Received: 23 September 2022 | Accepted: 3 May 2023

DOI: 10.1002/mar.21831

RESEARCH ARTICLE

Psychology & Marketing WILEY

Luxury is what you say: Analyzing electronic word-of-mouth marketing of luxury products using artificial intelligence and machine learning

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Abstract

Many luxury brands are investing heavily in creating dynamic video content to actively engage consumers. While it is straightforward to calculate the views or "likes" from a particular campaign to benchmark performance, analyzing consumers' comments on luxury brands' dynamic video content presents a challenge due to the unstructured nature of natural language and large comment volumes. Previous studies utilizing machine learning and artificial intelligence (AI) have not adequately examined the impact of brand types, brand luxuriousness, and consumer diversity. To address this research gap, this article tests a conceptual framework with over 29,000 comments from 88 YouTube campaigns for nine luxury brands using a combination of automatic text and image analyses. The results indicate significant differences in comments' psycholinguistic nature depending on the brand's luxuriousness (premium, prestige, and exquisite) and Copelandian classification (convenience, shopping, and specialty), as well as consumers' demographic characteristics (age, gender, and ethnicity). These findings suggest that brand managers can use machine learning and AI methods to better tailor dynamic content creation to further engage diverse target segments by refining the campaign message to encourage additional engagement.

KEYWORDS

automatic text and image analysis, brand luxuriousness, luxury marketing communications, machine learning and artificial intelligence (AI), nature of electronic word-of-mouth (eWOM), social media video advertising, YouTube

1 | INTRODUCTION

While broadcast television remains a relevant communication channel for many brands (Hengel, 2021), many luxury brands are increasingly embracing social media video platforms (e.g., Instagram, YouTube, and TikTok) to enthuse consumers with the latest trends (Arienti, 2020; Pentina et al., 2018). These platforms encourage more active forms of engagement as consumers may like, dislike, share, comment on videos or upload their video responses (Parent et al., 2011), thus facilitating a two-way flow between luxury brands and consumers (Okazaki et al., 2020). Marketers report that social media videos are twice as likely to be shared compared to other content, which in turn drives more website traffic and sales (Hubspot, 2021). Thus, it is not surprising that luxury brands are investing in social media video marketing campaigns to communicate messages of authenticity, trendiness, or heritage to younger consumers that make up the majority of these platforms' user base (Maguire, 2021). However, the marketing literature offers sparse insights into the effectiveness of social media video content, highlighting a need to explore consumer reactions and electronic word-of-mouth (eWOM) with these campaigns.

Dynamic (i.e., videos) rather than static (i.e., images) content can offer consumers experiences that transport them into the narrative of a luxury brand (Van Laer et al., 2014). On social media platforms in general, these videos have been shown to strengthen the intention to share the ad (Akpinar & Berger, 2017) and elicit positive affective and behavioral outcomes (Barney & Jones, 2023). Moreover, specifically on YouTube, there is evidence that social media video marketing increases brand awareness and purchase intentions (Dehghani et al., 2016; Filieri et al., 2023), as well as containing a variety of appeals and message tones (Park & McMahan, 2020). When consumers recommend luxury brands to others online, they are not only sharing information, but also expressing their social status and presenting themselves in distinctive ways (Han et al., 2010; Lee & Watkins, 2016; Lee, 2021). As a result, these eWOM behaviors are effective channels for marketers to communicate brand messages and influence or generate additional engagement around their brand's values that strengthens brand-consumer relationships (Delbaere et al., 2021; Dhaoui, 2014; Giakoumaki & Krepapa, 2020; Kastanakis & Balabanis, 2014; Santos et al., 2023).

Yet, much of the luxury social media literature focuses on other more static campaigns on Facebook, Instagram, and Twitter, leaving dynamic content campaigns less scrutinized by marketing scholars (Wies et al., 2023). Moreover, past social media video studies often adopt homogenous definitions of luxury and restrict their analysis to one type of good, as well as not considering how consumer characteristics can impact outcomes. To address these gaps in the marketing literature (see Table 1 for an overview), this article uses observable field data from YouTube assess the nature of eWOM inspired by social media video marketing. Specifically, we tackle the lack of heterogeneous scrutiny of eWOM by focusing on the influence of both brand luxuriousness (RQ1) and the type of good (RQ2), while also accounting for (RQ3) consumer diversity.

We posit that luxury brands vary in their luxuriousness. On one hand, many attempts have been made to define luxury brands in terms of their scarcity, value, and expense, whose combination allows consumers to say something about themselves (c.f., Keller, 2017; Ko et al., 2019). On the other, Berthon et al. (2009) contend that defining "luxury" is a futile endeavor and should instead be conceptualized multi-dimensionally, contingent on the consumer and the context in which they find themselves. For example, while many consumers might consider a BMW or Audi as luxury vehicles, Porsche customers might regard them as a mass-market brands—certainly not in the same category as a Porsche 911 or a Maserati GranTurismo. Yet, at a higher level, Ferrari or Lamborghini owners would view Porsche and Maserati as more widely available, less prestigious, and much less expensive alternative to a Ferrari 599 GTO or a Lamborghini Aventador. We, therefore, refer to brands such as BMW and Audi, with mass appeal and availability across many markets, as *premium luxury brands*, mid-level luxury brands like Porsche or Maserati as *prestige luxury brands*, and high-level luxury brands like Ferrari or Lamborghini as *exquisite luxury brands* due to their extreme price and scarcity. This applies classification of brand luxuriousness applies to other industries as well. For example, the fashion industry: premium luxury brands might include Burberry or Michael Kors, prestige luxury brands could be Hermes or Gucci, and exquisite luxury brands Alexander McQueen or Maison Goyard. Using Berthon et al. (2009) as a general framework, we use *brand luxuriousness* in this paper as a multifaceted concept includes material, subjective, and collective values. Luxury brands are more than merely scarce, sought-after, or prized (collective) high-quality products or services (material), as they also create a unique and desirable identity (subjective) that consumers aspire to have (Libai et al., 2010).

Applying Copeland's (1923) classification of goods, we construct a conceptual model that provides an overview of how consumers respond to social media video marketing by a variety of luxury brands that account for the brand's luxuriousness and type of good. Moreover, we include consumer characteristics to capture response heterogeneity that can be attributed to age, gender, and ethnicity. We empirically tested this framework by capturing over 29,000 consumer comments on 88 YouTube videos posted by nine luxury brands and running several automatic text and image analyses. Automated text analysis is a set of computational methods that researchers can use to uncover patterns in comments in a more objective and accessible fashion than manual content analysis (Humphreys & Wang, 2018). This analysis was aided by Linguistic Inquiry and Word Count (LIWC) software (Kietzmann & Pitt, 2020; Tausczik & Pennebaker, 2010). Three types of artificial intelligence (AI) algorithms were used to infer textual (Micu et al., 2017) and emoji sentiments (Klostermann et al., 2018; Kralj Novak et al., 2015), as well as many of the posting consumers' demographic characteristics based on automatic image analysis (Nanne et al., 2020).

This article offers two conceptual contributions that help researchers and managers better understand the effect of luxury goods communication on consumers. First, we identify how the luxuriousness (premium, prestige, exquisite) and the Copelandian classification (convenience, shopping, specialty) of a brand impact consumers' behavioral responses (i.e., eWOM) to social media video marketing campaigns. Second, we refine and delineate the effects of brand luxuriousness on eWOM behaviors by accounting for consumer heterogeneity (age, gender, ethnicity). In what follows, we first examine the behavioral engagement and brand luxuriousness literature for insights before classifying luxury brands and investigating the nature of eWOM on social media. Then, we report our methods and discuss our findings, as well as suggesting the implications for scholars and managers.

TABLE 1 Selected empirical studies on luxury social media marketing.

Study	Technology & context	Method	Brand luxuriousness			Copelandian classification			Consumer Characteristics
			Premium	Prestige	Exquisite	Convenience	Shopping	Specialty	
Kim and Ko (2012)	Facebook and Twitter posts	Survey			X		X		
Lee and Watkins (2016)	YouTube blogger videos	Online experiment					X		
Nikolinakou and King (2018)	Facebook video ads	Online experiment				X	X	X	Age
Kim et al. (2019)	Facebook videos and comments	Text analysis				X	X	X	
Amatulli et al. (2020)	Image ads on MTurk	Online experiment		X	X		X		
Choi et al. (2020)	Facebook posts	Online experiment	X	X	X		X		
Duong and Sung (2021)	Facebook and Instagram posts	Text analysis		X	X		X		
Giakoumaki and Krepapa (2020)	Instagram posts	Online experiment			X		X		
Mandler et al. (2020)	Facebook posts	Text analysis	X	X	X	X	X	X	
Delbaere et al. (2021)	YouTube videos	Text analysis	X	X	X	X			
Lee (2021)	Twitter posts	Text & image analysis	X	X	X		X		
Liu et al. (2021)	Twitter posts	Text analysis		X	X		X		
Wies et al. (2023)	Instagram posts	Eye-tracking & lab experiments				X	X	X	
The current research	YouTube videos	Text & image analysis	X	X	X	X	X	X	Age, gender, & ethnicity

Note: Luxuriousness was left blank for undisclosed brands in study's method section or if they fabricated a fake brand.

1.1 | Luxury brands on social media

Word-of-mouth (WOM) is among the highest forms of behavioral engagement (Parent et al., 2011). These WOM behaviors consist of information sharing between consumers concerning the sender's opinion, beliefs, expectations, experiences, and other aspects of a brand (Campbell et al., 2011; Campbell et al., 2014; Keller & Fay, 2012). WOM behaviors are "directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers" (Westbrook, 1987, p. 261). Among the most common types of WOM are comments and ratings shared online platforms (eWOM). These eWOM comments are predominantly textual but sometimes include visual elements (pictures, drawings, or videos) and summarize consumers' understanding and experiences of marketing, brands, products, services, and experiences (Marder et al., 2021; Pitt et al., 2021). Ratings are often either quantitative (a numeral) or pictographic (a thumbs up, stars, etc.) and compress the information conveyed in a comment into a single judgment (Watson et al., 2023). Compared to comments, ratings are simpler and can therefore be more readily processed by other consumers with less cognitive effort (Sparks & Browning, 2011). Given that this information often originates from those who are personally known by or share similar interests with the receiver, eWOM tends to be regarded as more reliable than formal marketing channels (Babić Rosario et al., 2020; Bazi et al., 2020; Filieri et al., 2023). Yet, eWOM behaviors may enable positive brand messages to be spread among consumers, thereby, strengthening the brand's image and increases in purchase intentions (Ismagilova et al., 2020; Marder et al., 2021).

Despite the potential benefits of eWOM behaviors to luxury brands and other consumers, it remains a complex phenomenon. For instance, tensions exist between such consumers' need for uniqueness and their desire to communicate engaging eWOM content (Berger, 2014). Consumers whose need for social distinction is particularly strong may feel this would be compromised by eWOM recommendations that encourage others to purchase the brand. In other words, positive eWOM may have detrimental effects on consumers with strong needs for uniqueness (Cheema & Kaikati, 2010). These consumers may ultimately consume a product less if it develops widespread popularity, in line with what has been termed a "reverse-bandwagon" effect (Granovetter & Soong, 1986). Further, luxury brands that seek to broaden their customer base by creating step-down brand extensions may also reduce the effectiveness of WOM. While this strategy may create affordable luxuries and increase profitability, leveraging the brand in such a way can weaken core consumer brand attachments as its image is diluted (Kapferer & Bastien, 2017).

Social media has changed the way brands create and distribute content, as well as the way they communicate with and among consumers (Tsai & Men, 2013). However, luxury brands were slower to adopt social media channels than their non-luxury counterparts (Hughes et al., 2016), given their desire for exclusivity (Chandon et al., 2016). Despite this initial reluctance, such brands now regularly use social media to deliver entertainment, interaction, trendiness, customization, and WOM (Kim & Ko, 2012). In fact, visual platforms like Instagram or YouTube offer opportunities for visual extensions of particular benefit to luxury fashion brands (Filieri et al., 2023; Sokolova & Kefi, 2020).

Social media has played a key role in the success of many luxury fashion brands (Phan et al., 2011), with the likes of Louis Vuitton, Burberry, and Calvin Klein livestreaming content from the catwalk via social channels (Plangger et al., 2021). This democratizes luxury and elite events (Kapferer, 2012), highlighting an important contradiction between social media and luxury. Social media is designed for mass consumption and therefore aims for inclusivity, interactivity, and accessibility; luxury is exclusive, controlled, and intended for a select group of consumers. As such, pushing social media engagement with a luxury brand may dilute its exclusivity (Blasco-Arcas et al., 2016). With luxury brands striving to create psychological distance between themselves and the mass market (Wiedmann et al., 2009), engagement via social media may damage the brand's core value perceptions if it is then perceived as overly accessible.

Nonetheless, consumers of luxury brands that successfully leverage social channels can experience indirect brand relationships generating high levels of WOM and viral online content (Mohr, 2013). This, in turn, allows luxury brands to preserve their overall integrity while simultaneously reaching a wide variety of current and prospective consumers and enthusiasts (Kim & Ko, 2012). This approach may lead to a range of other positive luxury brand outcomes, with studies highlighting, for instance, enhanced consumer trust and intimacy with such brands (Kim & Ko, 2010), strengthened consumer–brand engagement, and more fervent brand evangelism (Dhaoui, 2014). However, less is known about different types of luxury products and the particular WOM that their marketing efforts on social media inspire, which the next section explores.

1.2 | Understanding the nature of electronic word-of-mouth inspired by luxury marketing

Luxuriousness is a multifaceted concept that has been defined in various ways in previous studies. According to Berthon et al. (2009), luxury encompasses material, subjective, and collective dimensions. Keller (2017) identifies 10 defining characteristics of luxury brands (e.g., premium image, quality), while Ko et al. (2019) propose a theoretical definition based on high quality, authentic value, prestigious image, premium pricing, and connection with consumers. Overall, along with other defining characteristics, luxuriousness is a combination of material, subjective, and collective elements.

When investigating aspects of luxury products, the marketing and business literature has tended either to compare two luxury brands (Amatulli et al., 2020) or multiple brands within a luxury category (Pathak et al., 2019). Furthermore, while social listening or discourse analytical methods have been used to investigate eWOM about a particular luxury brand (Gardiner, 2019), few studies have explored the eWOM stimulated by marketing on social media platforms. Accordingly, we approached this study by first selecting luxury brands using a well-established product categorization theory before evaluating tools that might be used to determine the psycholinguistic characteristics of eWOM.

1.2.1 | Classifying luxury goods

Copeland (1923) classified all goods, including luxury goods, as either "convenience," "shopping," or "specialty" goods. *Convenience* goods are those customarily purchased easily. They are familiar to the consumer (who knows what he or she wants), they are widely available, and the consumer wishes to obtain them with minimal inconvenience. Examples of luxury convenience goods are fine beverages (e.g., Scotch whiskeys, classified Bordeaux wines, and rare teas), indulgent foods (e.g., Italian truffles, Belgian chocolates, and Kobe beef), or lavish beauty treatments. *Shopping* goods are those for which the consumer is willing to shop around to obtain what they want to compare prices, quality, and style. Luxury shopping goods would include haute couture items, extravagant home furnishings, high-end watches, limited edition shoes, and designer handbags. Beyond price considerations, *specialty* goods are those for which consumers are willing to exert particular efforts to obtain, even if this means delaying their purchase. Luxury specialty goods include, for example, sports cars, high-end grand pianos, or unique artworks. We chose luxury brands in three sectors exemplifying Copeland's (1923) categories: beauty brands (convenience), fashion apparel brands (shopping), and sports car brands (specialty).

Copeland (1923) argues that the type of consumer purchase determines a firm's marketing strategy. Distribution channels would be intensive for convenience products, selective for shopping products, and exclusive for specialty products. Typically, advertising would focus on brand *recognition* for convenience products, on *availability* for shopping products, and on brand *insistence* in the case of specialty products. Following this theory, we anticipate that the advertising of the luxury brands selected will follow similar patterns depending on the brand's product category. However, it is not clear how consumers would respond to these differences in terms of eWOM.

1.2.2 | Exploring the nature of electronic word-of-mouth

Due to the volume, variety, and velocity of eWOM on social media platforms, marketing academics and practitioners struggle to generate useful consumer insights using manual content analysis methods (Kietzmann & Pitt, 2020). Humphreys and Wang (2018) refer to online text as a "sea of language" that consumers regularly consult to guide their consumption decisions and marketers examine for insights into consumer behavior and attitudes. While some scholars posit that text only should be examined when accounting for the surrounding context, others propose that linguistic artifacts and words can be counted and analyzed using statistical methods (Büschken & Allenby, 2016). The advent of advanced machine learning and artificial intelligence techniques has automated text analysis methods that can produce useful insights from unstructured textual data (Büschken & Allenby, 2016; Campbell et al., 2020).

Among the automatic tools available to researchers, LIWC software has been widely applied to business and marketing contexts to understand a wide variety of textual data (Kietzmann & Pitt, 2020). LIWC was developed by Pennebaker and Francis (1996; see also Tausczik & Pennebaker, 2010) to research, assess, and evaluate how individuals and organizations use written language to communicate ideas and feelings. LIWC can calculate many variables from the linguistic data of a text, but four main variables reflect the mindset of its author: "analytical thinking," "clout," "authenticity," and "emotional tone." The *analytical thinking* variable shows the degree to which the text creator uses words that are formal, logical, and express hierarchical thinking patterns (Pennebaker et al., 2014). *Clout* measures the confidence, relative social status, or leadership that individuals articulate through their word choice, particularly through their consistent use of fewer first-person singular pronouns ("I") and more first-person plural ("we") and second-person ("you") singular pronouns (Kacewicz et al., 2014). The *authenticity* measure reveals the extent to which individuals use words associated with honesty, humbleness, or vulnerability (Pennebaker et al., 2014). Finally, *emotional tone* assesses whether a stretch of text reflects a negative, neutral, or positive affective state. Together these variables have been used to assess a range of textual data from postoperative patient reviews (Lord Ferguson et al., 2020) to official financial reports (Pitt et al., 2020) to movie synopses (Hung & Guan, 2020).

In tandem with LIWC, AI algorithms can help academic and practitioner researchers understand patterns in unstructured data to generate insights, evaluate campaigns, and benchmark outcomes (Kübler et al., 2020). For example, these algorithms can automatically assess the sentiment of a body of text, evaluate the polarity of an emojis, or even automatically identify the key demographic characteristics of consumers that posted comments (Liu et al., 2019).

AI-powered eWOM sentiment analysis provides considerable insight into the factors that determine important strategic outcomes (Ismagilova et al., 2020) such as consumer involvement and engagement (Naumann et al., 2020), purchase probability (Vázquez-Casielles et al., 2013), and trolling behaviors (Demsar et al., 2021). Outside of product experiences, there are many factors involved in the polarity of eWOM sentiment. These include, for example, customer relationships (Ismagilova et al., 2020), national culture (Lin & Kalwani, 2018), norm violations (Filieri et al., 2021), or reactions to images (Marder et al., 2021).

Automatic image analysis is relatively new in the marketing literature and has rarely been applied to eWOM data. However, both marketing practice and scholarship are increasingly being pushed to beyond the homogenous view of consumers to generate insight into how diverse consumers respond to marketing in different ways (e.g., de Ruyter et al., 2022). With some notable exceptions (e.g., Campbell et al., 2014; Lourenço et al., 2023), little is known of how

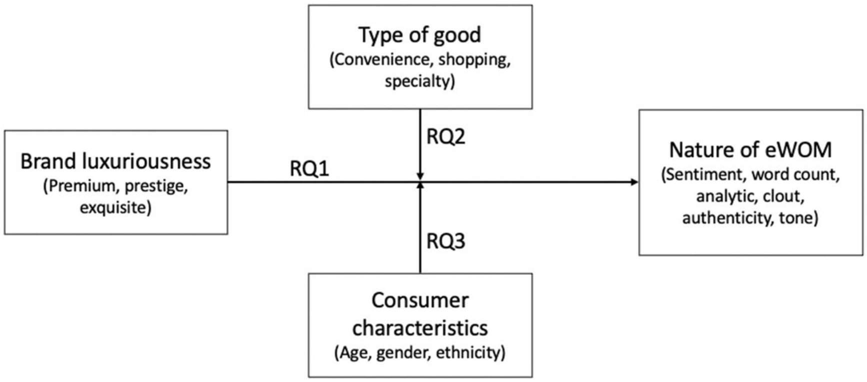

FIGURE 1 Conceptual framework.

demographic characteristics such as gender, age, and ethnicity are associated with differences in the nature of eWOM.

1.2.3 | Conceptual framework

In short, the above discussion points to three important questions about how consumers produce eWOM in response to social media video marketing campaigns created by luxury brands (see Figure 1). However, these brands vary in terms of their luxuriousness and their Copelandian type, so it stands to reason that consumers' eWOM might vary as well.

Research Question 1: In what ways does the degree of luxuriousness impact the nature of eWOM of a brand's social media videos?

Research Question 2: To what extent do variations in the type of luxury good offered by a brand affect the relationship between its luxuriousness and the nature of eWOM in relation to its social media videos?

Additionally, consumers themselves have heterogeneous characteristics, suggesting that these may be important to consider when assessing the nature of eWOM, leading to this final question:

Research Question 3: How do consumer characteristics shape the relationship between a brand's luxuriousness and the character of eWOM generated by its social media videos?

2 | METHODS

To generate the data and insights that pertain to the three research questions, we drew a sample of comments and leveraged a range of automated text and image analysis methods utilizing machine learning algorithms and AI. While many eWOM studies utilize online experiments (Choi et al., 2020) or automatic text analysis (Lee, 2021; Liu et al., 2021), we have directed an AI to apply automatic image analysis to recognize the faces of the commenters in line with recent calls for more advanced AI-assisted analysis (Choi et al., 2020; Duong & Sung, 2021). By combining machine learning and AI analysis techniques, our analysis more comprehensively explores the nature of eWOM behaviors across multiple psycholinguistic variables (LIWC and AI-inferred), independent brand conditions (luxuriousness, Copelandian classification), and consumer characteristics (age, gender, ethnicity).

eWOM on popular text- or image-based social media platforms has been extensively researched on, for example, Facebook (Settanni & Marengo, 2015), Twitter (Li & Xie, 2020; Okazaki et al., 2021), TripAdvisor (Van Laer et al., 2019), Instagram (Li & Xie, 2020), and Match.com (Farshid et al., 2021). However, less is known about the nature of eWOM on social media video platforms such as YouTube, with some notable exceptions (Berthon et al., 2008; Dehghani et al., 2016). This is surprising considering YouTube's status as the most frequently used social media platform and the increasing trend toward video marketing content on social media platforms (SimilarWeb, 2023). In addition, YouTube provides engagement opportunities to its diverse audience with few restrictions on the content they post. The following sections discuss our YouTube comment sample and the various methods used to analyze it.

2.1 | Sample extraction

Following established data extraction methods, we sought to gather consumer comments about social media video ads from three luxury brands that typify each of Copeland's (1923) classifications. We chose BMW, Porsche, and Ferrari as specialty products; Burberry, Hermes, and Alexander McQueen as shopping products; and Lush, Charlotte Tilbury, and Chanel Beauty as convenience products. Next, we assigned each brand a "luxury" classification based on the relative average price of its products as a signal of their status (Gong et al., 2022) resulting in "premium" (BMW, Burberry, and Lush), "prestige" (Porsche, Hermes, and Charlotte Tilbury), and "exquisite" (Ferrari, Alexander McQueen, and Chanel Beauty) brands. Then, we identified the 10 most popular videos on each brand's official YouTube account (min. 50 comments) and extracted the associated comments employing a self-developed Python algorithm based on open-source application programming interfaces (APIs) and libraries to scrape the data. This resulted in 33,251 extracted comments from 88 YouTube videos.[1] Non-English comments were removed ($n = 1736$, 5%) leaving a sample of 31,515 comments for analysis

[1]Nine videos only from the Hermes and Alexander McQueen official brand presences on YouTube met the criterion of 50+ comments per video, imposed to ensure diversity and minimize bias.

TABLE 2 Descriptive statistics of video comments by product type and brand.

Copelandian classification	Degree of luxuriousness (brand)	YouTube subscribers	Total comments	Average comments per video	Average "likes" per video	Average "dislikes" per video	Average views per video	Average video duration
Specialty	Exquisite (Ferrari)	923,000	6198	2079	31,888	1287	2,243,419	2.53
	Prestige (Porsche)	1,010,000	4885	1224	29,200	548	4,746,198	4.08
	Premium (BMW)	1,210,200	4964	1667	36,730	1167	4,994,414	2.24
	Total	3,143,200	16,047	1657	32,606	1001	3,994,677	2.95
Shopping	Exquisite (McQueen)	75,900	1335	208	3437	84	153,754	9.27
	Prestige (Hermes)	151,000	848	140	2,261	97	623,072	7.21
	Premium (Burberry)	360,000	4207	703	12,540	965	6,175,877	4.14
	Total	586,900	6390	350	6,079	382	2,317,568	7.27
Convenience	Exquisite (Chanel)	1,830,000	1335	208	6,510	313	563,985	2.39
	Prestige (Tilbury)	813,000	4534	812	35,425	869	2,022,729	16.21
	Premium (Lush)	N/A[a]	3209	1003	14,470	326	870,345	5.20
	Total	2,643,000	9078	674	18,802	503	1,152,353	8.33

[a]Lush's subscriber numbers are not publicly available on YouTube.com

(see Table 2). Comments, "likes," "dislikes," view numbers, and the commenters' publicly available profile pictures were also scraped to aid brand comparisons and generate AI-inferred demographics. Manual coders were engaged to contribute to the data collection process and check the quality of data (Li & Xie, 2020). We cleaned the raw data by deleting comments of less than two words, including those consisting solely of emojis, which left 29,128 comments of between 2 and 869 words, a mean of 13.54, and a standard deviation of 15.79.

2.2 | Artificial intelligence sentiment analysis

To complement the LIWC analysis, we conducted a sentiment and intensity analysis of the collected text comments using algorithms. We used a bottom-up sentiment extraction library, TextBlob Natural Language Processing (NLP) library in Python (Micu et al., 2017), to process the textual data and perform the sentiment analysis (https://textblob.readthedocs.io/). Bottom-up approaches are best at elucidating brand impression, satisfaction, and recommendation (Kübler et al., 2020; Tsao et al., 2019).

Due to the high volume of emoji usage in the comments, we used a Python library based on Kralj Novak et al. (2015) to calculate an emoji sentiment score (Klostermann et al., 2018), taking the average scores of emoji sentiments if more than one was used in each comment. The different text and emoji sentiment scores showed that people generally used emojis to express more positive feelings. We observed weak but significant correlations between the emoji and text sentiment scores ($r = 0.25$, $p < 0.001$) and the emoji sentiment and LIWC tone scores ($r = 0.25$, $p < 0.001$). On the other hand, the difference between the emoji and text sentiment scores was statistically significant ($t(3522) = -32.380$, $p < 0.001$). The LIWC tone scores were highly correlated with those for text sentiment ($r = 0.62$, $p < 0.001$) and also differed in a statistically significant way from the emoji sentiment scores ($t(3522) = 94.82$, $p < 0.001$). Table 3 demonstrates that the mean emoji sentiment scores were always higher than text sentiment scores for all brands across all industries.

2.3 | Linguistic inquiry and word count

The Linguistic Inquiry and Word Count (LIWC) software can assess important psycholinguistic concepts in a body of text. After naturally processing a piece of text (e.g., a comment) unsupervised, the LIWC algorithm automatically counts and calculates the percentages of words associated with various important psycholinguistic concepts such as thinking styles, emotions, and social concerns. Then, the software uses a dictionary compiled by the researcher to categorize individual words in a text that are linked with psychologically relevant categories. This produces a series of variables to which statistical tools can be applied for further analysis.

To classify and calculate the main LIWC variables, we used a preloaded dictionary composed of almost 6,400 words, word stems, and even a selection of emoticons. As discussed above, we focused on four summary variables ("analytical thinking," "clout," "authenticity," and "emotional tone") along with the word count variable. These summary variables were based on individual algorithms automatically constructed from other statistics generated by LIWC and are presented as standardized percentage scores ranging from 0 to 100.

TABLE 3 AI-inferred demographics of video commenters, by product type and brand.

Copelandian classification	Degree of luxuriousness (brand)	Profile number[a]	Age (%)			Gender (%)		Ethnicity (%)	
			<20	20–39	40+	Male	Female	White	BAME
Specialty	Exquisite (Ferrari)	2219	11.2	75.6	13.2	78.1	21.9	39.8	60.2
	Prestige (Porsche)	1715	9.9	78.4	11.7	76.2	23.8	40.5	59.5
	Premium (BMW)	1812	10.7	77.9	11.4	76.7	23.3	33.4	66.6
	Category total	5746	10.7	77.2	12.2	77.1	22.9	38.0	62.0
Shopping	Exquisite (McQueen)	347	8.1	79.5	12.4	48.7	51.3	46.4	53.6
	Prestige (Hermes)	1858	13.1	75.1	11.8	49.7	50.3	47.4	52.6
	Premium (Burberry)	609	10.0	81.1	8.9	48.1	51.9	45.6	54.4
	Category total	2814	11.8	76.9	11.2	49.2	50.8	46.9	53.1
Convenience	Exquisite (Chanel)	2301	10.5	84.7	4.7	15.0	85.0	50.7	49.3
	Prestige (Tilbury)	1666	14.8	81.3	3.9	24.3	75.7	49.6	50.4
	Premium (Lush)	597	11.7	83.2	5.0	27.6	72.4	48.4	51.6
	Category total	4564	12.2	83.3	4.4	20.0	80.0	50.0	50.0

Abbreviation: BAME, Black, Asian, and Minority Ethnicities.

[a]Profile number indicates the number of YouTube video comments linked to a profile picture analyzed by the Clarifai.ai algorithm.

2.4 | Consumer characteristics analysis

A facial recognition algorithm was used to determine the age, gender, and ethnicity of individuals who left public comments (see Table 3 for demographic statistics). Facial recognition research is based on a combination of neural networks, machine learning, and deep learning studies. Creating a facial recognition solution is a drawn-out and resource-intensive process requiring network configuration, training, and testing stages across many samples; for this reason, we used a reliable commercial API, Clarifai, as it has been shown to possess strong validity in previous studies (Nanne et al., 2020). Because many YouTube users do not add images of themselves as profile pictures, our sample was reduced to 17,587 profile pictures, 54.9% of the total.

The majority of the sample was aged 20–39. This age group comprised between 76.9% and 83.3% of the sample for each product category. The sample was generally younger for the "convenience" products and older for the "specialty" products, which also featured a more diverse sample of commenters (62.0% BAME) compared to those writing about the "shopping" and convenience product videos. The premium luxury brand sample was more diverse than those of the prestige and exquisite luxury brands in all categories. As expected, the sample's gender distribution was skewed toward males for the specialty products, as we had selected three automotive brands, and toward females for the convenience products, reflecting our decision to exemplify this category using beauty brands. There was no significant difference in gender representation for the shopping products.

3 | RESULTS AND DISCUSSION

The descriptive statistics shed light on YouTube audience behavior linked to different luxury brands (Table 4). For example, people used fewer words but more authentic and analytical language in their comments on specialty products than on shopping and convenience goods. In addition, their comments expressed less favorable views of specialty products, whereas, emoji sentiment scores did not differ greatly. Besides these exploratory observations, multiple comparisons between groups using the Scheffe test indicated significant differences among the premium, prestige, and exquisite brands in each product category for all the LIWC variables (except "tone" and "clout" for shopping products) and the AI-inferred variables for text and emoji sentiments. Table 4 summarizes the results of the automated text analysis procedure using LIWC. This process enabled us to compare the different product categories (convenience, shopping, or luxury goods according to Copeland's classification) and whether the luxury brands could be classified as "premium," "prestige," or "exquisite." There were several significant differences between the categories in the Copeland classification and between the different brands within the categories in terms of LIWC word count and the dimensions of "Analytic," "Clout," "Authenticity" and "Tone." In commenting on YouTube videos, consumers tended to use significantly more words to discuss the premium automobile ($\bar{x}_{\mathrm{WordCount}} = 14.08$) and skincare brands ($\bar{x}_{\mathrm{WordCount}} = 15.11$), but this pattern was reversed for the clothing brands ($\bar{x}_{\mathrm{WordCount}} = 12.41$) (see Figure 2a).

In the "analytical thinking" dimension, we observed several interesting differences, particularly between the automobile and

TABLE 4 Mean differences of the nature of eWOM for levels of brand luxuriousness.

Copelandian classification	Degree of luxuriousness (brand)	LIWC variables' means					AI-inferred sentiment means	
		Word Count	Analytic	Clout	Authenticity	Tone	Text	Emoji[1]
Specialty	Exquisite (Ferrari)	12.46[1]	63.45[8,9]	44.17[15,16]	36.95[19]	50.45[26,27]	0.16[31,32]	0.50[37]
	Prestige (Porsche)	12.05[2]	60.92[8,10]	48.33[16]	36.72[20]	54.70[26,28]	0.20[31,33]	0.46[38]
	Premium (BMW)	14.08[1,2]	55.95[9,10]	47.53[15]	40.77[19,20]	48.17[27,28]	0.13[32,33]	0.38[37,38]
Shopping	Exquisite (McQueen)	18.47[4,5]	53.47	48.91	25.63[21]	61.22	0.24	0.56[39]
	Prestige (Hermes)	16.20[3,4]	56.10[11]	52.03	24.75[22]	60.99	0.24	0.48[39]
	Premium (Burberry)	12.41[3,5]	51.90[11]	49.36	28.74[21,22]	58.86	0.23	0.51
Convenience	Exquisite (Chanel)	10.77[6,7]	53.97[13,14]	56.65[17]	20.60[23,24]	61.61[29]	0.23[34,35]	0.52
	Prestige (Tilbury)	14.81[6]	42.91[12,13]	56.30[18]	24.61[23,25]	71.97[29,30]	0.35[34,36]	0.51[40]
	Premium (Lush)	15.11[7]	40.13[12,14]	50.18[17,18]	33.28[24,25]	60.43[30]	0.20[35,36]	0.44[40]

Note: Within each product category, numerical superscripts indicate significant differences based on Scheffe post hoc pairwise tests with a familywise error rate of 0.05 that corrects for differences in sample sizes.

Abbreviations: eWOM, nature of electronic word-of-mouth; LIWC, linguistic inquiry and word count.

skincare brands ($F_{specialty} = 53.84$, $p < 0.001$; $F_{convenience} = 61.68$, $p < 0.001$). The results suggested that consumers were significantly more analytical in their comments about the "exquisite" and "prestige" brands than about their "premium" counterparts. For the automobile brands, we theorize that Ferrari and Porsche are merely aspirational for most consumers whereas owning a BMW model, particularly at the lower end of the product range, is a more realistic possibility. Of course, the low likelihood of ever owning a Porsche or a Ferrari does not reduce consumer interest in discussing the performance and technical specifications of these brands. Indeed, they would likely be more analytical when discussing the specifications, features, performance, and speed of Porsche ($\bar{x}_{Analytic} = 60.92$) and Ferrari ($\bar{x}_{Analytic} = 63.45$) than when commenting on a brand such as BMW ($\bar{x}_{Analytic} = 55.95$; see Figure 2b). A similar pattern was apparent for the skincare brands, and likely for the same reasons.

The LIWC dimension of clout concerns the relative social status, confidence, or leadership that people display in speech or writing. Here, the differences were apparent across product categories ($F_{specialty} = 28.83$, $p < 0.001$; $F_{shopping} = 2.73$, $p = 0.087$; $F_{convenience} = 34.53$, $p < 0.001$), especially in the case of skincare brands, where consumers communicated more clout regarding the exquisite ($\bar{x}_{Clout} = 56.65$) and prestige brands ($\bar{x}_{Clout} = 56.30$) than the premium brands ($\bar{x}_{Clout} = 50.18$). This also applied to a lesser extent to the automobile brands but in reverse ($\bar{x}_{Exquisite,Clout} = 44.17$; $\bar{x}_{Prestige,Clout} = 48.33$; $\bar{x}_{Premium,Clout} = 47.53$; see Figure 2c). No significant differences were observed among the clothing brands used to represent shopping goods according to the Copeland classification.

In the LIWC dimension of authenticity (speaking genuinely or honestly; being more personal, humble, and vulnerable), a clear pattern emerged for all product classifications and brand categories ($F_{specialty} = 15.39$, $p < 0.001$; $F_{shopping} = 5.04$, $p = 0.006$; $F_{convenience} = 79.22$, $p < 0.001$). Communication about premium luxury brands was more authentic than for prestige or exquisite luxury brands (see Figure 2d). This is understandable when one considers that the premium brands in each category are "feasibly accessible" to most consumers, unlike their prestige and exquisite counterparts. It would appear more difficult for consumers to express honesty and authenticity about brands that they do not own—and probably never will— than for brands that are more within reach.

The "tone" dimension combined scores for words expressing positive emotions and scores for words expressing negative emotions into a single summary variable, with a higher number denoting a more positive tone. This is in some ways akin to the "sentiment" variable now used in much content analysis of social media textual data. As Table 4 shows, the commentary surrounding every brand except for the premium automobile brand BMW was positive in tone. The prestige automobile and skincare brands scored significantly higher on tone than did the exquisite or premium brands (see Figure 2e).

We observed that the LIWC tone scores resembled those for AI-inferred text sentiment. While the scores for the "specialty" and "convenience" product types differed significantly, this was not true for the "shopping" products ($F_{specialty} = 56.53$, $p < 0.001$; $F_{shopping} = 0.213$, $p = 0.081$; $F_{convenience} = 153.06$, $p < 0.001$). However, similarities between tones and inferred sentiment were found for all pairs of premium, prestige, and exquisite brands of specialty and convenience product categories (Figure 2f).

Although the AI-inferred *text* sentiment and LIWC tone scores were highly correlated ($r = 0.62$, $p < 0.001$), the AI-inferred *emoji* sentiment scores differed considerably. Emojis were particularly used to communicate positive reactions to content, confirming the earlier results of Das et al. (2019). We found that emoji sentiment scores differed significantly by product type ($F_{specialty} = 14.48$, $p < 0.001$; $F_{shopping} = 3.36$, $p = 0.03$; $F_{convenience} = 4.83$, $p = 0.009$) and between all pairs of premium, prestige, and exquisite brands in each product category, except premium shopping brands and exquisite convenience brands (Figure 2g).

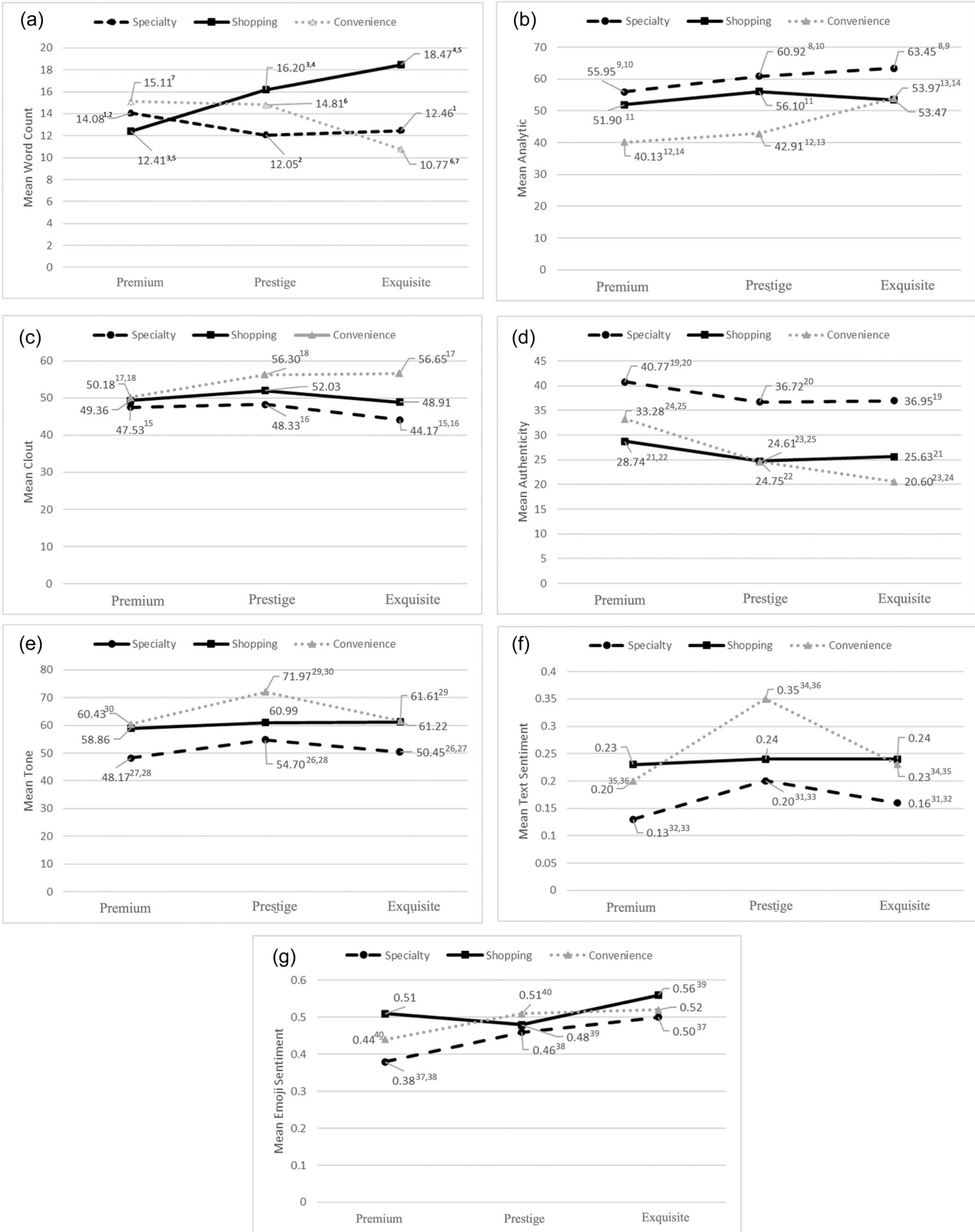

FIGURE 2 (See caption on next page)

Overall, there were significant differences in both the word count and the LIWC dimensions of analytical thinking, clout, and authenticity expressed by commenters on the social media videos uploaded to YouTube by the various brands studied. The significant differences were most apparent among the specialty and convenience brands, whereas the differences between the luxury shopping brand were less evident, and in most cases, insignificant.

Furthermore, we conducted a Multivariate Analysis of Variance (MANOVA) analysis on the same dependent variables to test the effects of brand luxuriousness and three consumer characteristics: age, gender, and ethnicity (see Table 5). The results revealed a number of significant main effects: age on analytical thinking, tone, and text sentiment; gender on all tested dependent variables; and ethnicity on word count, authenticity, and tone. More importantly, we found significant interaction effects between luxuriousness and the consumer characteristics. When luxuriousness and age increase, both the tone ($F = 5.14$, $p < 0.001$) and text sentiment ($F = 5.71$, $p < 0.001$) of comments significantly became more positive. When the comment is authored by a male and luxuriousness increases, the word count ($F = 8.10$, $p < 0.01$), analytic thinking ($F = 9.58$, $p < 0.001$), clout ($F = 5.83$, $p < 0.01$), tone ($F = 10.50$, $p < 0.001$), and text sentiment ($F = 7.30$, $p < 0.001$) of the comment significantly increases. When the comment is authored by a BAME consumer and luxuriousness increases, word count ($F = 3.09$, $p < 0.05$) and analytic thinking ($F = 3.42$, $p < 0.05$) of the comment increases. These effects show that the luxuriousness of a brand and the consumer characteristics of age, gender, and ethnicity all have significant impacts on how consumers respond to the brand, as measured through their comments. The interaction effects between luxuriousness and consumer characteristics suggest that the influence of

TABLE 5 MANOVA results for the effects of consumer characteristics and brand luxuriousness on eWOM.

Independent variables	Dependent variables Word count F (sig.)	 Analytic thinking F (sig.)	 Clout F (sig.)	 Authenticity F (sig.)	 Tone F (sig.)	 Text sentiment F (sig.)	 Emoji sentiment F (sig.)
Age (< 20 = 1, 20 to 39 = 2, 40 + = 3)							
Corrected model	1.22 (n.s)	31.85 (***)	10.13 (***)	5.25 (***)	20.95 (***)	30.70 (***)	1.66 (n.s)
Intercept	3329.46 (***)	8032.91 (***)	8602.71 (***)	2713.58 (***)	8071.97 (***)	1284.61 (***)	1021.68 (***)
Luxuriousness	0.86 (n.s)	33.15 (***)	7.80 (***)	1.10 (n.s)	9.93 (***)	16.20 (***)	2.06 (n.s)
Age	1.74 (n.s)	44.98 (***)	2.25 (n.s)	.56 (n.s)	3.23 (**)	6.55 (***)	.368 (n.s)
Luxuriousness × Age	0.22 (n.s)	1.31 9 (n.s)	1.07 (n.s)	1.25 (n.s)	5.14 (***)	5.71 (***)	1.26 (n.s)
Gender (Male = 1; Female = 0)							
Corrected model	11.59 (***)	72.26 (***)	21.45 (***)	14.82 (***)	52.36 (***)	61.52 (***)	4.51 (***)
Intercept	9791.15 (***)	22164.13 (***)	27366.86 (***)	8192.95 (***)	25995.47 (***)	4609.87 (***)	3580.14 (***)
Luxuriousness	1.23 (n.s)	61.39 (***)	26.49 (***)	14.29 (***)	49.33 (***)	83.32 (***)	4.05 (**)
Male	32.03 (***)	156.07 (***)	24.81 (***)	33.50 (***)	95.24 (***)	76.42 (***)	14.54 (***)
Luxuriousness × Male	8.10 (**)	9.58 (***)	5.83 (**)	2.57 (n.s)	10.50 (***)	7.30 (***)	1.32 (n.s)
Ethnicity (BAME = 1; White = 0)							
Corrected Model	7.91 (***)	33.85 (***)	14.84 (***)	9.65 (***)	30.22 (***)	45.21 (***)	2.54 (*)
Intercept	10314.68 (***)	22473.08 (***)	28248.69 (***)	8415.52 (***)	26777.89 (***)	4798.32 (***)	3567.02 (***)
Luxuriousness	2.98 (**)	82.99 (***)	36.51 (***)	17.12 (***)	71.10 (***)	105.30 (***)	3.68 (*)
BAME	21.98 (***)	.427 (n.s)	.465 (n.s)	7.49 (**)	5.22 (**)	8.50 (*)	1.52 (n.s)
Luxuriousness × BAME	3.09 (*)	3.42 (*)	.262 (n.s)	2.24 (n.s)	1.40 (n.s)	1.66 (n.s)	1.46 (n.s)

Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$, n.s = Not significant.

Abbreviations: BAME, Black, Asian, and Minority Ethnicities; eWOM, nature of electronic word-of-mouth; MANOVA, multivariate analysis of variance.

FIGURE 2 (a) Text analysis results: LIWC word count means (multiple comparisons between groups using the Scheffe test). (b) Text analysis results: LIWC "analytic" means (multiple comparisons between groups using the Scheffe test). (c) Text analysis results: LIWC "clout" means (multiple comparisons between groups using the Scheffe test). (d) Text analysis results: LIWC "authenticity" means (multiple comparisons between groups using the Scheffe test). (e) Text analysis results: LIWC "tone" means (multiple comparisons between groups using the Scheffe test). (f) Text analysis results: AI-inferred text sentiment means (multiple comparisons between groups using the Scheffe test). (g) Text analysis results: AI-inferred emoji sentiment means (multiple comparisons between groups using the Scheffe test). LIWC, linguistic inquiry and word count.

luxuriousness on consumer response is not the same for all groups of consumers. These findings highlight the importance of considering consumer characteristics when analyzing the impact of brand luxuriousness on consumer engagement.

4 | CONCLUSIONS

4.1 | Implications

Our findings suggest several implications for luxury brands and those responsible for managing them. Our findings align with previous research (Farshid et al., 2021; Pitt et al., 2021) in highlighting the utility of analyzing online text as a means of gaining critical insights into consumer behavior and perceptions. The results suggest that the use of software such as LIWC and other NLP tools are not only relevant for scholarly inquiry in marketing and consumer behavior, but also offers value for corporate marketing teams to comprehend conversations pertaining to their brands. For example, the study indicates that social media users tend to prefer more analytical and less authentic language when discussing high-end brands, and exhibit lower levels of confidence (as indicated by a lower clout score) when discussing these brands. While this study is limited to three brands in each of the Copeland classifications, it is feasible that the methods employed could be extended to encompass all brands and classifications.

For luxury goods marketers, this study highlights the need to understand the subtle differences between brands within the same category. For example, BMW, which we have termed a premium brand, might, to some consumers, epitomize luxury, while others (such as Porsche and Ferrari enthusiasts) might view it as just another run-of-the-mill automobile brand. Managers in premium brand environments will need to choose whether to simply accept this positioning given the market size it affords or whether to strive to elevate the brand's status to prestige or exquisite levels. While appealing, this strategy might be accompanied by lower unit sales volumes and higher marketing costs. In the automobile market, history is replete with stories of “trading up” (introducing an upmarket version of a brand at a higher price, as in the case of Toyota with Lexus or Nissan with Infiniti) and “trading down” (as in the US auto brand Packard's legendarily disastrous “Clipper” relaunch), where a less expensive version of a prestigious brand is launched with the hope of benefiting from the original brand name (Berthon et al., 2009).

We also offer implications for the use of face recognition analysis tools in profiling the demographics (i.e., age, gender, and ethnicity) of social media audiences in relation to luxury brands. Our analysis revealed that the percentage of Black, Asian, and Minority Ethnic (BAME) audience members who leave comments is lower for high-end luxury brands. To address this, luxury brands could focus on creating inclusive content to attract a more diverse audience. Our findings suggest that prestige and luxury brands have a lower reach to older (40+) audiences compared to high-end luxury brands. Brands may take necessary actions to address these issues by using the methodological approach employed in this study.

4.2 | Limitations and suggestions for future research

As with most social science research, this study has several limitations. First, we used Copeland's classification of goods as a theoretical backdrop to our identification of the product categories and the brands within them. However, a strict Copelandian classification would probably categorize all the brands we chose into the “specialty” group. For example, a skincare brand such as Chanel would not be a convenience good, nor would brands such as McQueen, Hermes, or Burberry be viewed as simple shopping goods. Our classification was motivated by the need to identify distinct luxury product categories: most consumers of skincare goods would regard these as simple convenience purchases obtainable from a supermarket, and everyday clothing items would be viewed as shopping goods. We, therefore, encourage researchers to examine other ways of categorizing luxury goods.

Second, the classification of brands to categories was also, in a sense, a subjective decision. Even though we utilized each brand's average price point as a reliable market signal of luxury, the question remains whether the differences between Hermes and Burberry items are sufficient to classify one as “prestige” and the other as “premium,” or whether a lower-end Ferrari product and an upper-end Porsche model are sufficiently distinctive to identify the former as “exquisite” and the latter as merely a “prestige” brand? For the clothing brands category in particular, we may not have found many variations along the LIWC dimensions simply because the three brands chosen were not sufficiently distinctive in terms of their luxuriousness. Consequently, we call for additional studies using a wider sample of brands and industries to ascertain if our results hold. Moreover, while our sample included English comments regardless of national culture or location, further research should examine the role of these social factors in more detail.

Third, we confined our study to only three categories (cars, clothing, and skincare). Including other or different categories might have produced additional insights. Furthermore, while we analyzed solely YouTube comments, brand discussions also occur in many other online venues, including blogs, product review websites, and discussion platforms. Therefore, we would encourage researchers to explore the nature of eWOM in these digital channels, as well as on emerging social media video platforms such as TikTok and Twitch.

Fourth, we acknowledge that the current investigation did not include other content analysis of the videos, which is an area that could be explored in future research. Specifically, investigating the impact of video content on the level of engagement among different demographic audiences. By examining this aspect of luxury brand social media marketing activities, we can obtain a more comprehensive understanding of how such content influences consumer behavior and preferences.

TABLE 6 Future directions for research and practice.

Strategic area	Potential questions for future research	Managerial guidance
Luxury brand positioning	• How can social media comments' features be used to determine better positioning for brands? • Which LIWC attribute is more meaningful for brands' positioning? • Can we identify different segments based on the social media comments analysis? • What are the impacts of different message framing strategies on consumer engagement with luxury brand video content across various demographic groups? • How do different luxuriousness tiers influence brands' communication strategies on social media platforms?	Different features have different levels of importance for various user segments. Managers should take into account distinct LIWC features when thinking about their brand positioning.
Marketing and advertising	• Which LIWC attributes would serve better to improve communication campaign effectiveness for different demographics? • Who are the most effective influencers to help to generate more authentic and confident responses from the audience? How can they be used in a communication campaign? • To what extent can the LIWC framework be applied to other non-luxury brands? • Can usage of face recognition based demographic analysis help to create better segmentation? • How do different content formats (e.g., images, videos, live streams) influence eWOM in luxury brand advertising campaigns on social media?	Our research found that social media users prefer more analytic and less authentic language for exquisite brands. They are also less confident talking about exquisite brands. Managers could benefit from these types of differences among the target audience while creating their communication campaigns.
Social media strategy	• Beyond text sentiment, what other user LIWC characteristic can explain engagement better? • How can brands incorporate age, gender, and ethnicity analysis into their social media content strategies? • How can brands use LIWC variables and face recognition-based demographics features to improve audience engagement on social media? • How does the content of the videos affect the engagement of different demographic audiences? • How does the experimental manipulation of brand luxuriousness affect consumers' perceptions and eWOM in social media comments? • What is the impact of real-time, interactive content (e.g., live streams, Q&A sessions) on audience engagement in the context of luxury brand social media strategy?	Engagement is one of the crucial metrics for social media performance. Managers can make use of different LIWC features to improve user engagement. For example, this study presented word count which can be used as a factor for measuring engagement. We found that, the percentage of BAME commenters is lower for exquisite brands. Luxury brands can develop more inclusive content strategy.

Abbreviations: eWOM, nature of electronic word-of-mouth; LIWC, linguistic inquiry and word count.

Fifth, our empirical approach focused on exploring observable field data from YouTube to better understand the influence of brand luxurious, type of good, and consumer characteristics on behavioral responses. However, we cannot claim causality between the variables analyzed in the study. Future research could employ experimental designs to manipulate social media marketing videos to test the casual relationships between brand luxuriousness and type of good, as well other important brand variables (e.g., brand personality, brand equity) and consumer characteristics (e.g., culture and values).

Finally, as digital technologies are rapidly developing (Plangger et al., 2022), new types of automatic text and image analysis may yield novel consumer insights. We close by encouraging future scholarship into how consumers respond to and interact with dynamic forms of marketing including more immersive experiences (see Table 6).

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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How to cite this article: Oc, Y., Plangger, K., Sands, S., Campbell, C. L., & Pitt, L. (2023). Luxury is what you say: Analyzing electronic word-of-mouth marketing of luxury products using artificial intelligence and machine learning. *Psychology & Marketing*, 1–16. https://doi.org/10.1002/mar.21831