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Conveyed Message in YouTube Product Review Videos: The discrepancy between sponsored and non-sponsored product review videos

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Ⅰ. Introduction

1.1 Research Background and Motivation

Online opinions and reviews are important for customers making purchase decisions and for companies seeking to understand customer opinions. Studies show that the majority of online shoppers rely on reviews to determine their selections among various products and services. A study conducted by Zhong-Gang et

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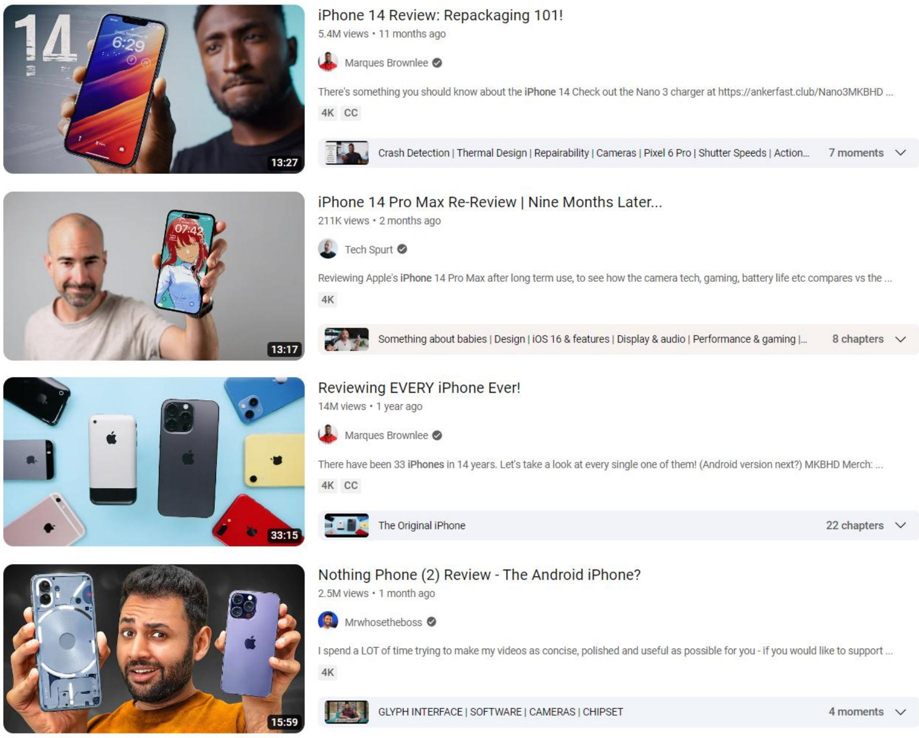
al. (2015) indicates that approximately 60% of shoppers explore online product reviews at least once per week. Among these, 93% consider these digital reviews beneficial in enhancing the precision of their buying choices, minimizing potential losses, and influencing their shopping options. Word-of-mouth (WOM) information, such as online reviews, is an important way for consumers to obtain necessary information for purchasing decisions. In particular, online reviews in blogs and shopping malls are more important than offline networks (Dellarocas & Narayan, 2006; Derbaix & Vanhamme, 2003).

Launching a new product or improving an existing one demands a substantial amount of information. With the progression of technology and increased competition among firms, companies' speed of information acquisition and analysis capabilities are becoming more important. Consumer reviews are a useful means to understand customer's requirements from the standpoint of companies that need to continuously improve and develop products to gain an edge in the fiercely competitive free market. Through the text analysis of online review, companies can enhance their understanding of aspects such as brand image and brand positioning (Alzate et al., 2022).

The rise of e-commerce has elevated the significance of studying consumer reviews. In the past, online reviews primarily referred to text or photo reviews posted on digital marketplaces following a purchase. However, there are now specialized platforms for writing and sharing reviews, and customers write reviews on social media to share experiences about products with close acquaintances. Yelp, which publishes crowd-sourced reviews about businesses, has more than 178 million unique visitors monthly across mobile, desktop, and app platforms (Marinova, 2020). Social network service allows users to differentiate reviews written by their friends from those written by strangers in the online community (Li et al., 2017). Among many SNS, this research focused on online review videos shared on YouTube.

To help them shop, check for tips, inspiration, or product reviews, people are increasingly turning to YouTube. According to Consumer Holiday Intentions Study 2015 conducted by Google / Ipsos MediaCT, 25% of shoppers say online videos are their go-to source for gift ideas, and 32% say they plan to use online video more for holiday purchases. The study also illustrates that Americans have watched 60 million hours of unboxing videos on YouTube, totaling 1.1 billion views in 2015 alone. Brand Building on Mobile Survey conducted by Google and Ipsos showed that YouTube has ingrained itself as a significant part of the consumer electronics purchasing process that 64% of smartphone video viewers would prefer to watch a YouTube video when they have a question, rather than resorting to



<Figure 1> List of videos (Keyword: iPhone review)

calling customer support or reading product manuals.

YouTube is the optimal platform for using branded content marketing strategies (Wang & Chan-Olmsted, 2020). Figure 1 is a list of videos that appear on YouTube when searching for videos on iPhone review. Among these videos, there are online review videos that honestly review the experiences that users felt after use, while other videos are made by content providers who received money or products from the company to create and upload review videos (Wu, 2016). The latter case has the advantage of breaking down the message containing the company image and product characteristics into the content. Consequently, the company can identify emerging YouTube channels and collaborate with the video creators (Gerhards, 2019). This approach underscores how YouTube can serve as a highly effective marketing channel for enterprises seeking to engage prospective customers.

However, there has been an undisclosed-advertisements issue among Korean YouTubers in 2020. Undisclosed- advertisements are a kind of a false advertising, referring to cases where the advertisement is not properly identified and indicated indirectly, even after receiving sponsorship or compensation from a company (Lee & Abidin, 2021). A review video with undisclosed advertisements hides the fact that it has been paid for by a company and discusses the good side of the product; thus, viewers of the review video would make a purchasing decision based on limited and biased information from the video without realizing these conditions. YouTube requires video creators to mark “include paid promotion sign” on the video if the video is sponsored by a company or contains advertisements. Nevertheless, it is impossible to identify YouTubers who violate the rule.

There has been a growing interest in YouTube as a source of introducing new products and a platform for online reviews in recent years. Although many studies have shown that YouTube can serve as a platform for sharing online reviews and be used as a marketing tool (Reino & Hay, 2011; Viertola, 2018), few studies have researched the effects of sponsored or paid review videos. In particular, there have been very few studies on whether the speaker's speaking behavior or speech acts change in the review video produced with sponsorship.

This study investigates whether there is a difference in the speaker's verbal behavior according to paid promotion in the product review video. Additionally, the study aims to explore whether differences in the speaker's verbal behavior result in divergent reactions among viewers who watch the video.

1.2 Research Goals and Research Questions

Based on the speech act theory, this study focused on using directive speech acts that the speaker uses to influence the listener to do something. To this end, this research studied the proportion of directive speech in the review videos. Then, sentiment analysis of video comments was conducted to determine the difference in consumers' sentiment on comments. Accordingly, this study proposes the following research questions:

- Are there differences in the relationship between the company's sponsorship and the degree of directive speech in the review video?

- Is the degree of directive speech by the speaker associated with the reaction of the customer?

The remainder of this article is structured as follows: This article will begin by introducing previous research on online reviews. Then, speech act theory will be introduced, followed by the hypotheses based on the theory. Then, the data and methodology of this research will be presented, followed by the results of analysis. Lastly, the discussion and conclusion of this research will be provided.

Ⅱ. Literature Review

2.1 Online Review

Online reviews generally provide reliable information. Prior studies have demonstrated the effect of online reviews using consumers' purchase intention (Park et al., 2007; Al-Abbadi et al., 2022), readership (Salehan & Dan, 2014), and sales (Hu et al., 2014; Liu, 2006; Wang et al., 2022). In addition, many research cases analyzed products and services through online reviews. Some studies analyzed automobile reviews using text mining and related rules (Kim, 2018; Singh et al., 2020), shopping mall purchase reviews (Oh & Jin, 2014), and hotel selection attributes of online reviews (Kim & Kim, 2017). These preceding studies suggest that online reviews have an important influence on the product selection of consumers and that they are an indicator of the direction of development and improvement from the perspective of the manufacturer and marketer of the product.

However, not all online product reviews contain useful information (Park & Kim, 2017). As product reviews accumulate more and more, it becomes difficult for consumers to check a large number of product reviews, and carefully written product reviews often make consumers feel uncomfortable. Thus, the quality and usefulness of the information they contain depend on the content characteristics. In addition, positive reviews have a greater influence on purchasing decisions than negative reviews (Zhu & Zhang, 2013). However, negative reviews provide clearer information about the product (Hu et al., 2009). It is important whether the contents of the review are positive or negative, but the author of the review also plays an important role. The author's expertise makes other consumers more trustful of the review and makes it more useful than other reviews (Kang & Park, 2015; Zhu et al., 2013). In addition, according to Hu et al. (2009), only consumers in the anode who are very satisfied or dissatisfied with the purchased product tend to write reviews.

Sellers often purchase fake reviews to manipulate product ratings and number of reviews. According to He et al. (2022), fake reviews for products sold on Amazon are being offered for sale on platforms like Facebook and other websites. These fake review purchases result in a significant but short-term increase in the average rating and the number of reviews. After stopping the purchase of fake reviews, the average rating decreased, and there was an increase in reviews receiving a rating of one-star indicating that this practice of buying fake reviews is primarily utilized by sellers of low-quality products.

Fake reviews disrupt buyers' decision-making, prompting research efforts to detect them. To identify fake reviews, Alsubari et al. (2022) employed supervised learning techniques such as naïve Bayes, support vector machine, adaptive boosting, and random forest. Similarly, Salminen et al. (2022) utilized methods including OpenAI, NBSVM (SVM with Naïve Bayes features), and fakeRoBERTa (RoBERTa fine-tuned with Amazon reviews) to detect fake reviews.

Previous studies on online reviews mainly focused on the characteristics of online reviews and confirmed the effect of these characteristics on sales. Recent research has focused on the impact of fake reviews and studies aimed at detecting them. Few studies have investigated the intended message in the online review. Accordingly, this study seeks to find out the difference in intended messages in the review videos depending on the manufacturer's sponsorship.

2.2 Sponsored Online Review

Platforms for sharing reviews are emerging, and the number of bloggers and YouTubers who specialize in reviews, are increasing. As a result, there is an increasing trend of sponsorship in consumer-generated blogs where businesses aim to gain positive attention by offering incentives to inspire bloggers to write favorable reviews (Corcoran, 2010).

Research has been conducted on the characteristics of sponsored reviews and their influence on consumer perception. Ballantine and Yeung (2014) examine the differences between organic (i.e., naturally occurring) and sponsored (i.e., marketer-influenced) consumer -generated blog reviews by analyzing how perceived credibility, brand attitude, and behavioral intent are influenced by blog source and review valence. They found that sponsoring a blogger does not actually generate more positive brand attitudes and behavioral intentions. More significantly, businesses that support bloggers could be in a vulnerable position, because blog readers are likely to pursue the blogger's interests due to the underlying effects of parasocial interaction.

The various features and effects of sponsored and organic online consumer reviews and the mechanisms by which consumers identify and process these two forms of reviews were investigated by Kim, Maslowska, and Tamaddoni (2019). They suggest that sponsored reviews generate more elaborate and evaluative content, but also that they are considered less helpful than organic reviews. In addition, disclosure of sponsorship raises concerns about the reviewer's ulterior motives and decreases the perceptions and purchasing intentions of customers when a review is favorable. However, disclosure of sponsorship does not hurt perceptions or buying intentions when a review is negative.

Although there have been studies on the characteristics of sponsored reviews and their influence on purchase intention and consumer perception, there have been few on the change in the content and intention of reviews depending on the sponsorship. In particular, there are no studies on the speaker's intention in reviews produced as videos. In this study, the intention of sponsored review videos on YouTube will be analyzed through speech act theory.

2.3 Speech Act Theory

2.3.1 Basic Concepts of Speech Act Theory

Searle (1969) claimed that speaking a language is engaging in a rule-governed form of behavior and that all linguistic communication involves linguistic acts. Speech act theory has been developed based on this assumption. Speech act is a term in linguistics and the philosophy of language referring to how natural language performs actions in human-to-human language interactions, such as dialogues (Rus, Moldovan, Niraula & Graesser, 2012). Speech act theory was first used in John L. Austin's theory of locutionary, illocutionary, and perlocutionary acts (Austin, 1962).

According to Austin, there are three kinds of acts in the speech acts; locutionary, illocutionary, and perlocutionary. Locutionary acts are roughly equivalent to uttering a certain sentence with a certain sense and reference, which again is roughly equivalent to meaning in the traditional sense (Austin, 1962). Then, there are the illocutionary acts, such as warning, informing, ordering, and undertaking, in which utterances have a certain force (Austin, 1962). Lastly, there is the perlocutionary act. Austin defined perlocutionary acts as what speakers bring about or achieve by saying something, such as convincing, persuading, deterring, surprising, or misleading. To sum up, the locutionary act is the act of saying something, the illocutionary act is an act performed in saying something, and the perlocutionary act is an act performed by saying something (Rus et al., 2012).

2.3.2 Speech Act Taxonomies

A predefined speech act taxonomy is required for speech act classification in the review video. Researchers have proposed various speech act taxonomies over the years. In this study, the categorizations proposed by Austin (1962) and Searle (1969), the most historical speech act categorization, was summarized. Then, speech act categorization used in speech act classification research was analyzed.

Austin (1962) classifies illocutionary acts into five types: verdictives, exercitives, commissives, behabitives, and expositives. Verdictives are acts in which a verdict or judgement is given usually by one in a position of power such as jury or arbitrator. Examples of verdictives are estimates, reckonings, or appraisals (Austin, 1962). Exercitives are the exercises of powers, rights, or influence. Austin's examples of exercitives are appointing, voting, ordering, urging, advising, and warning. Commissives commit speaker to do something or declare intention. Promising is one of the examples of commissives. Behabitives have to do with attitudes and social behavior and includes apologizing, congratulating, commending, and cursing (Austin, 1962). Austin himself acknowledged that the explanation of behabitives is too miscellaneous and remarked that the last categorization, expositives, is also difficult to define. According to Austin, expositives "make plain how our utterances fit into the course of an argument or conversation, how we are using words, or, in general, are expository". Austin's examples of expositives are 'I reply', 'I argue', 'I concede', 'I illustrate', 'I assume', 'I postulate'.

The taxonomy proposed by Searle (1969) consists of five major classes. They are representatives, directive, commissives, expressives and declarations. Representatives commit the speaker to something being the case, to the truth of the expressed proposition. Directives are attempts by the speaker to get the hearer to do something. According to Searle, these attempts may be as modest as inviting or suggesting, or fierce attempts such as insisting. This is the main category that the present study will use in the analysis. Verbs denoting directives are order, command, request, ask, question, beg, plead, pray, entreat, invite, permit, and advise. Commissives commit the speaker to some future course of action and include promising, vowing, and planning. Expressives express the psychological state specified in the sincerity condition about a state of affairs specified in the propositional content. Expressive verbs include thank, congratulate, apologize, condole, deplore, and welcome. Declarations change the state of the world.

Some researchers added more categories to the existing speech act taxonomy, whereas others selected only a few of the previously defined categories and used them for their research. Puksi (2016) did not classify hotel review data according to all the speech act categories mentioned above, but mostly focused on complaints. To explore speech act recognition on Twitter, Vosoughi and Roy (2016) established a list of six speech act categories that are commonly seen on Twitter: assertion, recommendation, expression, question, request, and miscellaneous. Table 1 shows the summary of speech act taxonomies studied in this research.

This paper used speech act classes defined by Searle to classify speech act in the YouTube product review video. Among the

<Table 1> Summary of Speech Act Taxonomies

Name	Speech Act Class
Austin (1962)	Expositives, Exercitives, Verdictives, Commissives, Behabitives
Searle (1969)	Representatives, Directives, Commissives, Expressives, Declarations
Puksi (2016)	Complaint, Justification, Criticism, Explanation of Purpose, Candidate's solution, Sarcasm, Threat, Apology, Below the level of the reproach, Disagreement, Charges and Warnings
Vosoughi and Roy (2016)	Assertion, Recommendation, Expression, Question, Request, Miscellaneous

classes defined by Searle, this research concentrated on directives. Directive speech acts in review videos refer to reviewers requesting and persuading consumers to take certain action. Directive speech acts in YouTube video include asking or persuading customers to purchase the product or visit the online store. This study analyzed whether these directive speech acts were more intensive in the review videos depending on whether they were sponsored.

2.4 Speech Act Classification

Many studies have classified speech acts in written text to know the writer's intention. Speech act classification has been done in online chat, email, tweet, and online review using traditional supervised learning methods to deep learning. Moldovan, Rus, and Graesser (2011) classified online chat using decision tree and naïve Bayes. Vosoughi and Roy (2016) classified tweets using naïve Bayes, decision tree, logistic regression, support vector machine, and baseline max classifier. Saha, Saha, and Bhattacharyya (2019) also classified tweets, but using a convolution neural network (CNN)-based deep learning (DL) architecture. If the text's length is long enough, the classification result using the traditional classification method is appropriate, but in online chat with short text elements, deep learning-based classification shows more accurate results. In this study, the naïve Bayes classification, one of the traditional classification techniques, is used because the speech act classification is performed on the script of a YouTube review video.

Ⅲ. Hypotheses Development

Economists believe that monetary incentives motivate individuals to devote more effort to a given behavior (Gneezy and Rustichini 2000; Lazear 2000). Social psychology theory indicates that monetary incentives could positively affect an individual's attitude toward the sponsors and the sponsored activities (Heider 2013; Shavitt 1990). Based on this theory, monetary incentives for creating a review video would positively affect creators' attitudes towards the reviewing task. In this regard, review video creators sponsored with incentives would devote more effort and be more positive about the product, resulting in the directive speech of inducing purchase.

H1: Review videos sponsored by the company will have a more directive speech act than videos that do not.

Consumer skepticism toward advertising has been defined as consumers' negative attitudes toward advertisers' motives and claims (Boush et al., 1994). Consumer skepticism may influence the processing of advertising. Friestad and Wright's (1994) persuasion knowledge model (PKM) explains that consumers learn knowledge about marketer's motives, strategies, and tactics from various sources. According to PKM, skepticism toward advertising will alter how consumers respond to the advertiser's persuasion. Then skeptical consumers may dismiss the points made in an advertisement and even generate source derogations. According to Kim et al. (2019), sponsorship disclosure increases suspicions about the reviewer's ulterior motives and decreases consumers' attitudes and purchase intentions when a review is positive. Therefore, sponsored review videos on YouTube with directive speech act in which a review is positive, and the reviewer asks viewers to take an act of purchase, viewers will react negatively to the video.

H2: Reviews videos with many directive speech acts to induce purchase will have more negative comments.

Ⅳ. Research Methodology

In this study, to analyze the change of speech act according to sponsorship and consumer reaction according to speech acts in the review video, the product to be analyzed was first selected, and the script and comment data of the review video for the selected product were collected. The speech act classification was classified by sentence units in the video using naïve Bayes and then expressed as a ratio of the total sentences in the scripts of each video. For the sentiment analysis of the comments on the video, each comment's sentiment score was calculated. Each sentence was classified as positive, neutral, or negative, and the proportion of negative comments in all comments was used.

4.1 Product Selection

YouTube is an online video sharing

platform. According to YouTube, it has more than 2 billion users, which amounts to almost one-third of Internet users. These users watch different types of videos such as commentary, tutorials, interview, gaming, and sports. Among the types of vides on YouTube, the product review video is one of the most popular types. There are also many types of products reviewed. Alsharo's (2016) research showed that major product categories reviewed on YouTube were video games, movies, and technology. In particular, tech reviewers who upload videos of unboxing and information of electronic products are gaining popularity. Marques Brownlee, one of the biggest tech YouTubers with more than 13.5 million subscribers, uploads videos of reviews on the latest smartphones, tech unboxings, and smartphone camera tests (Perelli, 2021). LinusTechTips, another tech YouTuber with more than 12.8 million subscribers reviews product such as computers, laptops, and monitors (LinusTechTips, 2021). The present study focused on review videos on laptop and monitor since they are one of the most reviewed product categories and often receive sponsorship from companies.

4.2 Data Collection and Preprocessing

The paper uses three sets of data: video statistics, video transcript data, and video comment data. Video statistics and comment data were collected using a Python package named ‘python-youtube 0.6.4’. Video transcript data was collected using a python package named ‘YouTube Transcript/Subtitle API’.

<Figure 2> Example of video with paid promotion sign

```
transcript
```


```
[{'duration': 6.319, 'start': 1.04, 'text': 'okay so'},
 {'duration': 5.36,
  'start': 3.52,
  'text': "hello everybody um in today's video"},
 {'duration': 3.921,
  'start': 7.359,
  'text': "i'm gonna be doing something or first of"},
 {'duration': 4.32, 'start': 8.88, 'text': 'all hey bursties'},
 {'duration': 3.12,
  'start': 11.28,
  'text': 'welcome to my channel god that feels so'},
```


<Figure 3> Raw Script Data Collected with Python

This Python API allows users to get the transcripts/ subtitles for a given YouTube video.

For the videos, the results of searching for ‘laptop review’ and ‘monitor review’ on the YouTube search engine were used. A total of 157 videos were collected. The collected videos were played and, as shown in Figure 2, sponsored product review videos contained the included paid promotion sign in the lower-left corner at the beginning of the video. The videos with these signs were classified as sponsored review videos. By creating a dummy variable, the sponsored videos were scored as 1, and those that were not were scored as 0.

After collecting the video statistics, subtitle data was collected from each video. The extracted subtitle data is shown in Figure 3. Since the subtitle data is not divided by sentence but appears in the order of appearance from the video along with duration and start time, preprocessing was done to extract the text and then divided into sentences.

4.3 Speech Act Classification

The Naïve Bayes classifier was used to classify directive sentences. Naive Bayes classifier, one of the machine learning techniques, is mainly used for classifying documents using spam filters or keyword searches. The basic principle of the naive Bayes classifier is to apply the Bayesian theorem to conditional probability and classify input vectors probabilistically by assuming independence of the probability that each element of a document or data will appear (Lantz, 2015). Since the 1950s, Naive Bayesian classifiers have been extensively studied. In addition, it is known that, after proper pretreatment, they show excellent classification performance to compete with a

<Table 2> Example of Directive Speech Act Classification

Sentence	Class (Directive = 1)
Please visit Samsung.com for Galaxybook	1
Go to squarespace.com for a free trial!	1
You may have heard about Squarespace	0
Dell has crushed it	0

<Table 3> Summary of Key Variables

Variable	Description
Sponsored	A dummy variable coded as 1 for sponsored review video, 0 for the non-sponsored review video
Number of Directive Speech Sentences	The number of directive speech sentences in the script
Directive Speech Rate	The rate of directive speech sentences in the script
Comment Sentiment	The degree of the sentiment of the comments

support vector machine. This model's main advantage is that it works with a small amount of data and can handle multiple categories. The Naïve Bayes classifier was used to classify the directive speech for each sentence in the script, and the number of directive sentences was used as a unit of analysis. However, if the absolute number is used, there will be a difference according to the video's length—that is, the number of sentences—thus, the ratio of the directive sentences in the entire script was used as a variable. Table 2 shows the example of directive speech act classification. First sentence in the Table 2, “Please visit Samsung.com for Galaxybook”, is a directive speech because speaker influence the listener to do something which in this case is visiting a company website to check out product. Second sentence in the Table 2 is directive speech because speaker wants listeners to visit a website for a free trial. Last two sentences in Table 2 are not directive sentence. Sentence, “You may have heard about Squarespace”, rather belongs to representative speech as speaker believes that listeners are well aware of the company named Squarespace. Lastly, sentence, “Dell has crushed it” is expressive since speaker feels that Dell did really well by making a good product.

4.4 Sentiment Analysis

sentiment analysis was conducted to confirm the reactions of consumers. Sentiment Analysis

(SA) or Opinion Mining (OM) is the computational study of people's opinions, attitudes and emotions toward an entity (Medhat, Hassan, & Korashy, 2014). In this study, Python package called 'NLTK' was used to analyze sentiment score of comments. NLTK, the Natural Language Toolkit, is implemented as a collection of independent modules, each of which defines a specific data structure or task (Looper & Bird, 2002). NLTK has a built-in, pre-trained sentiment analyzer called VADER (Valence Aware Dictionary and Sentiment Reasoner). VADER is a simple rule-based model for general sentiment analysis and best suited for language used in social media (Hutto & Gilbert, 2014). The sentiment analysis was performed on all comments for each video. VADER returns a dictionary of negative, neutral, and positive scores, which all add up to 1. Then compound score is calculated which range from -1 to 1. Then these scores were averaged and used as variables.

V. Data analysis and results

5.1 Result of Testing Hypothesis 1

Table 4 shows the results of the regression model testing Hypothesis 1. A linear regression model was utilized, taking 'Sponsored' as the predictor and 'Directive Speech Rate' as the dependent variable. The aim was to investigate the potential influence of incorporating sponsorships into review videos on the level of directive speech employed within these videos. The analysis outcomes revealed an F-value of 29.483 ($p < 0.001$), affirming the adequacy of the regression model. This model accounted for 45.7% of the variance present in the directive speech rate observed within the review video. Consequently, it was observed that a sponsored review video displayed a positive impact on the Directive Speech Rate ($\beta = 0.676$, $p < 0.001$). These outcomes suggest that the utilization of directive speech experienced an elevation in sponsored review videos. As a result, these findings provide support for Hypothesis 1.

<Table 4> Result of Regression

Variable	Unstandardized Coefficients		Standardized Coefficients	t(p)	*F(p)*	R^2	Durbin-Watson	VIF
	B	SE	β					
(Constant)	1.815	0.634		2.861**	29.483***	0.457	1.515	1
Sponsored	5.410	0.996	0.676	5.430***				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Result of Testing Hypothesis 2

Table 5 shows the results of the regression model testing Hypothesis 2. Multiple regression model with ‘Sponsored’ and ‘Directive Speech Rate’ as predictors and ‘Comment Sentiment’ as the dependent variable was used to investigate if the extent of directive speech acts in the review video influenced negative feedback from viewers. To address the concern of multicollinearity, Variance Inflation Factors (VIF) is calculated for the independent variables. All VIF values were below 2, indicating the absence of multicollinearity issues. Moreover, the Durbin-Watson statistic, which assesses the independence of residuals, yielded a value of 1.728. This value falls within the range of 1 to 3, implying that there are no significant problems with the residuals' independence. The model accounted for 50.8% of the variance in comment sentiment within the review video. Specifically, the Directive Speech Rate exhibited a negative impact on Comment Sentiment (β = -0.725, $p < 0.001$), signifying that a higher rate of directive speech is associated with decreased positive sentiment in comments. As a result, these findings provide support for Hypothesis 2.

VI. Discussion and Conclusion

6.1 Discussion

Online opinions and reviews play a crucial role in influencing purchasing decisions and aiding companies in understanding consumer perspectives. As various platforms have emerged, customers have extended their review-sharing activities to social media networks (SNS), beyond just e-marketplaces. However, there are two types of review videos:

<Table 5> Result of Regression Testing Hypothesis 2

Variable	Unstandardized Coefficients		Standardized Coefficients	t(p)	*TOL*	
	B	SE	β			
(Constant)	0.861	0.017		50.820	0.543	1.842
Directive Speech	-0.019	0.004	-0.725	-4.565***		
Sponsored	-0.002	0.033	-0.010	-0.061*	0.543	1.842
F(p)	19.549***					
adj.^{2}	0.508					
Durbin-Watson	1.728					

** p < 0.05, ** p < 0.01, *** p < 0.001* review videos created voluntarily, and review videos created for advertisements with sponsorship from manufacturers. This research aimed to examine the link between corporate sponsorship and the prevalence of directive speech in review videos. Additionally, it sought to analyze consumer sentiments based on the level of directive speech utilized by the speaker. Two hypotheses were tested, and they were both supported.

First, YouTubers endorsed by companies to generate review videos exhibit an increased use of directive speech acts, aiming to prompt viewers to make purchases or explore the company's website. Sponsored YouTubers are inclined to emphasize aspects that encourage buying decisions and online visits.

Secondly, the presence of directive speech acts related to advertising or purchase encouragement correlates with a rise in negative comments. In videos produced under sponsorship, viewers can identify the sponsorship due to the marked introduction of paid promotions. Additionally, instances of excessive praise and overly persistent purchase inducements often attract consumer criticism, as illustrated in Figure 4.

This research provides several significant academic revelations. Firstly, it represents a change in the focus of medium. While IS studies have largely concentrated on textual reviews on websites, this work pioneers an analysis of video reviews on YouTube, highlighting the changing landscape of content engagement. Secondly, it pioneers a new approach to data conversion. Going beyond the

<Figure 4> Sarcastic Comments on Sponsored Review Video

conventional textual analysis, this study uniquely quantifies verbal content from videos, introducing an innovative method for data gathering and interpretation. Finally, it uncovers fresh perspectives on viewer dynamics. Specifically, by exploring the impact of sponsorship on comment sentiment, this research reveals potential audience biases and emphasizes the complex interplay between content producers, sponsors, and their audience. In essence, this research not only broadens the scope of IS studies but also brings forth novel techniques and insights into uncharted territories.

6.2 Limitations and Future Research Directions

There are several limitations to this study. First of all, the analysis did not take into account the product's rating itself. It's plausible that the sentiment in the video's comments is closely tied to the rating of the reviewed product. This is because endorsing a positive product wouldn't raise concerns, but if a low-quality product is reviewed with wild exaggeration, viewers might respond negatively towards the video. Obtaining and analyzing product reviews spanning various rating levels could potentially enhance result accuracy.

Furthermore, for broader applicability of the findings, a wider array of product data needs to be collected. The study primarily focused on review videos related to technology items. Expanding data collection and subsequent analysis to encompass a greater diversity of products could facilitate more generalized conclusions.

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김 도 훈 (Kim, Do Hun)

서울대학교 경영석사를 취득하였으며 현재 서울대학교 박사과정에 재학중에 있다. 주요 관심 분야는 빅데이터 분석 및 자연어 처리이다.

서 지 혜 (Suh, Ji Hae)

서울대학교에서 경영학 박사를 취득하였다. 현재 서울과학기술대학교에서 경영학과 교수로 재직하고 있으며, 주요 관심 분야는 데이터 모델링, 자연어 처리이다.

<Abstract>

Conveyed Message in YouTube Product Review Videos: The discrepancy between sponsored and non-sponsored product review videos

Kim, Do Hun · Suh, Ji Hae

Purpose

The impact of online reviews is widely acknowledged, with extensive research focused on text-based reviews. However, there's a lack of research regarding reviews in video format. To address this gap, this study aims to explore the connection between company-sponsored product review videos and the extent of directive speech within them. This article analyzed viewer sentiments expressed in video comments based on the level of directive speech used by the presenter.

Design/methodology/approach

This study involved analyzing speech acts in review videos based on sponsorship and examining consumer reactions through sentiment analysis of comments. We used Speech Act theory to perform the analysis.

Findings

YouTubers who receive company sponsorship for review videos tend to employ more directive speech. Furthermore, this increased use of directive speech is associated with a higher occurrence of negative consumer comments. This study's outcomes are valuable for the realm of user-generated content and natural language processing, offering practical insights for YouTube marketing strategies.

Keyword: Video Reviews, Speech Act, Sentiment Analysis, Consumer Skepticism, User-Generated Content

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