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The dual role of video-based eWOM in an online digital environment

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ABSTRACT

The substantial growth of platforms like YouTube highlights the heightened personal interaction offered by video-based eWOM. This study investigates the dual role of video-based eWOM in the digital era, contrasting it with traditional text based reviews. Expanding on the existing literature predominantly focused on text-based eWOM, this study analyzes the impact of video-based eWOM on characteristics and perceived value in the context of review generation and consumption. Leveraging relative anonymity and social presence theory, we explore how platform identity policies influence review content. Employing AI speech recognition, text analysis, and empirical analysis, our findings challenge the expected effectiveness of video-based eWOM as opinion leaders in generating informative reviews. The study provides theoretical insights into the evolving dynamics of eWOM in the digital marketing landscape, offering valuable guidance for marketing strategies and consumer behavior analysis.

1. Introduction

In the digital era, electronic Word-of-Mouth (eWOM) has become a pivotal aspect of consumer decision-making, with individuals increasingly relying on the opinions of others to shape their perceptions of products and services (Litvin et al., 2008). eWOM can manifest in a variety of forms, such as text, audio, and video (Fitriani et al., 2020). Historically, the traditional landscape of eWOM has been dominated by text-based formats like blogs, reviews, or ratings in review platforms. However, the technological advancements and the rise of social media have increased the usage of video-based eWOM such as product review videos. For instance, 96 % of people have watched a video demonstration to learn more about a product or service in 2024 (Lukan, 2024). Also, 86 % of US people frequently use YouTube to learn new things (Lukan, 2024). These statistics indicate a significant shift towards video as a medium for product search and reviews.

The increasing prominence of platforms such as YouTube highlights the heightened personal interaction and the persuasive power offered by video-based eWOM, emphasizing its ‘dual role’ in both influencing consumer purchase and fostering community engagement around products. Unlike traditional text-based reviews, which primarily convey static information, video-based eWOM leverages dynamic visual content, making it a more engaging and immersive experience for consumers (Bi et al., 2019). Recent studies (Agrawal & Mittal, 2022; Filieri et al., 2023; Lee & Lee, 2022; Yin et al., 2024) also demonstrate that video reviews provide richer information due to their multimedia elements. This study investigates the dual role of video-based eWOM in the digital era, contrasting it with traditional text-based reviews, and explores how these differences reshape the landscape of digital marketing and consumer behavior.

The popularity of eWOM through videos is expected to rise in the next few years because, unlike other forms of reviews, video-based eWOM provides higher personal interaction (Bi et al., 2019). For instance, 90 % of individuals stated that watching a product review video is helpful for their decision-making (Bennett, 2024). Moreover, with an annual growth rate of 100 % in video consumption, platforms like YouTube are becoming central in the online video domain (Sprout Social, 2023). In addition, it has been found that consumers prefer to consume product reviews through videos, with only a mere 10 % opting for text-based reviews (Stemler, 2021). Thus, marketers are paying growing attention to video content, recognizing it as an effective form to influence consumer purchases.

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Furthermore, the rise of video-based eWOM has redefined the concept of opinion leaders in the field of consumer reviews. Historically, text-based eWOM saw early adopters as crucial in shaping product perceptions (Chen et al., 2011). Now, video creators have now emerged as new opinion leaders, providing visually engaging and interactive experiences that surpass those provided by text-based reviews. Video reviews on platforms like YouTube not only serve as direct feedback (termed 'first-level reviews') but also stimulate viewer interactions and discussions, which we categorize as 'second-level reviews'. These second-level reviews from a new community around the product, where viewers engage with the content and with each other, adding depth to the initial reviews and enriching the community's understanding of the product.

Although research highlights text-based eWOM's impact on purchase behavior and sales (Roy et al.,2024; Kim et al., 2023; Yang et al., 2019; Chen et al., 2018), there is limited exploration of video-based eWOM's role in initiating secondary review interaction. However, the new trend, such as increasing the consumption rate of video product reviews (Lukan, 2024), suggests that video-based eWOM becomes significant to support consumers' decision-making process and foster review engagement. The increasing significance of video-based eWOM underscores the need for studies to examine its unique dynamics and distinctions. In particular a research question remains unanswered:

RQ: What are the differences between traditional (textual) eWOM and emerging (visual) eWOM in terms of review content and their influence on secondary review generation?

To answer this research question, this study first explores the characteristics of product review videos as a new form of eWOM (YouTube videos) compared to more traditional forms of eWOM such as Amazon textual reviews. This approach aims to bridge a knowledge gap by examining the characteristics of product review videos as a new form of electronic word-of-mouth (eWOM) and subsequently exploring their role as opinion leaders in word-of-mouth communication. In our main analysis, we analyze two different datasets – YouTube and Amazon by employing a comprehensive methodology including AI speech recognition and text analysis.

Our results contribute to making theoretical and practical implications. Theoretically, we provide an extension to the literature and knowledge related to video-based eWOM, specifically its dual roles as reviews and opinion leaders in review generation and consumption perspectives. In particular, our findings demonstrate that product review videos do not lead to accompanying informative reviews, so they are not effective marketing strategies as opinion leaders. Accordingly, for marketers who use review videos for their marketing strategy, this study can describe how effective this type of review can be in terms of product information delivery. Furthermore, our proposed methods help enrich methodological perspectives in examining diverse forms of eWOM.

2. Literature review and theoretical framework

2.1. Text-based eWOM to video-based eWOM

With the development of digital technologies underpinning the digital transformation of business activities (Chen, Lin, Mariani, Shou, & Zhang, 2023; D'Ambra, Akter, & Mariani, 2022; Mariani & Dwivedi, 2024) and, more specifically, social media, there have been significant changes in the context of consumer behavior and customer interactions (Rauschnabel et al., 2012; Dwivedi et al., 2015; Rauschnabel et al., 2019; Mariani, Perez-Vega, & Wirtz, 2022) through eWOM communications (Dwivedi et al., 2021a). Historically, text-based eWOM has dominated review platforms such as Amazon, offering structured reviews that emphasize detailed product descriptions, specifications, and user evaluations (Deng et al., 2021; Kim et al., 2023). These reviews reduce information asymmetry by providing critical insights into product features and performance (Manes & Tchetchik, 2018). Consequently, text-based eWOM has served as a key enabler of consumer trust and informed decision-making (Lim et al., 2022; Zhang et al., 2021).

However, advancements in digital technologies and the proliferation of social media have given rise a new paradigm: video-based eWOM. Platforms like YouTube, in particular, have popularized video reviews as engaging and persuasive medium for consumers (Pfeuffer et al., 2021). Video-based eWOM is distinguished by its multimedia nature, incorporating elements such as tone, gestures, and visual aids that enhance credibility and relatability (Filieri et al., 2023). This shift from text to video has significant implications for how consumers engage with reviews and make purchasing decisions.

Unlike text-based reviews, which are often static and descriptive, video-based eWOM provides a dynamic and interactive experience. For example, video reviews often feature product demonstrations or real-life scenarios that help consumers visualize product use in context (Lee & Lee, 2022). The ability to combine visual and auditory elements makes video reviews more immersive and engaging, particularly for complex or experiential products. Furthermore, the rise of parasocial interactions in video-based eWOM—where viewers develop one-sided relationships with content creators—adds a layer of emotional connection that is typically absent in text-based reviews (Penttinen et al., 2022).

YouTube, as a leading platform for video-based eWOM, demonstrates the dual role of video reviews: first-level reviews (video content itself) and second-level reviews (comments that follow the videos). This layered interaction highlights how video-based eWOM extends beyond product information delivery to foster community engagement. The comments often expand the conversation, reflecting diverse perspectives, debates, and supplementary information. This duality highlights how video-based eWOM transcends product reviews to become a social and interactive experience.

Despite such importance of video-based eWOM, existing research primarily focuses on text-based reviews, overlooking how video-based reviews engage consumer differently (Delre & Luffarelli, 2023; Liu et al., 2021; Shan et al., 2024). Furthermore, the unique dynamics of second-level reviews (e.g., YouTube comments) have not been thoroughly analyzed in the context of their interactivity and influence on community. Thus, a critical gap exists in understanding the comparative effectiveness of first-level and second-level reviews relative to traditional text-based reviews. To fill this gap, this study adopts a comprehensive approach, leveraging theoretical perspectives and empirical analysis to compare video-based and text-based eWOM.

2.2. Theoretical framework

Understanding the differences between text-based and video-based eWOM requires considering how platform characteristics shape the way information is produced, communicated, and evaluated by consumers. In online retail environments, text-based reviews – such as those found on retail platforms – often present information in a structured, product-focused manner. The design of these platforms, with features such as "verified purchase" tags, fosters a degree of accountability that encourages reviewers to provide factual, specification-oriented content.

In contrast, video-based platforms introduce richer sensory cues and more dynamic interaction patterns. Audiovisual presentation creates a heightened sense of social presence, allowing viewers to perceive reviews as authentic and relatable to individuals (Short et al., 1976). The interactive nature of comment threads and reply features fosters conversational exchanges that can quickly expand beyond the focal product, incorporating personal experiences, humor, or tangential discussions (Ogara et al., 2014). At the same time, user identify presentation on such platforms is highly flexible – ranging from complete anonymity to curated online personas – enabling varying levels of self-disclosure (Deng et al., 2021; Vishik & Finocchiaro, 2010; Zimbardo, 1969). This context-dependent or relative anonymity, in combination with high social presence (Short et al., 1976; Vishik & Finocchiaro, 2010) and interactivity (Agnihotri & Bhattacharya, 2016; Penttinen et al., 2022), can encourage more expressive and informal contributions, but may reduce the proportion of detailed product specifications in second-level reviews.

By viewing these platform characteristics as an interconnected set of influences – rather than isolated factors – it becomes possible to explain systematic differences in the informational focus and perceived value of eWOM across formats. Richer sensory cues and greater interactivity can enhance engagement and community building, yet when paired with weaker accountability, they may shift emphasis away from structured, specification-based content. Conversely, more structured, less-interactive environments with greater accountability tend to yield information that is more detailed and product-specific (Dyussembayeva et al., 2020; Pu et al., 2020).

Taken together, three dimensions – relative anonymity, social presence, and interactivity – should be viewed as mutually reinforcing platform attributes. For instance, Amazon represents a context where lower relative anonymity (through verified purchase cues), weaker social presence, and limited interactivity reinforce accountability and encourage structured, product-specific reviews. By contrast, YouTube combines higher relative anonymity (through pseudonymous accounts), stronger social presence (via audiovisual and parasocial cues), and greater interactivity, which together promote conversational, experiential, and sometimes less specification-oriented contributions. This integrated perspective underpins our hypotheses regarding the linguistic and structural distinctions between textual and video-based eWOM, and their influence on consumer perceptions.

2.3. Hypothesis development

2.3.1. Content length and depth

Social presence theory (Short et al., 1976) posits that platforms encouraging highly personalized communication (e.g., YouTube comments) often foster shorter, more conversational interactions. In contrast, Amazon – which is primarily transaction-driven – tends to support lengthier, product-specific contributions due to its explicit review framework. Extant eWOM research consistently finds that platforms structured around informing prospective buyers (like Amazon) encourage contributors to provide comprehensive, descriptive reviews (Mudambi & Schuff 2010; Wang et al., 2019; Zhu et al., 2020).

Meanwhile, engagement on YouTube frequently centers on reciprocity and rapid exchanges, particularly in the comments section (Agnihotri & Bhattacharya, 2016). Although videos may contain extensive product demonstrations, the subsequent comments generally feature shorter, informal reactions. Therefore, even when discussing the same product, YouTube commenters typically focus on quick observations or personal remarks, rather than in-depth product information.

Drawing on these insights, we posit that Amazon text-based reviews, designed to convey product-specific details to future buyers, will be more substantial than YouTube comments in terms of word count.

H1. Text-based online reviews will exhibit greater word count and detail compared to secondary video-*based online review comments.*

2.3.2. Semantic similarity and information delivery

The concept of semantic similarity is anchored in the information intent of consumer-generated reviews. Prior literature suggests that review content reduces uncertainty for prospective buyers by illuminating product features and performance (Bang & Jang, 2024; Manes & Tchetchik, 2018). On platforms such as Amazon, where reviews are structured around product-specific details, contributors are incentive to provide content that closely aligns with official product specifications, thereby enhancing clarity and facilitating informed purchase decisions.

In contrast, second-level reviews on YouTube – specifically, user comments – are shaped by relative anonymity, in which the relatively anonymous and highly interactive environment fosters more expressive yet less structured discourse (Christopherson, 2007). Although such engagement often yields broader, more spontaneous conversations, I can also lead to a diminished emphasis on factual or product-specific details. Consequently, YouTube commenters may deviate from directing mirroring formal specifications, instead focusing on personal reactions, opinions, or entertainment-related topics.

In light of these theoretical underpinning, we propose that Amazon text-based reviews, by virtue of their transactional context and structured format, will exhibit higher semantic similarity to product specifications than the second-level reviews commonly found in YouTube comments.

H2: Text-based online reviews will exhibit higher semantic similarity to product specifications compared to secondary video-*based online review comments.*

2.3.3. Anonymity and language

The context-dependent or relative anonymity perspective (Vishik & Finocchiaro, 2010) offers a lens for understanding how differences in platform-level identity cues influence the tone and style of user communication. Context-dependent or relative anonymity refers to the degree to which a platform reveals or conceals user identity, shaping perceived accountability and social norms (Vishik & Finocchiaro, 2010). On video-based platforms such as YouTube, individuals often employ pseudonyms that may not reflect their real identities, enabling a more casual — and at times more critical — communicative style (Deng et al., 2021). In contrast, text-based review platforms that display transaction-linked cues, such as “verified purchase” tags, provide a stronger connection between the review and the consumer’s actual purchase behavior. These cues can encourage more socially desirable behavior, as users may seek to preserve credibility and reliability in the eyes of potential consumers.

Existing research on online language usage corroborates that users operating under limited identity cues are likelier to employ negative or informal expressions (Deng et al., 2017; Huang et al., 2017). This tendency is magnified in interactive digital contexts, where users experience fewer social barriers and thus may feel less constrained by normative expectations. Hence, it is anticipated that user comments on YouTube, characterized by higher anonymity and interactivity, will feature more candid or negative linguistic elements than their Amazon counterparts.

H3: Secondary video-*based online review comments lead to less socially desirable language compared to text-based online reviews, where user identities are more structured (*e.g.*, verified purchases).*

2.3.4. Review content and perceived helpfulness

Online reviews that exhibit a higher degree of similarity with YouTube content are likely to be perceived as more helpful by consumers. This relationship can be explained through Information Diagnosticity Theory (Mudambi & Schuff, 2010), which suggests that consumers find information more useful when it reduces uncertainty and facilitates decision-making. YouTube videos provide a rich, multimodal source of information, combining visual, auditory, and contextual cues that enhance consumer understanding of a product. Reviews that align closely with the content of these videos reinforce key product attributes, creating information consistency and improving consumer confidence in the review’s reliability. Additionally, the cognitive fluency effect suggests that when information is presented in a familiar structure, it is processed more efficiently and perceived as more credible (Alter & Oppenheimer, 2009). Because YouTube videos often provide product demonstrations, specifications, and user experiences, reviews that reflect these elements are more likely to align with consumer expectations, increasing their perceived helpfulness. Given these theoretical underpinnings, we propose the following hypothesis:

H4a: Online reviews that exhibit higher similarity with video *content are perceived as more helpful by consumers.*

Consumers rely on online reviews as a crucial source of information when making purchase decisions. The Elaboration Likelihood Model (ELM) (Petty et al., 2015) suggests that individuals process information through either a central route, which involves careful and analytical evaluation of message content, or a peripheral route, which relies on superficial cues. When consumers engage in high-involvement purchases, such as electronics or appliances, they are more likely to process information through the central route, making structured, specification-based reviews particularly valuable. Since product specifications provide objective and verifiable details, they enhance the diagnosticity of information, a key concept in Information Diagnosticity Theory (Mudambi & Schuff, 2010). This theory posits that consumers perceive information as more useful when it reduces uncertainty and aids in decision-making. Reviews that emphasize product specifications improve decision-making efficiency, as consumers frequently compare multiple products before purchasing. Clearly outlined specifications facilitate direct comparisons, minimizing cognitive effort and increasing the perceived usefulness of the review. Additionally, these reviews align with consumer search intent, as shoppers often seek precise answers regarding a product's technical attributes. Finally, reviews containing technical specifications signal expertise, increasing perceived credibility and helpfulness. Given these factors, reviews that highlight product specifications are expected to be perceived as more helpful than those that do not.

H4b: Online reviews that emphasize product specifications are more likely to be perceived as helpful by consumers.

3. Methodology

3.1. Data Collection

In this study, we employed two types of information sources. The first comprises Amazon reviews for the 30 most popular tablets on Amazon.com. The second involves YouTube sources, from which we selected 8 videos with the highest viewership for each tablet. Industrial demand for AI algorithms, such as text mining and natural language processing (NLP), has grown to analyze unstructured data in marketing literature (Akter et al., 2023; Dwivedi et al., 2021b; Dwivedi et al., 2023). In line with this trend, this research employs an AI algorithm to transform video content into text data for further analysis. Specifically, the content of these 8 videos was translated into textual content using a specific Python package (AssemblyAI), which is an advanced speech-to-text service designed to transcribe audio files into text by leveraging deep learning and artificial intelligent. Additionally, we collected comments from these YouTube videos as our research explores a new type of electronic word of mouth: YouTube comments.

To investigate differences in review content and influence, we distinguish between first-level reviews (YouTube video transcripts) and second-level reviews (YouTube comments) and compare them to Amazon text-based reviews. This distinction recognizes the layered nature of video-based eWOM, where video content serves as primary reviews and comments represent user-generated reactions. Given that Amazon reviews are increasingly supplemented with multimedia elements, our focus on textual content ensures comparability in written expression and product-specification information. Metrics such as word count, semantic similarity, and topic diversity were chosen to capture the distinction effectively.

In our conceptual framework and hypotheses, we refer to these datasets more generally as text-based online reviews (Amazon reviews) and video-based online review comments (YouTube comments) to maintain platform-neutral terminology. Amazon reviews are used here as a representative source of text-based online reviews because of their structured format, product-specific focus, and widespread consumer use, making them an appropriate proxy for this category. Similarly, YouTube comments, drawn from product review videos, represent video-based online review comments, capturing user engagement and discussion following video content.

3.2. Text analysis

3.2.1. Topic modeling

We use the Latent Dirichlet Allocation (LDA) modeling method (Blei et al., 2003), which stands out as the most frequently employed approach for topic modeling, to understand hidden topics across an unstructured corpus of documents (Griffiths & Steyvers, 2004; Pugliese et al., 2024). It enables the assessment of the likelihood that a selected review pertains to each topic, categorizing reviews based on their proximity concerning each considered term. This technique has gained traction in marketing research (Cano-Marin et al., 2023; Zhong and Schweidel, 2020), particularly for reviews or user-generated content (Tirunillai and Tellis, 2014). The LDA model is particularly suited for this study as it allows the discovery of structures within user-generated content, providing an empirical basis for understanding the key topics driving consumer discussion. This aligns with the marketing literature where understanding topic distribution enhances the interpretability of eWOM dynamics (Birim et al., 2022; Kim et al., 2023; Verma & Yadav, 2021).

Prior to executing the topic modeling analysis using the LDA technique, we eliminated punctuation, potentially problematic symbols, whitespace, and stop words from the dataset to ensure that only content words remain as a corpus. Then, we utilize the coherence score, which assesses a single topic by gauging the semantic similarity between high-scoring words in the topic, to determine the optimal number of topics. As a result, we selected 6 topics for YouTube video content and 4 topics for YouTube comments and Amazon reviews.

We conducted the topic analysis to investigate the differences in content creation between YouTube and Amazon. Based on a prior review of relevant literature, users in the two platforms have different purposes in content creation. For instance, YouTube creators tend to provide more dynamic and diverse content through their videos to engage with more viewers. Furthermore, analyzing hidden topics can examine whether the second-level reviews (comments) on YouTube product review videos are likely to be influenced by those videos' contents. If YouTubers provide more diverse content than Amazon users, the comment writers influenced by the videos may show different content focuses compared to Amazon reviewers.

3.2.2. Semantic similarity

To measure semantic similarity between reviews written on different platforms, we employ a methodology rooted in natural language processing and vectorization techniques. First, we preprocess the textual data by performing tasks such as lowercasing, removing punctuation, and eliminating stopwords to ensure a cleaner representation of the content. Next, we transform the reviews into numerical vectors using a suitable vectorization method, such as Term Frequency-Inverse Document Frequency (TF-IDF; Ramos, 2003). This conversion allows us to represent each review as a high-dimensional vector in a multi-dimensional space, capturing the semantic nuances of the text.

Once the reviews are vectorized, we compute the cosine similarity (Rahutomo et al., 2012) between corresponding pairs of reviews from the two datasets. The cosine similarity metric measures the cosine of the angle between two vectors, providing a normalized measure of their similarity. A cosine similarity score close to 1 indicates high similarity, while a score close to 0 suggests dissimilarity. This approach is advantageous for comparing datasets as it is insensitive to the magnitude of the vectors, focusing solely on the direction in the multi-dimensional space. By applying this methodology, we gain insights into the degree of semantic similarity between reviews from different platforms, enabling us to identify commonalities and differences in the content.

The main objective of semantic similarity is to examine the level of information delivery about product features. Semantic similarity helps to quantify the degree to which the content of eWOM aligns with specific product attributes, addressing the critical need to evaluate information delivery in consumer reviews. The integration of semantic similarity analysis enables us to validate whether eWOM effectively bridges consumer uncertainty and product specifications (Yang, 2017). In particular, reviews written in traditional review platforms such as Amazon are likely to focus on product descriptions for information sharing. So, we investigate the level of information delivery by calculating the semantic similarity between reviews and the official product specification. The higher similarity can refer to a higher level of information delivery on product features. Since product review videos on YouTube are also one type of review, we also examine the similarity between product review videos and product specifications.

The combination of LDA and semantic similarity analysis provides a comprehensive analytical framework. LDA uncovers the latent topics driving consumer engagement, while semantic similarity measures how closely these discussions align with product details. This dual approach ensures a robust analysis, addressing multidimensional nature of consumer-generated content. As a result, this study can achieve a more holistic understanding of the eWOM landscape and its implications for consumer behavior.

In addition, we use text analysis to calculate the length of words in reviews and the percentage of swear words to examine the differences in eWOM between two different platforms – Amazon and YouTube. According to the anonymity and social presence perspectives (Short et al., 1976; Vishik & Finocchiaro, 2010), the level of anonymity can influence the way people communicate in reviews. For instance, anonymous reviewers are more likely to express true feelings and impersonal words. So, we examine this review characteristic based on the percentage of swear words in reviews.

4. Analysis 1 – Content characteristics across platforms

4.1. Model-free comparison

The two figures below show the frequency distributions resulting from Topic Modeling. Amazon reviews might show higher frequencies of words related to product features, quality, and customer experience. In contrast, YouTube comments may display a wider range of topics, including personal opinions, reactions to content, and broader discussions not strictly tied to products. These variations in frequency distributions reflect the unique user behaviors and content focuses of each platform. In Fig. 1-1, reviews focusing on value for money occur with the highest frequency, whereas in Figs. 1-2, reviews involving comparisons with tablets are the least frequent. Within the Amazon reviews, the topic 'for gaming' appears least frequently, whereas it is the most frequent topic among YouTube comments.

Table 1 presents the descriptions of the primary variables utilized in this study. We examine the dual roles of YouTube Videos, which serve both as product reviews and as catalysts for generating responses (YouTube comments). Consequently, we identify two distinct types of reviews on YouTube: the first being the YouTube Videos themselves, and the second being the responses (comments) to these videos.

Fig. 2 is presented to clarify the distinction between YouTube Content and YouTube Comments, showcasing the latter to eliminate any potential misunderstandings.

Table 2 titled Summary Statistics of the Primary Variables provides an overview of key statistics for several variables based on a dataset of 66,719 observations. It includes a binary variable 'YouTube', which has a mean of 0.840, indicating a high presence of YouTube comments. The table also examines "Similarity with Product Specifications", with means of 340. Additionally, it covers "Word Count", averaging at 25.771 words, and the frequency of "Swear Words", which has a mean value of 0.161. For the analysis of "Word Count" and "Swear Words", we employed the Linguistic Inquiry and Word Count (LIWC) tool. The Linguistic Inquiry and Word Count (LIWC) is a tool extensively utilized for the quantitative analysis of language in texts (Harmon & Mariani, 2024; Yousaf & Kim, 2023). It effectively measures emotional, cognitive, and linguistic structure.

Table 3 displays a correlation matrix of the primary variables in the study. It shows the relationships between variables like "YouTube", "Similarity with Product Specifications", "Word Count", and "Swear Words". Asterisks signify the statistical significance of these correlations. For instance, "Word Count" has a strong positive correlation with "Similarity with YouTube Content", suggesting that as word count increases, so does the similarity with YouTube content.

Table 4 showcases a comparison of data between two groups: Amazon and YouTube. The table includes the mean, standard error, difference, t-value, and probability for each group. The results of the second variable "Similarity with Product Specifications (S.P.S.)" show the average score for Amazon reviews is 0.367, while for YouTube comments, it is 0.335. This difference is statistically significant, indicating that Amazon reviews more accurately reflect product specifications compared to YouTube comments. This finding suggests that Amazon reviews tend to be more focused and relevant to specific

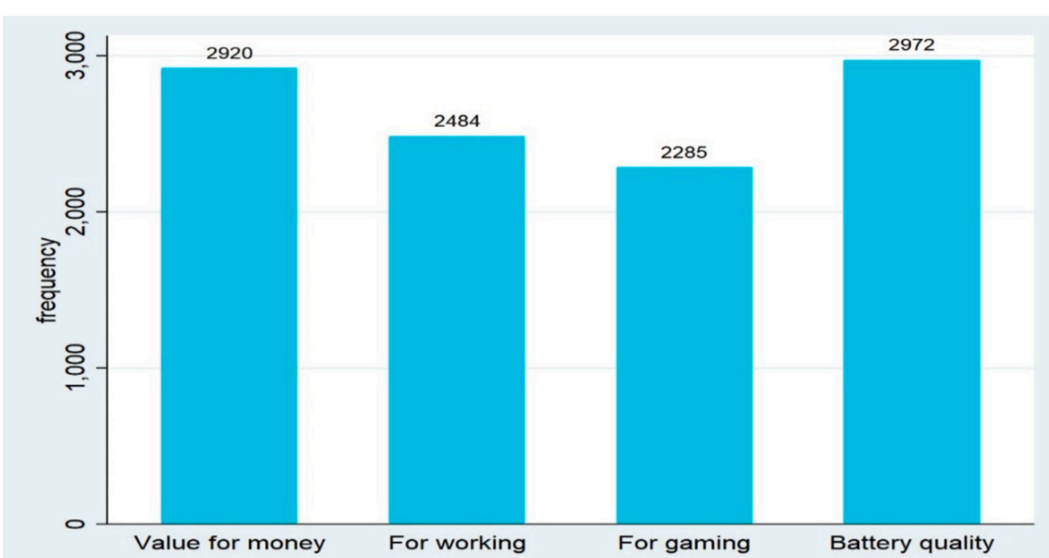

Fig. 1. 1–2. Topic Distribution of YouTube Comments Fig. 1-1. Topic Distribution of Amazon Reviews where "Comparison" is comparison with laptop, and "Review video" refers to product review video quality.

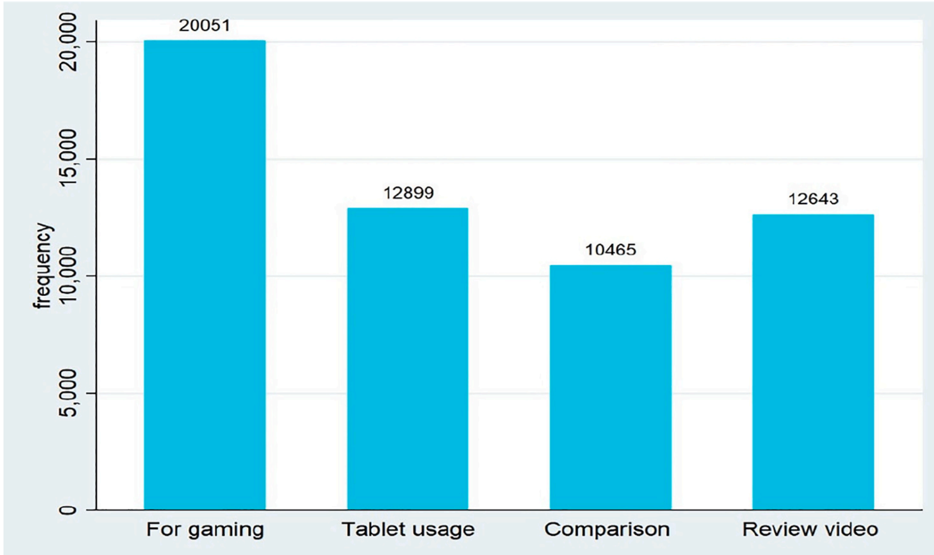

Fig. 2. Screen Shot of YouTube.

Table 1
Descriptions of the Primary Variables.

Name	Description
YouTube Content	"YouTube Content" refers to the content of YouTube Videos, which frequently includes reviews of products. The YouTube videos in this context include the videos (review videos) with the highest number of viewers for the most popular 30 tablets on Amazon.
YouTube Comments	"YouTube Comments" refer to people's responses to YouTube videos. People watch YouTube videos and leave their reactions to them.
Amazon Reviews	"Amazon Reviews" refer to the reviews by Amazon users on the 30 most popular tablets.
Similarity with Product Specifications	"Similarity with Product Specifications" measures the degree of similarity to product specifications. It enables a comparison between the similarity found in Amazon reviews and that in YouTube comments.
Word Count	"Word Count" measures the length of Amazon reviews and the length of YouTube comments.
Swear Words	Swear Words indicate the level of swear words used in reviews and comments. For this measurement, we utilized the LIWC (Linguistic Inquiry and Word Count) tool.

Table 2
Summary Statistics of the Primary Variables.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
YouTube	66,719	0.840	0.366	0	1
Similarity with Product Specifications	66,719	0.340	0.176	−0.312	0.974
Word Count	66,719	25.771	37.269	0	1,288
Swear words	66,719	0.161	1.889	0	100

Table 3
Correlation Matrix of the Primary Variables.

Variables	(1)	(2)	(3)	(4)
YouTube (1)	1.000			
Similarity with Product Specifications (2)	−0.066***	1.000		
Word Count (3)	−0.339***	0.325***	1.000	
Swear words (4)	0.027***	−0.044***	−0.026***	1.000

where ***<.01.

Table 4
Model Free Comparison.

Variable: Similarity with Product Specifications (S.P. S.)					
Group	Mean	Std. Err.	Diff.	t-value	Probability
Amazon	0.367	0.001	0.032	17.225	0.000
Youtube	0.335	0.000			
Variable: Word Count					
Group	Mean	Std. Err.	Diff.	t-value	Probability
Amazon	54.807	0.669	34.558	93.309	0.000
Youtube	20.249	0.099			
Variable: Swear words					
Group	Mean	Std. Err.	Diff.	t-value	Probability
Amazon	0.041	0.010	−0.142	−7.138	0.000
Youtube	0.183	0.008			

product details and specifications, whereas YouTube comments might be broader in scope, possibly encompassing a wider range of topics and personal expressions that extend beyond the confines of product specifications. This trend underscores the distinct nature of user engagement and content focus across these two platforms.

The analysis of the third variable, "word count," reveals a significant difference in the average length of Amazon reviews compared to YouTube comments. The average word count for Amazon reviews is 54.807, while for YouTube comments, it is significantly lower at 20.249. This disparity can likely be attributed to the nature of each platform. Amazon is primarily a platform for product-related reviews, where users focus on sharing detailed experiences and evaluations of their purchases. These reviews often encompass various aspects, including the product's features, usage experience, and pros and cons, naturally leading to a higher word count. In contrast, YouTube comments tend to be shorter and more concise, typically reflecting quick reactions or opinions about the video content. YouTube users usually prefer to share their thoughts in a rapid and straightforward manner, resulting in comments with fewer words. This difference in word count underscores the distinct purposes and user interaction styles of the two platforms. Amazon prioritizes in-depth reviews of products, while YouTube fosters immediate and succinct communication.

The analysis of the final variable, "the level of usage of swear words," indicates a significant difference between Amazon and YouTube. Amazon reviews have a notably lower average usage of swear words (0.041) compared to YouTube comments (0.183). This result reinforces the findings of the fourth variable regarding negative emotions and aligns with existing research on online behavior (Huang et al., 2015). It suggests that platforms with higher levels of anonymity, like YouTube, tend to have a higher frequency of swear word usage. This can be attributed to the reduced sense of personal accountability and social constraints in anonymous environments, which may lead users to express themselves more freely, sometimes using language that is more candid or aggressive. This trend confirms the impact of anonymity on user behavior, particularly in the context of language and expression used in online platforms. In the table below, we examine whether these findings persist when incorporating product fixed effects into the linear regression model specification.

4.2. Electronic Word-of-Mouth generation

Table 5 presents the empirical results of a linear regression analysis. The dependent variables (DVs) in this analysis are "Similarity with Product Specifications (S.P.S.)", "Word Count (W.C.)", and "Swear Words (S.W.)". The table includes coefficients for each variable along with their standard errors and indicates the inclusion of an intercept and product fixed effects. Additionally, the R-squared values and the number of observations for each regression are provided. The findings in this table corroborate the model free comparison (*t*-test) results presented in the preceding table.

This result supports H2. The estimated coefficient of S.P.S. is also significantly negative ($\beta_{S.P.S.}$ = -0.048, *p-value* < 0.01), indicating that YouTube comments contain less product-specific information. This result supports H2. The estimated coefficient of S.P.S. is also significantly negative (βS.P.S. = -0.048, p-value < 0.01), indicating that YouTube comments contain less product-specific information. We also tested this hypothesis using an alternative measure, Similarity with YouTube Content (S.Y.C.), which compares the extent of similarity between Amazon reviews and YouTube video transcripts, as well as between YouTube comments and YouTube video transcripts. Since the video content typically introduces product specifications, this alternative measure effectively evaluates how closely each type of review aligns with those specifications. The empirical results again showed a significantly negative estimated coefficient (βS.Y.C. = -0.075, p-value < 0.01), reinforcing the finding that YouTube comments provide less product-specific information than text-based reviews.

This finding stems from the nature of search goods and differences in consumer information-seeking behavior. While YouTube videos contain both informational and entertainment elements, their effectiveness as an information source depends on how viewers engage with them. Consumers typically rely on structured sources like Amazon for factual product evaluations, where reviews focus primarily on assessing product attributes. In contrast, YouTube videos often blend product information with engaging formats such as unboxings or influencer opinions. However, YouTube comments tend to focus more on reacting to the video's style or the personality of the content creator rather than discussing the product in detail. As a result, YouTube comments exhibit lower semantic similarity with product specification compared to Amazon reviews, which are more explicitly centered on product evaluation.

On the other hand, Amazon reviews tend to be longer than YouTube comments ($\beta_{W.C.}$ = -0.048, *p-value* < 0.01), while YouTube comments are more likely to include swear words in the comments ($\beta_{S.W.}$ = -0.048, *p-value* < 0.01). These results confirm those in the model free comparison in Table 2.

Table 5
Empirical Results of the Linear Regression.

Variables	Linear Regression		
DV:	S.P.S.	W.C.	S.W.
YouTube	−0.048***	−34.696***	0.136***
	(0.001)	(0.696)	(0.016)
Intercept	Included	Included	Included
Product Fixed Effect	Included	Included	Included
R-squared	16.81 %	12.52 %	1.65 %
# of Observations	66,719	66,719	66,719

where S.P.S. denotes "Similarity with Product Specifications", W.C. refers to "Word Count", and S.W. represents Swear Words. ***<.01.

5. Analysis 2 – Helpfulness and perceived value across platforms

5.1. Model specification

In this section, we analyze the value of eWOM generated on different platforms. Given the absence of helpful votes on YouTube, we adapt our measures of review helpfulness to include 'likes' as indicators of viewer engagement and approval, providing a nuanced approach to assessing the impact and value of different eWOM forms (Agnihotri and Bhattacharya, 2016; Mudambi and Schuff, 2010). This adjustment acknowledges the different contexts of these platforms and aims to offer a clearer understanding of consumer engagement and the perceived value of eWOM in a digital age where visual and textual content play varying roles in shaping consumer behavior.

With these measurements, we conduct separate linear regression analyses for Amazon reviews and YouTube comments. To investigate the values of the eWOM generated on each platform, we utilize a specific model specification:

$$\begin{aligned} ValueofeWOM_{i,p} &= \beta_0 + \beta_1 {*} S.P.S._{\cdot i,p} + \beta_2 {*} \ln(W.C.)_{i,p} + \beta_3 {*} S.W._{\cdot i,j} \\ &+ \beta_4 {*} PositiveEmotion_{i,p} + \beta_6 {*} (PositiveEmotion)^2{}_{i,p} \\ &+ \sum\nolimits_T \tau_t {*} To._t + \sum\nolimits_P \sigma_p {*} Pr._p + \varepsilon_{i,p} \end{aligned}$$

where we account for differences in characteristics such as "Similarity with Product Specifications", the logarithmic transformation of "Word Count", and the level of "Swear Words". $\sum_T \tau_t {*} To._t$ is the vector of topic dummies, $\sum_P \sigma_p {*} Pr._p$ is the vector of product dummies. Because we do not have review ratings for YouTube comments, we utilized the level of positive emotions instead. Previous studies (Kim et al., 2020; Mudambi and Schuff, 2010) have indicated that review ratings impact perceived helpfulness in a nonlinear manner, and there is a positive correlation between review ratings and positive emotions. "i" is a review or comment poster and "j" is a product (tablet). Table 4 presents the empirical findings from the linear regression analysis conducted in the study.

Table 6
Empirical Results of the Value of eWOM.

Variables	Linear Regression	
	Model (1) DV: ln(Helpful Votes)	Model (2) DV;ln(Likes Votes)
Similarity with Product Specifications (S.P.S)	0.233***	0.210***
	(0.051)	(0.029)
ln(Word Count)	0.216***	0.194***
	(0.014)	(0.007)
Swear Words	0.002	0.005
	(0.002)	(0.002)
Positive Tone	0.003***	0.003***
	(0.001)	(0.001)
Positive Tone^2 (Positive Tone*Positive Tone)	−0.001***	−0.001
	(0.001)	(0.001)
Topic2	−0.001	−0.100***
	(0.001)	(0.010)
Topic3	−0.031	0.038***
	(0.021)	(0.013)
Topic4	−0.027	0.061***
	(0.020)	(0.011)
Intercept	Included	Included
Product Fixed Effect	Included	Included
R-squared	25.05 %	6.47 %
# of Observations	10,661	56,055

where ***<.01.

5.2. Linear regression results

Table 6 presents the empirical findings related to the value of electronic word of mouth (eWOM). To address the right-skewness of the dependent variables, we applied a log transformation. This transformation reduces skewness, thereby bringing the distribution of the dependent variables closer to normality. The results provide strong support for our hypotheses. Model 1 demonstrates the impact of textual characteristics of Amazon reviews on log-transformed helpfulness votes, while Model 2 illustrates the effects of textual characteristics of YouTube comments on log-transformed likes votes. The outcomes are essentially similar, confirming the findings of previous studies (Mudambi and Schuff, 2010). In Model (1), the estimated coefficient of S.P.S. is also significantly positive ($\beta_{S.P.S.}$ = 0.568, *p-value* < 0.01), suggesting that when Amazon reviews emphasize product specifications, they are more likely to be voted as helpful.[2] Using the same model specification, we also examined an alternative measure – Similarity With YouTube Content (S.Y.C.) – and found a similarity significant positive effect ($\beta_{S.Y.C}$ = 0.568, *p-value* < 0.01). This indicates that when Amazon reviews closely reflect the information presented in product review videos, consumers tend to rate the value of these reviews more highly.

As confirmed by Mudambi and Schuff (2010), review length positively influences the value of electronic word-of-mouth (eWOM) ($\beta_{\ln\,(Word\ Count)}$ = 0.216, *p-value* < 0.01). In contrast, positive emotions show an inverse U-shaped impact on the helpfulness of votes, as indicated by the coefficients ($\beta_{Positive\ Tone}$ = 0.003, *p-value* < 0.01; $\beta^2_{Positive\ Tone}$ = -0.001, p-value < 0.01).

Swear words do not exhibit any significant impact on the value of Amazon reviews ($\beta_{Swear\ Words}$ = 0.002, *p-value* > 0.01). Furthermore, when analyzing specific topics, Topic 1 is used as the reference group. The estimated coefficients for the remaining three topics (Topic 2, Topic 3, and Topic 4) do not show any significant differences compared to Topic 1 (β_{Topic2} = -0.001, *p-value* > 0.01; β_{Topic3} = -0.031, *p-value* > 0.01; β_{Topic4} = -0.027, *p-value* > 0.01), indicating that these topics do not have an additional significant impact on the review value.

In Model (2), the estimated coefficient for S.P.S. is significantly positive ($\beta_{S.P.S.}$ = 0.210, *p-value* < 0.01), suggesting that when comments reflect product specifications, viewers tend to evaluate the value of the eWOM (electronic word-of-mouth) more highly. The length of comments is found to be positively evaluated by viewers ($\beta_{\ln(Word\ Count)}$ = 0.194, *p-value* < 0.01), while the presence of swear words does not correlate with the number of likes received ($\beta_{Swear\ Words}$ = 0.005, *p-value* > 0.01). Contrary to Model (1), positive emotion does not demonstrate an inverse U-shaped relationship with the helpfulness of votes at the 99 % confidence level, as indicated by the coefficient values ($\beta_{Positive\ Tone}$ = 0.003, *p-value* < 0.01; $\beta^2_{Positive\ Tone}$ = -0.001, p-value > 0.01).

Interestingly, the coefficient for Topic 2 (tablet usage) is significantly negative (β_{Topic2} = -0.100, *p-value* < 0.01). This suggests that, compared to comments focused on gaming, those discussing tablet usage are associated with fewer likes from viewers, indicating a lower perceived value or interest in tablet usage discussions in this context. However, the coefficients for Topic 3 (comparison with laptop) and Topic 4 (product review video) are significantly positive (β_{Topic3} = 0.038, *p-value* < 0.01; β_{Topic4} = 0.061, *p-value* < 0.01). This indicates that comments which compare the product to laptops, as well as those that are formatted as product review videos, receive more likes compared to the gaming reviews. These topics appear to resonate more with viewers, possibly due to the value of comparative information or the engaging format of review videos, which can enhance the perceived helpfulness or appeal of the content.

5.3. Robustness Check: Cross-Category comparison of search vs. Experiential goods

To examine the robustness of our findings beyond search goods, we extended the analysis to experiential goods (movies) using the same analytical framework described in Section 4.2. This cross-category comparison allows us to assess whether the differences between text-based and video-based eWOM observed for search goods persist for experiential goods.

In Section 4.2, we find that YouTube comments exhibit lower similarity with product specification compared to Amazon reviews ($\beta_{S.P.S.}$ = -0.048, p-value < 0.01. This result may be attributed to the nature of search goods, where consumers primarily seek structured, factual information. Since YouTube videos on search goods often emphasize entertainment aspects rather than detailed product specifications, comments tend to focus more on reactions to the video's presentation style or the content creator's opinions. In contrast, for experiential goods, where consumer discussions are naturally more aligned with shared emotional and narrative experiences, YouTube comments may exhibit higher similarity with the video content.

To investigate whether this phenomenon varies across product categories, particularly in the case of experiential goods, we conducted an additional empirical analysis focusing on movies. We selected the 20 most highest-grossing films from each year between 2021 and 2023 and collected consumer reviews from Amazon Prime. Simultaneously, we identified the three most-viewed YouTube videos discussing each film and gathered the corresponding comments. We applied the same analytical framework as in Section 4.2 to evaluate whether the initial hypothesis was supported.

As shown in Table 7,[3] our results remain consistent with the main findings. The estimated coefficient of S.P.S. remains significantly negative ($\beta_{S.P.S.}$ = -0.079, *p-value* < 0.01), reinforcing the idea that Amazon reviews aligns more closely with structured, platform-provided product descriptions, even in the context of experiential goods. Additionally, YouTube comments tend to be shorter than Amazon reviews ($\beta_{W.C.}$ = -2.633, *p-value* < 0.01) and are more likely to contain swear words ($\beta_{S.W.}$ = 0.358, *p-value* < 0.01).

6. Conclusion

6.1. Discussion

This study focused on analyzing the 'dual roles' of video -based eWOM in comparison with the traditional text-based eWOM, particularly regarding review generation and consumption perspectives. Our findings indicate that product review videos on YouTube, while

Table 7
Empirical Results of the Linear Regression.

Variables	Linear Regression		
DV:	S.P.S	W.C.	S.W.
YouTube	−0.079***	−2.633***	0.358***
	(0.001)	(0.744)	(0.026)
Intercept	Included	Included	Included
Product Fixed Effect	Included	Included	Included
R-squared	17.19 %	2.68 %	064 %
# of Observations	59,858	59,858	59,858

where S.P.S. denotes "Similarity with Product Specifications", W.C. refers to "Word Count", and S.W. represents Swear Words. ***<.01.

[2] With the same model, the estimated coefficient for "Similarity with YouTube Content" is also significantly positive ($\beta_{S.Y.C}$=.568, *p-value*<.01), indicating that when Amazon reviews are focused on the product, consumers tend to rate the value of these reviews more highly.

[3] Due to space limitations, only the results are reported, but it should be noted that the analysis follows the same methodology as outlined in the previous sections.

significantly influential as a new form of eWOM, do not entirely fulfill the role of opinion leaders in the way anticipated. Specifically, the comments generated for each product review video ('second-level reviews') often do not strictly follow the content of the review videos themselves, suggesting a divergence in the influence exerted by the original review content.

Our findings demonstrate that the differences in relative anonymity, social presence, and interactivity across platforms meaningfully shape the nature and perceived value of online reviews. The interplay between these dimensions suggests that while social presence may increase message impact, higher relative anonymity can also shift communication style toward greater informality or critical tone. These patterns have important implications for understanding how platform design shapes both content and audience perception in multimodal eWOM environments.

Furthermore, the similarity analyses reveal that text-based reviews tend to contain more product-specific information than video-based comments, reinforcing the notion that identity-linked platforms may foster more structured and utilitarian content (Kaushik et al., 2018). Conversely, video -based platforms, despite their rich sensory cues, often elicit conversational and experiential sharing, which can be influential in different ways.

Our robustness check provides additional empirical support for these findings. Specifically, we confirmed the distinction between textual and video-based eWOM remains consistent across different product categories. Regardless of whether the product is a search good (tablets) or an experiential good (movies), Amazon reviews continue to align more closely with product specifications, whereas YouTube comments remain shorter, more informal, and less structured. This robust consistency across product types reinforces the distinct functional roles of text-based vs. video-based eWOM and underscores the importance of platform characteristics and consumer expectations in shaping online review behaviors.

Additionally, our results highlighted key features influencing the perceived helpfulness of eWOM. YouTube comments that engage more directly with the content of the video, particularly those that reflect on the video's information or echo its sentiments, tend to be more valued by other reviews. This findings underscores the importance of relevance, quality, and engagement in the perception of review helpfulness on social media platforms (Mudambi and Schuff, 2010). In contrast, Amazon reviews, which are often more detailed and focused directly on product usage experiences, tend to be viewed as more helpful when they provide specific information that can guide purchasing decisions. The different expectations and uses of the review platforms dictate the nature of the content that is more valued by their respective audiences.

6.2. Theoretical implications

This study makes several important theoretical contributions to the eWOM literature by providing empirical evidence of the distinct roles played by video-based and text-based eWOM. Our findings challenge the assumption that video-based eWOM is inherently more engaging and informative than text-based eWOM, demonstrating instead that the effectiveness of different eWOM formats depends on the platform and product context.

First, this study extends existing research by showing that the divergence between video-based and text-based eWOM persists across multiple product categories. Our findings demonstrate that for both search and experiential goods, Amazon reviews exhibit greater alignment with product specifications, while YouTube comments remain less structured and more engagement-driven. These insights suggest that platform design, user motivations, and content structure play a greater role in shaping eWOM effectiveness than the medium itself.

Second, this study refines the application of relative anonymity perspective, social presence, and interactivity theories (Short et al., 1976) to the eWOM context by identifying platform-specific boundary conditions. Our results indicate that the influence of social presence on perceived helpfulness is moderated by the platform's communication format (video vs. text). These findings suggest that the explanatory power of these theories in the eWOM context depends on the alignment between platform affordances and user motivations.

Lastly, this study makes a distinctive methodology contribution by deploying sophisticated tools such as video speech recognition and text analysis to examine various forms of eWOM. This is the first attempt to translate video content into text to analyze linguistic features, uncover hidden topics, and assess semantic similarities with both corresponding comments and reviews on another platforms. Unlike previous studies that relied primarily on survey-based approaches (Bi et al., 2019; Muda and Hamzah, 2021; Penttinen et al., 2022), our approach offers a data-driven, empirical examination of the linguistic and structural differences between textual and video-based eWOM. These methodological innovations highlight the need for further development of multi-modal analysis techniques to better understand and evaluate the influence of diverse eWOM formats on consumer decision-making.

6.3. Managerial implications

For managers, our results emphasize the need for platform-specific eWOM strategies. On text-based platforms, encouraging structured, detail-oriented reviews enhances credibility and perceived helpfulness, consistent with prior research demonstrating that specificity and product focus increase consumer trust (Mudambi & Schuff, 2010). Marketers can achieve this by prompting reviewers with product-feature checklists or providing incentives for detailed feedback. On video-based platforms, marketers should embed clear product specifications directly into video content to counter the lower informational content typically found in second-level comments. This aligns with recent findings in influencer marketing, where blending entertainment with concise, product-focused information increases persuasive impact (Filieri et al., 2023).

Furthermore, adopting cross-platform strategies can leverage the strengths of both formats. For example, linking YouTube product demonstrations to detailed text-based reviews can create an integrated information ecosystem that satisfies both high-engagement viewers and information-driven buyers. This approach is consistent with current omnichannel content marketing trends, where brands coordinate messaging across multiple touchpoints to maximize reach and conversion. Lastly, platform managers can enhance review quality by integrating multimedia elements into text-based platforms and introducing structured prompts in video comment sections, thereby bridging the gap between engagement and informational value.

6.4. Limitations and Future Research

Our study has several limitations. Firstly, it concentrated on a single product category—tablets—to illustrate the impact of video-based eWOM. Future research should encompass a more diverse array of product categories to assess the generalizability of our findings. Nonetheless, this study still illuminates the value of product review videos as both reviews and opinion leaders in the context of review generation and consumption.

Secondly, the empirical results are derived from just two platforms, namely Amazon and YouTube. In subsequent research, collecting datasets from various platforms (see the multi-platform study by (Mariani & Borghi, 2020)) becomes crucial to control for platform-specific nuances. However, given that YouTube and Amazon represent key sources of eWOM, our findings still contribute to bridging the understanding gap regarding the distinctions between these two forms of eWOM.

Lastly, future studies should delve into additional features of product review videos. While our study primarily focused on video content, it is imperative to explore the visual characteristics of videos, such as graphical tones, for a more comprehensive analysis.

CRediT authorship contribution statement

Keeyeon Ki-cheon Park: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Jong Min Kim:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Marcello Mariani:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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