruistic motive, that is, individuals may want to share content that warns others of fear, shame, or sadness-inducing outcomes that may befall them when using (or not) a given product. Another explanation for our results is the possibility that cognitively involved readers prefer double-sided reviews or even that the degree of the persuasiveness of the information is driven by underlying psychological factors like consumption goals of the content creator (Kujur & Singh, 2018). In this sense, negative messages tend to include more diagnostic features associated with the product/service, and thus, tend to be more informative (Chen, 2020).

The previous argument is aligned with ELM theory, since high engagement in information acquisition leads to higher elaboration and to the central processing route. Overall, our findings suggest that consumers prefer videos with moderate levels of emotion and low levels of arousal. Discrete positive emotions are helpful as they associate with socializing motivations for consumer engagement (Tellis et al., 2019). Nevertheless, consumer engagement on YouTube is evidently a more complex behavior than just emotional valence and depends on several other factors, such as consumption goals and previous experience/relationship with the channel/digital influencer.

Regarding the date and time of posting, our analysis shows that videos posted during non-business hours during weekdays receive a greater number of likes and views (and fewer dislikes), especially on Mondays, Tuesdays, and Thursdays. This may be a particularity of user behavior on YouTube, as consumers need more time to watch a video than to read a post on Facebook, Instagram, or Twitter. However, this strategy should be taken with a grain of salt because, as shown by Sabate et al. (2014), the decision of the most effective time is still context-dependent and controversial.

Finally, regarding video duration, consumers seem to like medium-length and long videos (i.e., 10 min or longer) more than short ones. This means that those willing to watch more than a few minutes of a video are more prone to like and comment on it.

This study highlights the importance of several content factors in information processing, such as argument quality (i.e. the linguistic construction and word choice) and message valence. Deliberation and cognitive processing are an integral part of message evaluation/adoption and hence, these factors contribute significantly to consumer engagement. However, it is important to note that our findings represent general tendencies and that different consumers can use their own combinations of quality content and creator attributes when processing and evaluating videos. Each consumer adopts a cognitive resourceful strategy based on their own personal characteristics, as well and the video content and embedded sentiments for purchase decision and engagement (Srivastava & Kalro, 2019).

5.2 | Practical implications

This study is useful for digital influencers and brands alike who wish to engage users in their social media activities. Our findings provide insights into how influencers should better perform their social media communication strategy, not only by focusing on content but also on the linguistic style, as shown by the summary of our findings in Table 3. Overall, these results suggest that managers wanting to boost the number of likes and comments should focus on medium-length and long videos that are less action- and tense-focused and have subjective content.

Unlike users of other social media sites (e.g., Facebook, Twitter), YouTube users seem to favor medium and long videos. The more time viewers have to process information within the content/advertisement, the more familiar they become with the product and other information contained (Newell & Henderson, 1998). As a result, longer videos become more popular (as shown by the number of likes and comments, as well as, partially, by the number of dislikes). Thus, managers can improve viewer recall of brand messages by concentrating their efforts on these videos.

Moreover, as shown by our results, the use of function words seems to be associated not only with higher information processing, but also with more comments and a reduced number of dislikes. Hence, using more function words in YouTube videos may have positive impacts on marketing campaigns since, as shown by Yoon et al. (2018), a higher number of comments can foster an increase in company's revenues. In the same way, a more personal and closer conversation can help to build a relationship with users.

Marketing managers should avoid videos loaded with extremely positive emotion, which are shown by our results to lead to less engagement. In order to entice consumers' attention and, consequently, increase the chance they will consider the brand's product or service, it is helpful to balance these videos with moderate emotion, and even some negative ones (e.g., sadness, anger and shame). However, despite the fact that negative emotions may increase consumer engagement, their level of influence in the effective experience of people may be also comparatively low when compared to positive emotions (Aleti et al., 2019; Kujur & Singh, 2018; Tellis et al., 2019; Xu & Zhang, 2018).

Posting during non-business hours also helps to increase the number of views, likes, and comments, possibly because most people are working or busy at that time and cannot dedicate enough time to

TABLE 3 Summary of findings

Variable	Post views Low elaboration likelihood	Post likes	Post dislikes High elaboration likelihood	Post comments
Linguistic elements	Regular verbs (–) Analytic thinking (–) Subjectivity (+)	You (–) They (–) Regular verbs (–) Subjectivity (+) Positive emotion (–)	Function words (–) She/he (+) They (–) Regular verbs (–) Analytic thinking (–) Subjectivity (–) Positive emotion (–)	Function words (+) You (–) She/he (+) They (–) Regular verbs (–) Subjectivity (+) Positive emotion (–)
Content category	Home (–) Fitness (–) Fashion (–) Entertainment (+)	Travel (–) Kids (–) Home (–) Fitness (–) Fashion (–) Entertainment (+)	Home (–) Fashion (–)	Gaming (+) Food (+) Fashion (–) Entertainment (+)
Posting and duration	Business hour (–) Thursday (+) Sunday (–) Monday (+) Video longer (–) Video medium (–)	Business hour (–) Thursday (+) Sunday (–) Monday (+) Video longer (+) Video medium (+)	Business hour (–) Wednesday (–) Tuesday (–) Thursday (–) Sunday (–) Video longer (+) Video medium (–)	Business hour (–) Wednesday (–) Tuesday (+) Saturday (+) Monday (+) Video longer (+) Video medium (+)

Note: (+) = Marketing managers should consider these elements to increase digital engagement actions; (–) = Marketing managers should avoid these elements. For number of dislikes, the analysis is the opposite.

watch long videos (even if they get notifications of new video posts during business hours). This is a particularity of YouTube, in the sense that content on its platform requires more effort and attention from consumers than contents posted on other social media such as Facebook, Instagram and Twitter.

In the other hand, our analysis revealed that videos posted on certain weekdays (Monday, Tuesday and Thursday) were significantly more popular than those posted during the weekend. Since previous literature (for instance, Sabate et al., 2014; Devereux et al., 2020) has found no effect of day of posting on video popularity, it is possible that this finding is very context-dependent. For this reason, managers should not focus so much on the day of posting and instead prioritize the attributes of language style and emotion previously discussed, as well as video length. For instance, if the main objective is to avoid dislikes, managers should prioritize videos with medium duration, whose contents are associated with positive valence emotions, and use more subjective language and a narrative style.

Finally, managers may want to prioritize sponsoring or associating their ads with categories such as entertainment, gaming, and food rather than others like fashion and fitness. However, the increased engagement with these videos may also bring a higher number of dislikes.

For managers and content creators, the key to creating and sustaining consumer engagement may come from the ability to adequately use cohesive social media strategies across different channels (Oh et al., 2017). Given the advancements in machine learning and natural language processing in marketing, managers should learn to use these techniques in order to better understand which features of social media content signal good quality content to their specific customers. Thus, brands will be more prepared to improve communication and aggregate value to their own consumers.

5.3 | Limitations and further research

This study is subject to several limitations. First, our computerized technique extracted all available autogenerated captions from the videos in our sample as textual data. Relying on these captions is not always ideal, as they are the products of an automatic conversion of audio into text, and the quality of this process is dependent on several factors, such as the presence of noise, and semantic errors. We executed the preprocessing phase in sentiment analysis to clean up the dataset, but flaws may remain.

Second, the current version of LIWC's word dictionary is not fully able to capture the diversity of internet slang and codes, as well as various types of sentiment expressed using emoji. Moreover, since linguistics studies often present controversial findings, future studies should investigate more deeply the use of personal pronouns, function words, and other grammatical categories in YouTube videos.

Third, the unit-level of analysis in this study was the video rather than the content creator, which leaves room for further investigation into how the characteristics of digital influencers influence video popularity. Finally, the study's conceptual model focused only on video aspects and ignored audience profiles. Hence, future research could examine if different audience profiles, personal goals, and involvement levels react differently to different language styles.

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CONFLICT OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Forbes Top Influencers (https://www.forbes.com/top-influencers/#574bf4272dde).

[2] YouTube Data API: https://developers.google.com/youtube/v3.

[3] YouTube Transcript/Subtitle API: https://github.com/jdepoix/youtube-transcript-api.

[4] Available at: http://www.cs.cornell.edu/people/pabo/movie-review-data/.

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