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‘I could eat a horse’: The Impact of Hyperbole on Product Sales on Short Video Platforms

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Completed Research Paper

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Abstract

How to design video content to promote sales remains unclear, despite the fact that short video has become a popular tool for brand advertising. This study proposes a novel content strategy of utilizing hyperbole in short videos and investigates its potential for driving product sales. Hyperbole, which involves exaggerating text, audio, and video features, can stimulate interest and catch audience's attention, but may also hurt credibility if perceived as misleading. This study employs machine learning algorithms to measure multimodal hyperbole, and assesses its impact on actual sales from short videos. Our findings indicate that hyperbole has a positive and significant impact on product sales. However, the effect of hyperbole is weaker for products and influencers with higher reputation. This study contributes to the literature on advertising content and video marketing by providing insights for effective content design strategies to promote purchase behaviors in the short video context.

Keywords: Hyperbole, advertising content, video marketing, reputation

Introduction

Short videos have gained immense popularity across various social media platforms. Typically lasting less than 10 minutes, this new type of digital content offers an efficient means to attract and engage consumers through intensive information and strong sense of social interaction. TikTok, one of the key players of short video platforms, has reached 800 million users worldwide in 2023 (Yuen 2023).

Video has also become a powerful content tool for brands (Dong et al. 2023). By utilizing both verbal and visual components, video content creators are able to present product attributes and express their personal opinions vividly, which helps arouse user attention and interest. Furthermore, the length of the short video ranges from seconds to minutes, reducing the time for decision-making and enabling a faster and more intuitive purchase procedure. This can lead to impulse buying when users come across short videos, get fascinated by the entertaining content, and then decide to buy the embedded product right away (Chen et al. 2019).

Although the importance of video marketing has been realized, how to utilize short videos to promote product sales remains blurred in academia as well as in the industry (Han et al. 2020). While there is extensive research on the effect of advertising content on consumer attitudes (Lee et al. 2018; Meire et al. 2019; Tellis et al. 2019), the emergence of the novel short-video context presents new challenges to the traditional content framework. Firstly, due to the limited duration of short videos, users may feel pressured to make quick purchasing decisions. As a result, content creators need to employ more effective techniques to demonstrate and highlight the key features of products within limited time periods. Secondly, compared to traditional text-based social media posts, videos contain richer information in terms of auditory and visual features. Therefore, it is necessary to develop new techniques to extract and analyze various dimensions of content. Last but not least, the time sequence of videos creates a dynamic viewing experience that has the potential to shape the perceptions of the audience. Hence, it is crucial to investigate the effect of video-related dynamic features on consumer behavior (Song et al. 2021).

Given the popularity of using short videos to promote products, our research aims to explore how to design video content in order to best drive sales. Researchers have investigated the effectiveness of informational and emotional content (Goh et al. 2013). However, in the context of short videos, creators have the opportunity to utilize alternative persuasive strategies beyond emotions. Specifically, our research focuses on a novel content strategy, which is the use of hyperbole, and explore its effect on product sales. In practice, content creators frequently use the hyperbole strategy in their videos, which involves using exaggerated claims, heightened vocal pitch, as well as large body movements (Ferré 2014). By creating content that makes the product seem more exciting, impressive, or unique, the implement of hyperbole may grab attention and stimulate interest among the video audience, and thus lead to better sales performance. However, hyperbole may also trigger consumer skepticism if the content is seen as puffery or misleading, potentially undermining its credibility. Therefore, it is worthwhile to examine whether this hyperbole approach can be effective in short videos. Several studies have investigated the effect of hyperbole on user behaviors (Bochkay et al. 2019; Zhang et al. 2020). Nevertheless, there are discrepancies in research findings among various contexts, and the identification of certain boundary conditions where hyperbole is effective or not remains unclear. Additionally, the majority of research has focused on assessing hyperbole in textual content, leaving a gap in the measurement of auditory and visual hyperbole. In light of recent research findings indicating that richer media formats, such as images and videos, might have a greater influence on consumer preferences and behavior (Zhou et al. 2021), it is imperative to investigate the effect of hyperbole in video contexts.

Thus, in our study, we aim to measure and examine the effect of hyperbolic content on product sales on short video platforms. To begin with, we develop a measurement for the intensity of hyperbole in videos. The generation of visual or vocal features usually requires domain knowledge and manual coding, which is impractical when handling extensive datasets on short video platforms (Shin et al. 2020). In our study, we utilize machine learning algorithms to extract multimodal attributes from short videos. With these technological advancements, we are able to establish a scalable and interpretable measurement for multimodal hyperbole.

After that, we examine the effect of hyperbole using real-world sales data. Moreover, we explore the heterogeneity of the effects of hyperbole in product and influencer characteristics. Our research findings indicate that hyperbole has a positive impact on the product sales. Additionally, the effect of hyperbole is more pronounced for products and influencers with lower reputation.

Our study makes significant contributions to both the methodological and theoretical aspects of the literature on advertising content and video marketing. From the methodological perspective, we propose a comprehensive approach for the measurement of multimodal hyperbole. While previous studies have mainly focused on measuring hyperbole in written messages, our research expands on this by incorporating visual and auditory features in short videos. Our proposed approach could have broader implications for the analysis of unstructured data in various research fields. This research also contributes to the literature in the following aspects. First, we explore the impact of hyperbole as a new kind of advertising content, which has not yet been fully understood. Despite the importance of what people say in persuasion, how content is expressed to effectively influence consumers has not been well studied. By examining the effectiveness of hyperbole, we provide a more comprehensive understanding of how persuasive content affect consumer behavioral outcomes. Second, this study extends the literature of video marketing by examining online purchase behaviors in the short-video context. Short video provides a unique yet challenging scenario for business to convert consumers. Our study could provide valuable insights into effective content design strategies for promoting impulse purchase behaviors.

Theoretical Background

Advertising Content

Advertising works due to its informational and persuasive effects (Guitart and Stremersch 2020). The informative effect of advertising refers to providing product-related information in order to enhance consumer awareness of the brand and reduce uncertainty (Sun et al. 2021). The persuasive effect of advertising refers to providing elaboration on the value of the product to create consumer product preferences (Colicev et al. 2019). Correspondingly, the informative effect is accomplished by incorporating informational content including product attributes, price, availability and so on (Goh et al. 2013; Lee et al. 2018). The persuasive effect can be achieved by employing emotional and figurative content (McGuire 2000). Emotional content encompasses the utilization of various emotions, such as anger, surprise and happiness (Yin et al. 2014). Figurative content is defined as artful deviations in expressions, including the use of metaphor, hyperbole and so on (Kronrod and Danziger 2013).

A significant portion of research concentrates on the persuasiveness of emotional content. For example, Tellis et al. (2019) found that positive emotional content has a positive effect on sharing. Guitart and Stremersch (2020) noted that emotional content is more effective for promoting sales, particularly for high-price products. However, the extent to which figurative expressions contribute to persuasion remains underexplored. This becomes particularly important when considering video content, where content creators possess the capability to convey their consumption experiences and opinions not just through emotions, but also by incorporating exaggerated statements, unexpected actions and so on (Ferré 2014). Therefore, there is a need for further research to explore the impact of figurative content in video-based advertising. In this paper, we specifically focus on hyperbole, which is a frequently used figurative element in short videos to capture attention, and examine its potential for driving product sales. By understanding the role of hyperbole in video contexts, content creators and marketers can develop more effective video content strategies that engage consumers in unique and creative ways.

Hyperbole

Hyperbole is a rhetorical device that involves the use of exaggerated or extravagant statements for persuasive purposes (Baginski et al. 2016; Ferré 2014). It involves various elements, such as exaggeration, overstatement, extremity and excess (Burgers et al. 2016). Hyperbole is commonly utilized to express intense feelings or produce a strong impression on the audience. Since the message is conveyed in a way that deviates from common expectations, it can affect perceptions of the audience, potentially prompting behavioral shifts.

On the one hand, hyperbole helps attract user attention and therefore raises favorable attitude of the audience. For example, Bochkay et al. (2019) find that the investors response more strongly to the extreme words in earning calls, resulting in a subsequent increase in both corporate trading volume and stock price. Becker et al. (2018) also point out that exaggerated messages lead to greater ad effectiveness. This could due to that consumers expect some hyperbole content in advertising to make it more humorous. On the other hand, hyperbolic content has been subject to criticism for its perceived lack of credibility, which may result in negative reactions form the target audience. According to Callister and Stern (2007), hyperbolic advertising claims are often met with skepticism from consumers, who perceive them as less credible and authentic. Meanwhile, Baginski et al. (2016) point out that hyperbole reveals sender overconfidence, and the exaggeration of content reduces the amount of information transmitted.

In conclusion, while current research has provided valuable insights for the impact of hyperbole on user attitudes and behaviors, there remains several research gaps. Firstly, there is a lack of investigation into the heterogeneous effects of hyperbole. Understanding the circumstances in which the use of hyperbole could potentially lead to credibility loss would offer valuable insights into the strategic utilization of this rhetorical technique. Secondly, it is worth noting that the majority of studies have focused on hyperbole in written texts or transcripts of spoken corpora, and little is known about the audio and video aspects of hyperbole (Ferré 2014). This is particularly important given the incorporation of various content formats, including text, image and video on social media platforms. Consequently, there is a need to develop methods for measuring hyperbole in a multimodal manner, and comprehensively assess its effects in emerging contexts where verbal and non-verbal exaggerated behaviors are integrated.

Hypotheses Development

Based on the previous literature on advertising content, our study aims to investigate the impact of hyperbole on product sales on short video platforms, taking into account the informational content as well. The research model we propose is illustrated in Figure 1.

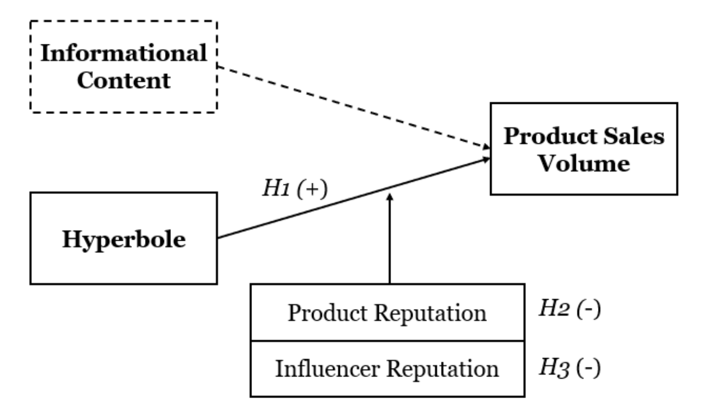

Figure 1. Research Framework

While the studies above examine the impact of hyperbole on traditional advertisements, few have investigated its effects within the context of short videos. Short videos are primarily intended to entertain and engage viewers within the limited time duration (Liu et al. 2018), which presents a significant challenge for content creators when crafting their video content. The attention-grabbing ability of short videos is crucial in driving user engagement and ultimately, sales. Additionally, most short videos are created by social media influencers rather than brands themselves. As influencers are perceived as more intimate and trustworthy by the users (Schouten et al. 2020), their hyperbole strategy may also be seen as more authentic and credible. Therefore, hyperbole serves as an essential way for influencers to produce interesting and engaging content. By incorporating extreme words, exaggerated body movements, intense vocal tone, influencers are able to emphasize the distinctive features of a product, express their personal attitudes and opinions regarding it, and then elicit strong reactions and raise product value perception in viewers (Krishnan et al. 2013). As a result, when users come across short videos with hyperbolic content, they are easily get attracted by the vivid expressions, and becoming curious about the focal product. Hence, even though hyperbolic content may raise skepticism, we believe that its ability to catch user attention would be more significant in the context of short videos. Accordingly, we propose that hyperbolic video content stimulates consumers to purchase the product.

H1: The intensity of hyperbole in short video positively influences product sales volume.

We also intent to investigate how the impact of hyperbole changes with perceived uncertainty, which is crucial for consumer decision making (Tellis et al. 2019). Perceived certainty in purchasing arises from imperfect information about selling and product-related factors (Pavlou et al. 2007). In situations where there is greater uncertainty since the product quality or performance is unknown, consumers often seek quality signals to help inform their purchasing decisions. In our study, we specifically focus on two significant factors that can serve as information signals: product reputation and influencer reputation. Our research takes a unique approach by investigating how hyperbole interacts with these two reputation factors to influence consumer behavior in short videos.

Product reputation reflects consumers' direct and indirect experiences with a particular product (Campbell and Keller 2003). It serves as a significant indicator of product quality and performance. In the case of products with a higher reputation, consumers have more knowledge or experience regarding the brand's offerings and have already established their own preferences. As consumers have prior product experience, they tend to become more skeptical and less likely to change their attitudes based on advertising exposure (DeCarlo et al. 2013). Therefore, compared with lesser-known products, using hyperbolic content to sell products with higher reputation may not catch as much attention and interests (Liadeli et al. 2023). In fact, hyperbole might even be perceived as less effective or even disingenuous in promoting well-known products (Becker et al. 2018). Therefore, we expect that the effectiveness of hyperbolic content in persuading consumers would be diminished for products with higher reputation. Formally, we propose the following hypothesis:

H2: The effect of hyperbole on product sales volume will be weaker for products with higher reputation.

Social media influencers play an important role in introducing the product and influencing purchase decisions in commercial short videos. Consumers decide to buy the featured product due to their identification with the influencer and their desire to follow their recommendations (Schouten et al. 2020). Therefore, understanding the interplay between influencer reputation and hyperbolic content is also important for brands and marketers to develop effective influencer marketing strategies. Influencer reputation refers to the perceived credibility associated with influencers endorsing the product. It is often evaluated based on their cumulated number of followers on social media platforms, which stands out as a prominent characteristic for determining their influence and reach (Wies et al. 2023). Influencers gain reputation due to their expertise and shared interests with their followers. Influencers with higher reputation are often perceived as more likeable and attributed to for higher opinion leadership (De Veirman et al. 2017). However, as the reach of audience expands, influencers also face higher expectations and intensified public scrutiny (Summers and Johnson Morgan 2008). As a result, they are expected to be trustworthy and provide authentic information rather than exaggerated statement. Therefore, influencers with stronger reputation would appear less credible when hyperbolic content is employed in their short videos. We hypothesize that the effect of hyperbole on product sales may be weaker when the reputation of the influencer in the video is stronger. Formally, we propose the following hypothesis:

H3: The effect of hyperbole on product sales volume will be weaker for influencers with higher reputation.

Research Context and Empirical Data

Data Description

We test our research framework using data from Douyin, one of the most popular short-video platforms in China. In April 2021, Douyin has announced its new focus on “interest-based e-commerce”, enabling collaboration between content creators and brands by adding clickable product links to short videos. Without the effort of searching for products, these commercial short videos are automatically delivered to users through the recommendation algorithms. As depicted in Figure 2, users can effortlessly access the product page by clicking on the shopping link located at the bottom of the video, which provides detailed information about the product description, price, brand, and other relevant details. Subsequently, users can make purchases of the showcased items without leaving the app, creating a seamless shopping experience.

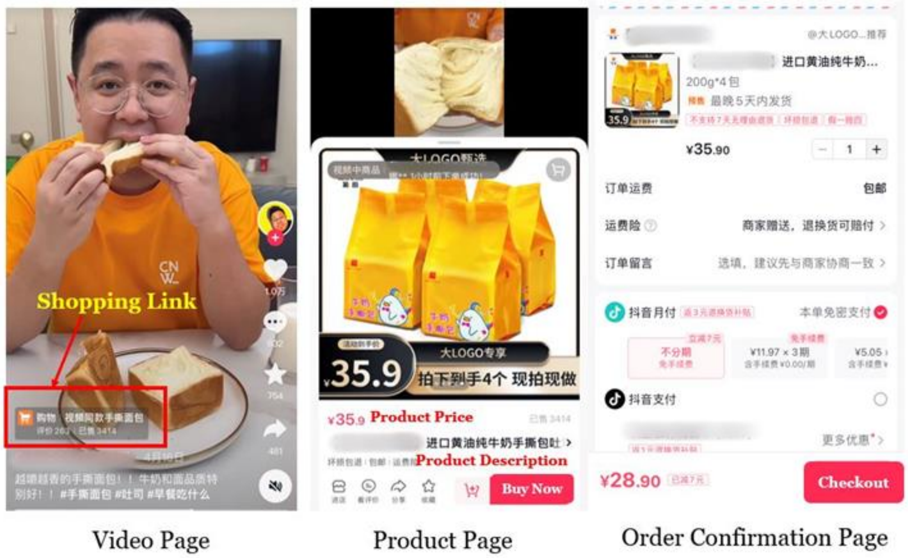

Figure 2. Douyin Commercial Short Videos

We collected a sample of 2240 commercial short videos advertising groceries, which is one of the most popular product categories in Douyin. All the videos were released from March 26th, 2022 to March 31st, 2022. By refining samples that contain textual, auditory and visual data, the final sample consists of 2122 videos. The average length of the short videos are 66.69 seconds.

Table 1 represents the definition and descriptive statistics of our data. We take the product sales volume from commercial short videos as our dependent variable. In order to account for the popularity of videos, we further account for the number of views of the video. Furthermore, we include a comprehensive set of control variables in order to account for influencer characteristics, product characteristics, as well as video filming characteristics that may affect the purchases in short videos. For influencer characteristics, we gathered demographic information including influencer gender and verification status, along with metrics of the influencer's popularity, including follower count and the number of views on videos created by the influencer within the previous three days. We also recorded data related to the product embedded in the commercial short video, including price, brand, product rating and page view information. Specifically, we utilized the Baidu Index of the focal brand to determine product reputation, which measures the search volume of the brand on Baidu, the largest search engine in China, one month before the commercial short video was posted. Given that new brands are typically not mentioned as often, we considered a brand to be well-known if its Baidu Index exceeded zero. Furthermore, building on existing literature (Zhang et al. 2021), we evaluated the aesthetic properties of the video, such as the saturation, brightness and warm hue, along with filming properties such as the number of shots and scenes.

Variable	Definition	Mean	SD	Min	Max
ln_sales	Log number of product sales volume of the commercial short video	4.135	1.828	0.000	10.098
Product Characteristics					
ln_price	Log price of the video-embedded product (in RMB)	3.206	0.741	0.010	6.907
product_reputation	Whether the product belongs to a well-known brand (0-lesser-known; 1-well-known)	0.155	0.362	0.000	1.000
prod_rate	Product rating	4.657	0.904	0.000	5.000
ln_pv_count	Log number of product page view in 30 days	11.282	2.235	0.000	14.834
Influencer Characteristics					
gender	0-male; 1-female	0.540	0.499	0.000	1.000
verification_type	0-no verification; 1-verified individual; 2-verified corporate	0.532	0.813	0.000	2.000
ln_follower	Log number of followers of the video content creator	12.802	2.138	0.000	17.159
ln_videoview	Log average number of views of videos produced by the influencer in 3 days	12.560	2.563	0.000	18.183
Video Characteristics					
ln_playcount	Log number of views of the video	12.292	1.339	0.000	16.983
saturation	The richness of color in a video	87.235	25.057	21.484	199.512
brightness	The level of overall image illumination in a video	143.508	24.956	35.431	229.333
hue	Image warmth in a video	0.965	0.076	0.266	1.000
ln_shot_num	Log number of video shots	2.500	0.992	0.693	4.804
ln_scene_num	Log number of video scenes	0.963	0.386	0.693	2.565
N	2122				

Table 1. Variable Definition and Descriptive Statistics

Measuring Advertising Content

Machine learning has emerged as a prominent approach for effectively extracting extensive textual, visual and vocal attributes from video content. In our study, we employ natural language processing (NLP) and computer vision (CV) methods to measure informational as well as hyperbolic content. To the best of our knowledge, our paper is among the first to apply machine learning methodologies in assessing multimodal hyperbole in the context of short videos.

Video advertising differs from text-based and image-based advertising in that it incorporates two additional features, namely multimodality and temporality. Multimodality is reflected by the fact that video-based advertising stimulates audiences from multiple perspectives of textual, auditory and visual meaning at the same time. Temporality is reflected by the fact that video-based advertising gives different degrees of stimulation to audiences as time changes. In this study, we aim to examine the informative and persuasive effects of video advertising by measuring informational value and hyperbole, both in a multimodal as well as a temporal way.

Data Preprocessing

To account for the temporal characteristics of video advertising, we segment the short videos into 5-second intervals and evaluate the informational value as well as hyperbole of each segment separately. To capture the multimodal features of the advertising content, we extract audio data and text data based on the following procedure. First, short videos usually contain both the influencer's voice and other sounds such as video background music, so to exclude the other sounds, we extract the influencer's voice as audio data by speaker diarization (Bredin and Laurent 2021). After that, we transcribe the influencer's voice into text by automatic speech recognition technology (Zheng et al. 2021) to obtain text data.

Informational Content

Consumers expect to obtain relevant product information while watching commercial short videos. If the information presented in a video is uniform or repetitive, its informational value is low and may not be useful for audiences in making informed purchase decisions. Recently, information entropy, defined as measure of the amount of information the system contains, has been used by many scholars to measure the informational value of content (Koh and Cui 2022; Shin et al. 2020). Considering the multimodality of short videos, our work will measure two types of informational value based on information entropy: text entropy, and video entropy. Table 2 summarizes the summary statistics of these two types of informational value.

Variable	Mean	SD	Min	Max
Informational Content				
text_entropy	1.349	0.576	0.005	2.544
video_entropy	0.454	0.110	0.007	0.861
Hyperbole				
multimodal_hyperbole	0.417	0.084	0.085	0.573
Text Features				
text_exagger_words	0.177	0.077	0.000	0.667
text_imageability	0.154	0.082	0.000	0.591
text_subjectivity	0.326	0.171	0.000	1.000
text_unexpectedness	0.517	0.126	0.009	0.797
text_emotion	0.709	0.174	0.009	0.983
Audio Features				
audio_speech_rate	0.418	0.136	0.000	0.735
audio_pitch	0.451	0.140	0.009	0.770
audio_intensity	0.193	0.119	0.000	0.667
audio_emotion	0.890	0.209	0.000	1.000
audio_pauses	0.050	0.072	0.000	0.429
Video Features				
video_unexpectedness	0.247	0.088	0.025	0.552
video_emotion	0.644	0.203	0.000	0.996
video_gesture_size	0.283	0.150	0.000	0.858
N	2122			

Table 2. Descriptive Statistics for Advertising Content

We use the following procedure to measure the informational value of text. Firstly, we construct an LDA model on the whole video text corpus (Blei et al. 2003). LDA is an unsupervised machine learning technique that exposes the topics embedded in the video text and represents a short video text as a probability distribution about the topics. After that, we measure the text entropy of video i according to the formula of information entropy:

$$text\_entropy_i = -\sum_{j=1}^{k} p_{ij} \log(p_{ij}), \tag{1}$$

where p_{ij} is the contribution of the j topic in video i. We choose 7 topics in our work based on the perplexity score (Wallach et al. 2009).

In terms of visual informational value, we adopt the method suggested by Koh and Cui (2022) to measure video entropy. First, the image classification pre-training model Resnet50 is employed to get the probability of the objects contained in each frame, which was trained in ImageNet containing 21,841 classes with a total of 14,197,122 images. After that, according to the information entropy formula, we measure the visual informational value of each frame. Finally, we obtain the video entropy of each video by calculating the average of the visual informational value of all its frames. The formula is as follows:

$$video\_entropy_i = -\frac{1}{l}\sum_{j=1}^{l}\sum_{o=1}^{N} p_{ijo} \log(p_{ijo}), \tag{2}$$

where l is the number of frames of the video, p_{ijo} is the probability of the object o contained in the jth frame of video i and N is the number of classes of ImageNet.

Multimodal Hyperbole

Based on the data, we propose a comprehensive approach for the measurement of video hyperbole. Deriving from the literature of pragmatics and advertising, we identify three components of hyperbole, which are non-literal meaning, upsurge on a semantic scale, and connotative trait (Burgers et al. 2016; Troiano et al. 2018). Correspondingly, we employ machine learning methods to extract 13 interpretable features from text, audio, and video modalities of the video content, in order to capture the multifaceted nature of hyperbole in video information (Balducci and Marinova 2018). Afterwards, we generate a composite summary variable of multimodal hyperbole by combining the features of three modalities.

The first component of hyperbole, non-literal meaning, refers to the use of figurative language to convey a message that is different from its propositional meaning (Burgers et al. 2016). If an object has characteristic X, hyperbole will present more of X than it really is, such as amplifying the characteristic that I am hungry in "I could eat a horse". This discrepancy between the linguistic expression and the reality will bring a sense of "unexpectedness" and "rich imageability". Considering that linguistic information is expressed mainly by text and video modalities, we propose three features to reflect this component, which are *text imageability*, *text unexpectedness* and *video unexpectedness*.

The second component is upsurge on a semantic scale, which refers to the magnitude of the difference between the propositional and intended meaning of an utterance. For instance, "It took the waiter a week to get me my coffee" and "It took the waiter a year to get me my coffee" have the same non-literal meaning, but their hyperbole intensity is different. This component captures the intensity of hyperbole through the mode of expression. In text, hyperbole involves the use of more exaggerated words to convey intensity. In audio, hyperbole is expressed as higher pitch, louder volume, faster speech rate, and more pauses. In video, hyperbole is expressed as larger body gestures (Ferré, 2014). Therefore, we utilize six features to indicate the upsurge on a semantic scale component, which are *text exaggerated words*, *audio pitch*, *audio intensity*, *audio speech rate*, *audio vocalized pauses* and *gesture size*.

The third component, connotative trait of hyperbole, highlights the positive and negative views of reality. When we exaggerate, we emphasize some evidence that supports our thoughts and opinions, thus presenting a more favorable or unfavorable view toward the subject. The emotion-related features in text, audio and video all play a role in conveying the intended connotation of the hyperbole. Firstly, text emotion captures the overall emotional tone of the content presented the influencer. Text subjectivity measures the extent to which the text expresses personal feelings or opinions. Additionally, audio emotion detects the influencer's emotion by utilizing the voice. Furthermore, video emotion captures the facial expressions and body language of the influencer, which are critical in conveying emotions to the audience. Therefore, we extract emotion-related features from three modalities including *text emotion*, *text subjectivity*, *audio emotion* and *video emotion*.

In general, the three components capture distinct aspects of hyperbole across multiple modalities. Non-literal meaning emphasizes the gap between the actual meaning conveyed by the hyperbole and the literal meaning of the words used. Upsurge on a semantic scale highlights how hyperbole is expressed to convey the degree of intensity. Meanwhile, the connotative trait explores the subjective thoughts and opinions underlying the hyperbole. In order to build a comprehensive measurement of hyperbole based on the multimodal video data, we extract features from short videos based on the three components of hyperbole. The measurement methods for all features are discussed in the following paragraphs. To ensure comparability among all features, we normalize each one after measurement and then calculate the average value of all the features as the multimodal hyperbole score for each video. Table 2 summarizes the descriptive statistics of all the features within the three modalities as well as the multimodal hyperbole score at the video level.

Text Imageability. Imageability is the degree to which a word can evoke a mental image (Troiano et al. 2018). It is common for influencers to utilize graphic language and vivid images to arouse the audience's imagination and establish a connection between the intended meaning and anticipated interpretation. This feature is extracted from the MRC psycholinguistic database (Wilson 1988), which provides the imageability values of words. For each sentence, we average the imageability values of all its words.

Text Unexpectedness. Unexpectedness refers to the fact that hyperbolic expressions are less predictable than literals (Troiano et al. 2018). Hyperbole exaggerates specific features of the description object, so that these features are inconsistent with the rest of the features of the object, presenting an unexpected effect to the audience. We use an embedding algorithm to create embedding vectors representing word. If a word is considered as more unexpected, it is likely to be more distant from its context, resulting in a lower cosine similarity to the embedding vector of that context. The embedding method is proposed by Song et al. (2018), which collects a large amount of text from the Chinese network for training. The final embedding vector contains Chinese slang and latest vocabulary, which has higher coverage and freshness and better fits our short video sample. We measure the textual unexpectedness using the following equation:

$$\text{text\_unexpectedness} = 1 - \frac{1}{l^2}\sum_{i=1}^{l}\sum_{j=1}^{l}\frac{v_i^T v_j}{\|v_i\|\|v_j\|}\ , \tag{3}$$

where v_i is the embedding vector of word i and l is the number of words. A more hyperbolic sentence would have greater textual unexpectedness.

Text Exaggerated Words. The frequent usage of adjectives or adverbs is a key indicator of hyperbole (Zhang et al. 2020). The use of adjectives and adverbs increases the degree of hyperbole in the utterance. In order to compute the proportion of adverbs and adjectives in a sentence as exaggerated words, we label the part of speech for each word in a sentence by using Lexical Analysis of Chinese (Jiao et al. 2018).

Text Emotion. Emotional intensity measures the strength of sentiment and is conveyed through text, sound, and images. It quantifies the emphasis with which such position is communicated (Baginski et al. 2016). We utilize PaddleNLP, a BiLSTM model that is trained on a large-scale Chinese sentiment corpus, to measure text emotional intensity.

Text Subjectivity. Subjectivity specifies if a statement conveys an objective information or a personal opinion (Troiano et al. 2018). The stronger the connotative trait of an expression, the more subjective it becomes, and the more likely the audience perceives it as hyperbole. We compute the textual subjectivity by using TextBlob, which specifies if a statement conveys an objective information or a personal opinion. The higher the subjectivity score, the greater the likelihood of hyperbole in a sentence.

Audio Pitch and Intensity. Hyperbole will appeal to a combination of prosodic features such as higher pitch and intensity (Ferré 2014). To calculate the pitch and intensity of the sound, we use Librosa (McFee et al. 2015) to extract the Fundamental frequency (F0) and root-mean-square from the audio data.

Audio Speech Rate and Vocalized Pauses. When expressing hyperbole, people tend to show certain prosodic features, such as a faster speech rate and an increased number of vocalized pauses during speech

(Ferré 2014). We use the algorithm proposed by (de Jong et al. 2021) to measure the speech rate in the as well as vocalized pauses in the audio.

Audio Emotion. Using the CASIA natural emotional audio-visual database (Bao et al. 2014), which includes six emotions from four professional speakers and a total of 9600 different pronunciations totaling 300 identical and 100 different texts, we extract 384-dimensional sound features based on openSMILE and train a deep neural network for audio emotion recognition. The probability of each type of emotion is used as the intensity value of that type of emotion. Finally, we take the mean value of non-neutral emotional intensity as the reflection of audio emotional intensity.

Video Unexpectedness. By considering the video as a "sentence" and each frame as a "word", we can compute video unexpectedness in the same way as textual unexpectedness by representing each frame as a vector. We use an image pre-training model, which is Resnet50, for image embedding. It is trained on an ImageNet dataset (Russakovsky et al. 2015) with 14,197,122 images to fully capture the semantic information contained in the images, and is commonly used for image classification tasks.

Video Gesture Size. Large gestures are a common feature of hyperbole in conversations, as they provide a way of expressing the degree of intensity (Ferré 2014). Similarly, influencers use large size gestures as carriers of information to convey varying degrees of hyperbole in the short video content. To focus on the influencer's gestures, we utilize the Human Segmentation algorithm (Liu et al. 2021) to isolate the influencer from the other elements in each frame by saving only the pixels of the portrait and setting the other parts of the pixels as blank. After that, we calculate the Structural Similarity (SSIM) between each frame of the portrait and its corresponding frame 0.5 seconds. Then, we take the average of all the structural similarities as the gesture size. The following equation represents this process:

$$\mathrm{gesture\_size} = 1 - \frac{1}{\mathrm{l} - 0.5 * \mathrm{fps}} \sum_{\mathrm{i}=1}^{\mathrm{l}-0.5*\mathrm{fps}} SSIM(i, i + 0.5 * fps)\,, \tag{4}$$

where $SSIM(i, j)$ is the structural similarity between the ith frame and the jth frame, l is the number of frames contained in the video, and fps is the frames per second of the video.

Video Emotion. DeepFace is used to recognize face emotions (Serengil and Ozpinar 2021). This is a hybrid framework combining state-of-the-art models with powerful face emotion recognition capabilities. Finally, we take the average of non-neutral emotional intensity as the reflection of video emotion.

Model and Results

Model Specification

We investigate the effects of hyperbole on product sales, as well as the moderating role of product and influencer characteristics by estimating a regression model as follows:

$$\begin{gathered} ln\_sales_{ijk} = \alpha_{ijk} + \beta_0 multimodal\_hyperbole_{ijk} + \beta_1 text\_entropy_{ijk} + \beta_2 video\_entropy_{ijk} \\ + \beta_3 multimodal\_hyperbole_{ijk} \times Moderator_{ijk} + \beta_4 ln\_playcount_{ijk} \\ + \beta_5 Product\_Controls_i + \beta_6 Influencer\_Controls_j + \beta_7 Video\_Controls_k + \varepsilon_{ijk}, \end{gathered} \tag{5}$$

referring influencer j promoting product i in short video k. In turn, ln_sales_{ijk} is the log number of product sales volume, $multimodal\_hyperbole_{ijk}$ captures the intensity of hyperbolic content in the video, $text\_entropy_{ijk}$ and $video\_entropy_{ijk}$ are variables representing the text level and video level information complexity. $ln\_playcount_{ijk}$ represents the number of views of the short video. $Moderator_{ijk}$ represents the moderating characteristics, including product reputation as well as influencer reputation. We create a dummy variable for influencer reputation using a median split based on the influencer's follower count. A value of one is assigned to influencers with a larger follower base. $Product\_Controls_i$ is a vector of control variables related to product characteristics (product price, brand, rating, number of views of product page). $Influencer\_Controls_j$ is a vector of control variables related to influencer characteristics (gender, verification type, number of followers, number of short-video views). $Video\_Controls_k$ is a vector of control variables related to video filming characteristics (saturation, brightness, hue, number of scenes and shots).

Results

We begin by examining the relationship between video hyperbole and product sales, as predicted in *H1*. Model 1 in Table 3 reports the results. The coefficient of *multimodal_hyperbole* is 1.991 and significant at 1% level. It suggests that hyperbole is a powerful persuasive tool for stimulating product sales volume in short video contexts, thus supporting *H1*. In terms of the informational content, we find that the coefficient of *video_entropy* is -0.680 and is significant at 5% level, indicating that visual informational value has a negative effect on product sales. As the visual complexity of video content increases, short video viewers are less inclined to make a purchase of the product. This could be attributed to the fact that the presence of diverse visual features in a video may require more cognitive effort from viewers, which contradicts their primary objective of seeking entertainment while watching short videos (Shin et al. 2020). The textual informational value does not have a significant impact on product sales, as the coefficient of *text_entropy* is not significant. This may due to that users tend to focus more on visual aspects of a short video rather than textual features (Jiang and Benbasat 2007).

	Model 1	**Model 2**	**Model 3**	**Model 4**
multimodal_hyperbole	1.991***	2.391***	2.263***	2.645***
	(0.411)	(0.438)	(0.422)	(0.448)
multimodal_hyperbole* product_reputation		-2.811***		-2.734**
		(1.078)		(1.077)
multimodal_hyperbole* influencer_reputation			-0.579***	-0.565***
			(0.212)	(0.212)
text_entropy	0.036	0.042	0.038	0.044
	(0.055)	(0.055)	(0.055)	(0.055)
video_entropy	-0.680**	-0.665**	-0.699**	-0.684**
	(0.298)	(0.298)	(0.298)	(0.297)
ln_playcount	0.796***	0.799***	0.800***	0.802***
	(0.025)	(0.025)	(0.025)	(0.025)
product_reputation	-0.417***	0.770*	-0.410***	0.745
	(0.090)	(0.464)	(0.090)	(0.464)
influencer_reputation	-0.046**	-0.045**	-0.002	-0.002
	(0.019)	(0.019)	(0.025)	(0.025)
_cons	-6.501***	-6.756***	-7.038***	-7.272***
	(0.623)	(0.630)	(0.653)	(0.658)
N	2122	2122	2122	2122
Product Controls	YES	YES	YES	YES
Influencer Controls	YES	YES	YES	YES
Video Controls	YES	YES	YES	YES
adj. R^2	0.382	0.383	0.384	0.385

Table 3. Regression Results

Note: Robust standard errors in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

We then include the interaction terms to examine whether the effect of hyperbole would vary based on different product and influencer characteristics. The results are presented in Model 2 and 3 in Table 3. First, we find that the interaction term between hyperbole and product reputation is negative. The coefficient of the interaction term is -2.811 and is significant at 1% level. It shows that hyperbole has a stronger effect on encouraging the purchase of lesser-known products, while its impact weakens for products from well-known brands. Thus, *H2* is supported. It indicates that the hyperbole content strategy is more effective for products that consumers are less familiar with.

Our findings also reveal that hyperbolic content has a more significant impact on the sales of products promoted by influencers with lower reputation. The coefficient of the interaction term is -0.579 and is significant at 1% level. It shows that influencers with a smaller follower base could benefit more from implementing hyperbolic content in their short videos, which is in line with our expectations in *H3*. Model (4) represents the regression result of a full model including all the moderators. The results remain similar, which further confirms the robustness of our findings.

To ensure the robustness of our analysis, we conduct a negative binomial regression model as an alternative to the linear regression model used in our main analysis. Since our dependent variable, product sales volume, is a count variable, negative binomial regression helps account for the overdispersion that may be present in count data. We estimate the negative binomial model using the same independent and control variables as in the linear regression model. The results of the negative binomial model are consistent with those of the linear regression model, providing further support for the robustness of our findings. Furthermore, to disentangle the effects of emotional content and hyperbole, we create two separate variables based on multimodal hyperbole. The first variable includes the non-literal meaning and upsurge on a semantic scale components of hyperbole, which does not involve emotional content. The second variable is based on the connotative trait component, which captures the emotional content conveyed in the short videos. After including these two variables, along with all other variables in our regression model, we find that hyperbolic content still has a significant impact on product sales even without the emotion related features. This finding further supports that hyperbole is a distinct construct that goes beyond emotion and has not been adequately captured in previous research.

Discussion

The dynamic and vivid nature of videos enables content creators to effectively communicate with their audience through body movements, facial expressions, and vocal tones, while also providing a unique context for product advertising that can persuade potential consumers to make a purchase. In this research, we focus on a novel type of advertising content, which is hyperbolic content, and investigate its impact on product sales volume in short videos. The results suggest that the hyperbole content strategy can effectively stimulate consumer engagement and encourage purchase behavior. This could be attributed to its attention-grabbing ability, which is crucial for short videos to capture viewer interest (Bochkay et al. 2019). Furthermore, this study also highlights the importance of the role of perceived uncertainty in consumer decision-making. We find that the impact of hyperbole may be amplified in situations where the featured products in the short video are from less established brands and are priced lower, and when the influencer promoting the product has a smaller number of followers.

This study makes several theoretical and practical contributions. Firstly, our study integrates the literature on advertising content to investigate the effect of hyperbole on product sales in the context of short video platforms. Existing studies have mainly focused on the persuasive effect of emotional content (Goh et al. 2013). Our research extends the previous studies by focusing on a significant while underexplored content design strategy, which is the use of figurative language. Specifically, we examine the effect of hyperbole in commercial short videos, thereby enriching the understanding of how persuasive content affects consumer purchase behavior on social media platforms.

Additionally, this study extends the existing research on the effectiveness of hyperbole. By shedding light on the interplay between hyperbole and product as well as influencer characteristics, we suggest that hyperbolic content would have differential effects under certain conditions associated with perceived uncertainty (Hong et al. 2004). Our results provide knowledge on how hyperbole functions in the short video context and offers insights into the heterogeneous effects it may have on consumer behaviors.

Furthermore, our study makes substantial contributions in terms of methodology by introducing an interpretable computational framework for the measurement of multimodal hyperbole. By leveraging natural language processing and computer vision techniques, we establish a comprehensive metric that effectively operationalizes the construct of hyperbole in the context of short videos. Our method not only advances the assessment of exaggerated content, but also offers an efficient and scalable solution for examining multi-dimensional constructs on video platforms (Shin et al. 2020).

Our results also offer valuable insights for both brands and marketers who seek to leverage influencer marketing on short video platforms. Specifically, our results suggest that influencers can benefit from implementing hyperbolic expressions in their videos, as this can elicit strong reactions from their audience and potentially increase product sales. Moreover, this study also highlights the importance of considering the characteristics of the product and the influencer when designing content and developing marketing strategies. When incorporating hyperbole into short video content, marketers need to ensure that it aligns with the brand and resonates with their target audience. Overall, our study provides practical insights that can be utilized by practitioners to enhance the effectiveness of their content design.

There are also limitations of our work that we plan to address in future. Firstly, our video data were collected from the grocery category. It is worthwhile to reexamine our hypotheses with products in different genres to improve the generalizability of our findings. Secondly, although we construct multimodal hyperbole based on its linguistic components, a future study could employ surveys to gather consumer perception data and assess whether the calculated multimodal hyperbole score aligns with the perceived hyperbole. Thirdly, this study focuses on how the utilization of hyperbolic content may influence the purchase behavior of the audience. Future studies could also consider other behavioral outcomes, such as viewers' liking and sharing behaviors while watching short videos.

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