경영학석사 학위논문

An Analysis of Comment Patterns based on the Properties of Review Video
: Focusing on YouTube

리뷰 동영상의 속성 기반
리뷰 동영상 코멘트의 패턴 분석
유튜브 동영상 분석

2022 년 7 월

서울대학교 대학원
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최윤영

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An Analysis of Comment Patterns based on the Properties of Review Video
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ABSTRACT

Due to the gradual increase in the use of YouTube, the categories of YouTube videos have also been diversified. Review videos have become a significant part of YouTube. They explain the product in detail, thus many people watch the review videos to get help in the decision-making stage before purchasing the product. In this study, we examine the relationship between the attributes of review videos and the patterns of comments. Moreover, we explore the impact of the interaction between characteristics of reviews and types of products on the comment patterns.

Keyword : Youtube, Online review video, Comment analysis, Topic modeling
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TABLE OF CONTENTS

1.1. Research Background

In today's rapidly changing society, there is a variety of ways to disseminate information. Consumers searching online for product information sometimes have access to a number of product evaluations from others (Mudambi et al., 2010). Consumers will increasingly turn to product reviews in order to get additional information about the products which they are considering to buy. As a result, videos are now being used for a wide range of purposes, including conveying information. Because of developments in web 2.0, consumers may not share their opinions, thoughts, and experiences on goods, services, or brands by writing online reviews for others. These reviews can be helpful or critical in nature (Filieri & Raffaele, 2015). User-generated online product reviews have proliferated rapidly on the Internet, and such user-generated content has had a profound impact on electronic commerce (Forman et al., 2008). Review videos naturally increased as consumers shared experiences, opinions, and feedback about products, services, or brands in the form of reviews for other consumers to read and watch. Consumers from all around the globe are reading online product reviews, which are the electronic Word of Mouth (eWOM), before making purchase decisions (Senecal & Nantel, 2004). With the advancement of technology, consumers may now communicate with one another through user-generated contents such as online reviews and other forms of social media (Jiang et al., 2021). An increasing number of consumers are gaining information through online product reviews created by more users and using this information to continue transactions in e-commerce. Consumers have an interest in gathering knowledge about products and services, and one resource they may turn to for this is online user reviews. Since they provide indirect product experiences, the consumer-oriented information presented here is helpful in making purchase decision (Lee & J, 2008). Consumer-oriented information has the potential to be more credible and relevant than seller-oriented information (Bickart et al., 2008). As a result, online user reviews may be utilized to establish consumer confidence (Baek et al., 2012). Consequently, buyers typically have to spend a significant amount of time for searching, browsing, and processing multiple evaluations before they can acquire beneficial and relevant information (Li et al., 2022). For example, users are allowed to vote on the usefulness of reviews, and the number of votes are then posted on the website for other users to use it as a reference. This is one option that has been considered for purchase decisions (Filieri et al., 2018; Lopez & Garza, 2021). Due to the activation of online reviews, comments in online reviews are also becoming a factor influencing consumers.

More and more people are posting reviews related to product evaluations online, and there are also various ways to review products. A solid grasp of advertising is essential for boosting development and the viability of both new and current service businesses (Stafford et al., 2002). The interest in product marketing strategies has risen along the increase in popularity of product review videos. For this reason, the purpose of this research is to get a better understanding of the responses of consumers in accordance with the review qualities. In service advertising, rational appeals include precise information or convincing and logical reasoning – for example, a Subway commercial stresses the healthful elements of a sandwich. In contrast, emotional appeals in services advertising try to elicit emotional responses from consumers – for example, a Hallmark greeting card commercial dramatizes a person's key events in life (Moore et al., 1995). Therefore, in order to find out what patterns appear in reviews based on their attributes, each review analyzes the comment patterns to examine which comments have what characteristics.

1.2. Research Question

It is feasible to examine the process related to a variety of consumer decision-making through analyzing the comments left on YouTube videos; thus this research has the potential to be regarded as an extremely essential one (Siersdorfer et al., 2010). Not only can viewers of online review videos acquire extra information about the product by watching them, but they can also obtain this knowledge by reading the comments that other viewers have left on the videos. What is notable about this situation is the potential that various kinds of comments might be made according to the characteristics of the review videos or of the product type from the perspective of viewers. Therefore, the primary objective of this study is to investigate if the aspects of comments in the video may appear in a different manner depending on the attributes of product reviews. In addition, since the product types can be engaged in the aspects of these comments, we further explore this relationship brings up different consequences. The following questions may be found in this research:

RQ1. Will the attributes of review videos affect the contents of comments within product review videos?

RQ2. Is there an effect of the attributes of product line itself in this process?

First of all, this study begins with introducing prior research on online consumer reviews and their comments. It also deals with the attributes of product review videos. After that, based on literature research, we will classify the attributes of the review videos and figure out what patterns appear in the comments depending on those features. This procedure will also demonstrate whether or not the product types have an impact on those patterns. Then, all those results are combined to show the conclusion and the limitations of this study.

CHAPTER 2. LITERATURE REVIEW

2.1. Online Consumer Review

When purchasing goods from an online retail market, consumers have difficulty making purchase decisions based on information provide by suppliers. However, the Internet and Information Technology have made it possible for them to post their product reviews online (Avery et al. 1999). Now, online consumer reviews are keys to the success of a wide variety of businesses, including those who sell books, electronics, games, films, music, and beverages (Yubo & Jinhong, 2008). Consequently, individuals look for more details about specific products on the Internet, namely in reviews written by other consumers. (Baek et al., 2012). Chen and Xie (2008) argued that online consumer reviews, as user-created information, are more likely to be relevant to consumers than seller-created information. The information of products, created by sellers, is more likely to be product-centric. This is due to the fact that seller-created product information frequently describes product qualities in terms of technical specifications and evaluates product performance using technical standards. On the other hand, information developed by consumers is user-oriented so that it typically specifies product attributes in terms of different applications and evaluates product performance from the users' persepctives (Bickart & Schindler 2001). Furthermore, practitioners and public media are paying a lot of attention to the fact that online consumer product reviews are playing an essential role as a new aspect of marketing in purchase decisions. As a consequence of this aspect, consumers now have access to a substantial number of online reviews, which they may utilize to become more informed about products or services that they consider buying.

The introduction of Web 2.0 has transformed the Internet's role from that of a simple medium for information distribution to that of a collection of venues for technology-mediated social involvement (Chua & Banerjee 2015). For instance, YouTube has become the go-to site for releasing personal videos, commercial promotion, and political remarks due to the fact that it receives 10 billion video views every single month (Preece & Shneiderman, 2009). As such, it is currently being used for various purposes. Among them, it is possible to say that YouTube is one of the platforms that may be used for posting videos which provide product reviews.

As the usage of online reviews increases, many existing researchers have studied that online reviews are deeply related to purchasing products. Chevalier and Mayzlin (2006) discovered a link between consumer evaluations on retail websites and book sales (e.g., Barnes & Nobel and Amazon.com). Online reviews are becoming a vital information source for customers to discover the quality of online items or services, as well as a driving force for product sales performance, in today's e-commerce (Wang et al., 2022). Users are able to share their experiences and opinions via online reviews, which helps others make more informed purchase choices (Chua & Banerjee, 2015; Goes, Lin, & Au Yeung, 2014; Shen, Zhang, & Zhao, 2016). According to recent studies as well as previous published research, user reviews have increasingly influenced consumer’s buying decisions and the overall sales of products. Forrester Research found that more than half of individuals who looked at online store websites with consumer reviews reported that the feedback they received was essential when making a purchase (*Los Angeles Times* 1999). Li et al (2019) believe that review sentiment has a consistent beneficial influence on product sales.

To sum up, the usage of review videos is naturally expanding as the use of web-based platforms, such as YouTube, grows in the digital era and prospective consumers obtain information about items on these platforms. As more and more features are added, it allows users to create and share video clips on a broad variety of topics, as well as to interact with one another. Users also may score and comment on videos they have seen and express their opinions (Madden et al., 2013). Next, we additionally investigate previous studies to analyze the characteristics of comments in review videos consistent with review attributes.

2.2 Online Review Comments

Comments on YouTube allow users to exchange information and collaborate with others. Sharing information via comments occurs freely, and users engaged in information sharing activities do so by making the information they have saved both internally and externally accessible to others. Making one's information public generally does not result in any kind of financial gain for the one doing so. In order to obtain and disseminate information online, which takes time and effort, sharing information means giving others something one has, often without knowing who will benefit from it (Fu et al., 2016; Wise et al., 2014).

Madden et al (2013) mentioned that the user comments has developed into a has evolved into a forum for conversation unrelated to videos themselves. Not only are direct comments on videos themselves allowed, but also self-expression, emotional support, recall, grief, and advice are encouraged via the use of comments. The large amount of video comments found on YouTube can be classified into various categories. Furthermore, the reading of comments is vital in assisting readers in communicating with one another. The comments represent many points of view on specific issues, as well as exchanges amongst commentators (Yang et al., 2009). According to Madden et al (2013) showed various characteristics and classification of comments were found in their journal in Table 1 below.

Categories	Definition	Example
Information	Comments that request or offer factual information about anything in the video content, video context, or a completely unrelated issue are classified as information comments.	"The old VXR was equivalent to the Pontiac G8 but this newer VXR is equivalent to Buick Regal."
Advice	Advice comments are ones in which individuals ask for or provide advice on what to do in a certain scenario.	"[...] but it sort of gives off the wrong impression. Like you think being beautiful is all that matters. You are also sorta giving the wrong impression to

		men as well:\”
Impression	Impression comments capture people's quick reactions to what they've seen in a video or read in the comments.	“Awesome!”, “Lol”, etc.
Opinion	Opinion comments are those in which commentators ask for or express their opinions about a video, person, object, or issue.	“do you really think she did better than Shakira?”
Responses to previous comments	Comments in which the commentator states that they agree with a prior commenter or the video poster, or that what someone has stated is factually right, are considered agreeable.	“[...] yea its true i seen that alot.”
Expression of personal feelings	These are comments in which the writer expresses their personal emotions or reactions to the video content, video topic, or something expressed in a prior remark.	“Seriously you two are STUNNING ! And I get soooo happy when I see you've posted a new video! Love your videos:) 태”
General conversation	Status descriptions are often brief representations of what the poster is doing at the time of writing, and will mimic status updates on social networking sites such as Twitter and Facebook.	Greetings like: "Hello", "How are you?"
Site processes	Request another video's posting or Suggest Content for a Future Video, putting up proposals for topics that the uploader or other YouTube users should include in their future output.	Use words like: "watched", "viewed" or "saw"
Video content description	These comments may include direct quotations of words and phrases from	“[...] at 31sec the dhl commercial board gets

	the film, as well as paraphrased summaries of the visual or aural material.	destroyed at 4 m height!!!!!!”
Non-response categories	Spam comments are ones that provide unsolicited messages such as adverts or connections to dating or pornographic websites.	Such comments are hidden from view and replaced by the message "This comment has been flagged as spam".

Table 1. Comment characteristics and classification notes (Madden et al., 2013)

Research conducted in the past by Jansen et al (2009) and Park et al (2008) provides some foundational concepts for different kinds of comments. By offering categories such as “order” and “consume”, researchers found a number of particular categories connected to marketing and branding on Twitter. It is possible that this will not transfer exactly into the YouTube environment, but it may be considered equivalent to concepts like “request regarding objects.” In addition to that, it provided helpful recommendations and expectations for future items, as well as ideas that certain more general categories might be broken down into more specific subcategories. According to Jansen and other researchers (2009), the sample that they looked at included comments that fell into the following distinct categories: announcement, answer, chitchat, comment, confirmation, consuming, expecting, forwarding, maintenance, missing, negative comment, notification, order via Twitter, patronizing, positive comment, question, recommendation, recommendation request, research, response, suggestion, supplement. This data may be mined for studies on communication and information-seeking because of YouTube’s popularity and the ease with which comments can be placed. Thelwall et al. (2011) performed one of the few studies to examine the types of YouTube comments, analyzing the length, subject, and sentiment of comments. These past studies are useful in identifying common themes among online comments and inventing new methods for analyzing them. Other scholars, Knautz and Stock (2011), have used YouTube to investigate how videos might be classified according to the emotions they convey. This study distinguishes between different types of comments based on textual analyses, and as a result, demonstrates that comment types that have similar patterns appear in videos that have the same characteristics. Previous research on the topic of classifying comments within YouTube videos took a different approach than the one that is the focus of this study.

2.3. Review Property

It is possible to construct a review video in a number of different ways due to the fact that it is developed with regard to the intention or purpose of video creators.

Understanding comparison procedures also requires having a solid grasp on many kinds of information that are used. Attribute-based strategies need not only an awareness of and application of certain characteristics at the time of evaluation, but also the implementation of comparisons of one brand's characteristics to those of other brands. Processing based on attitudes makes use of general attitudes, summary impressions, intuitions, or heuristics; throughout the judging process, no explicit comparisons of one feature with another are carried out (Mantel & Kardes, 1999). Therefore, the attributes of these review videos will be different in each video.

Another difference between attribute-based and attitude-based judging procedures is the amount of time and effort required for each. A comparison of certain properties connected with each brand is required for an attribute-based assessment. As a result, this procedure will take more time, effort, and is typically more accurate than the global comparisons used for an attitude-based evaluation. In a particular context, motivation and opportunity to process information work together to decide whether attribute-based or attitude-based processing will be employed (Sanbonmatsu & Fazio 1990). Furthermore, Mantel and Kardes (1999) show that individuals are more likely adopt analytical, data-driven, attribute-based processing when there is an increased motivation to make a good judgment and certain attributes are accessible from memory. When attributes cannot be recalled, the assessment will be dependent on global attitudes and impressions that were formed throughout brand exposure from individual, noncomparative evaluations of each brand.

In addition, Sanbonmatsu et al (1990) discussed the main difference that exists between decision makings based on attributes and attitudes. In an approach known as attributed-based strategy, decision making requires an understanding of individual qualities of the alternatives. It is the premise of reasoned action that individuals make conscious choices about their actions. To put it another way, a method centered on attitudes rather than facts helps people make judgment. The idea of reasoned action, as the name implies, posits that people make intentional and considered decisions about how to behave. An attitude-based decision approach, on the other hand, guides decisions by the global attitudes connected with the decision options. The selection is made by picking the alternative or option that has received the highest positive overall evaluation. In this approach, earlier research categorized characteristics of attribute-based decision making and attitude-based decision making. Additionally, literature studies were carried out by associating these characteristics with the attributes of reviews via the potential consumers who would have purchased items.

2.4. Product Type

Involvement derives from social psychology and the concept of 'egoinvolvement,' which refers to the link between an individual, a problem, or an object (Sherif and Sherif, 1967). This conceptualization has served as the foundation for implementing participation in consumer behavior. However, because there are so many different definitions and treatments of participation in social psychology, its use in this domain remains complex (Michaelidou, & Dibb, 2006). Most researchers in the consumer arena define participation as the degree of psychological connection between an individual and the stimulus item (Hupfer & Gardner, 1971; Lastovicka & Gardner, 1979; Rothschild, 1979; Zaichkowsky, 1985).

Depending on the product type, information-processing techniques are likely to change. The primary reason for the availability of distinct informationprocessing methods depending on product type is because the participation type is likely to change depending on product type (Park & Moon, 2003). Product participation is seen as an essential component in affecting consumerbrand processes, cognitive reactions, brand loyalty, and consumer-brand interactions (Hudson et al., 2015). Product engagement refers to personally relevant knowledge about a product and is defined by the amount of interest and arousal in customers (Sheeraz et al., 2018). It is regarded as the forerunner in various product-related consumer choices (Park & Mittal, 1985) and compels customers to get extensive knowledge about the brand (Higie & Feick, 1989). The involvement concept may be traced back to the psychology literature and described as the amount of affect and care about an item (Lesschaeve & Bruwer, 2010). There are three techniques to involvement: cognitive approach, individual approach, and reaction approach (Laaksonen, 1994). Depending on the product type, the process of consumers looking for information itself can be seen as different.

Consumer buying decisions are strongly influenced by their interest, attention, and self-interest, self-concept toward a product (Bloch, 1981). When customers are involved with a product, they digest information thoroughly. As a result, highly invested customers will be more motivated to engage in the cognitive work for self-verification (Petty & Cacioppo, 1986). Product engagement is seen as an essential component in shaping consumer-brand processes, cognitive reactions, brand loyalty, and consumer-brand relationships. Therefore, it may be characterized as a high-involvement product if there was a relatively high intervention in cognitive effort, and it can be categorized as a relatively low-involvement product if there was a relatively low intervention in cognitive effort (Sheeraz et al., 2018).

CHAPTER 3. HYPOTHESIS DEVELOPMENT

As the use of review videos for products increases, we conducted a reference survey on product review videos and comments running on them, and in this paper, we studied the relationship between the properties of a review video and video comments. Mantel et al (1999) included the way individuals process product information into their study and offered attributed-based (objective) and attitude-based processing (subjective). Specifically, attributed-based judgement allows consumers to apply their knowledge and specific qualities throughout their product evaluation, and it entails the process of comparing attributes among brands. Attitude-based judgment, on the other hand, refers to the use of general attitude, summary perceptions, overall evaluation, intuitions or heuristics during judgement, with essentially no attribute-by-attribute comparisons involved (Luan et al., 2016).

As can be seen in past studies, various review videos and studies related to the attributes of reviews were found. And among various studies, quite a few studies on YouTube comments were found. However, Madden et al (2013) mentioned that YouTube comments have been comparably understudied in comparison to other areas of the site, owing to the vast volume of comments, lack of organized organization, and varying quality in terms of spelling, grammar, and expression, which has made performing analysis challenging. Furthermore, we could find that the majority of study has concentrated on interaction patterns related to comments (Lee et al., 2010). This paper also focused on the analysis process of YouTube comments. We would like to study the relationship between the nature of the review and the pattern of comments. Therefore, we hypothesize “The comment pattern will be different depending on the review type of a video.” Thus, this study examines what context of comments focus on according to review attributes. Therefore, we hypothesize:

Hypothesis 1: The attributed-type review video is positively associated with the ratio of comments related to request.

In Hypothesis 1, we hypothesize based on the hypothesis that attribute-based review videos have a significant correlation with the proportion of opinions related to requests, and that the relationship between them can act as a positive among them. Among the comment patterns of the review video, the purpose was to analyze the correlation between the product opinion and the ratio of comments related to the product opinion. Similarly, additional hypotheses were established as follows:

Hypothesis 2: The attitude-type review video is positively associated with the ratio of comments related to product evaluation.

Furthermore, we further analyze the effect of the product groups among variables that may significantly affect the relationship between the properties of the review video and the pattern of comments. Antil (1984) mentioned that many researchers have accepted the premise that many instances in consumer behavior emerge when the amount of interest in the stimuli is quite low, and that "low-involvement level," a customer's cognitive and behavioral actions are considerably different from situations with "high-involvement level." For this reason, we study how the product type, a variable that may play an important role in decision-making, will affect the relationship between the attributes of review videos and the pattern of video comments. In addition, a hypothesis for the product type is:

Hypothesis 3: The product type will positively affect the relationship between the review type of a video and its comment pattern.

Siersdorfer et al., (2010, April) argued that comments are one of the most essential factors in making a decision (comment rating, topic categories, etc.) regarding a certain video. And also, by evaluating the emotion of comments, it is possible to determine if a user is positive or negative about a video. (Lee et al., 2014, November). As a result, the research model that we hypothesize is the figure below.

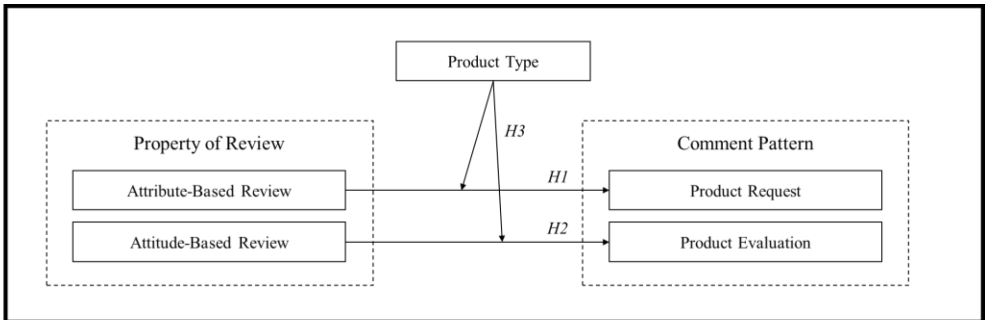

Figure 1. Research Model

Figure 1. Research Model

CHAPTER 4. METHODOLOGY

4.1. Data Collection

The overall data for this research has been collected through the open API, 'YouTube Data API' suing Python. To begin, the YouTube API gathers URLs for videos based on their category and uploaded date. For category, we choose two types of products by involvement level –high- and low-involvement – from prior research. According to the findings of earlier studies, the concept of "involvement" is intimately connected to the purchase of psychological risk. Antil (1984) defined the concept of product involvement as "one of the most important variables in consumer research." Moreover, product involvement indicates how personally significant or engaged consumers are in using a product, as well as how much information they require to make a choice (Miller and Marks, 1996). Therefore, the degree of engagement in purchasing choices is seen as a continuum, with quite regular decisions at one end and decisions that require a lot of thoughts and a high level of involvement at the other end. Therefore, we have selected "laptop review" and "beer review" from each level and put them as keywords to collect video reviews.

Uploaded date has been set from January 1st, 2021 through December 31st, 2021. The results are sorted according to their relevancy to the search query in the YouTube search engine. Then, we gather all video details and comment data for certain videos after gathering all the video URLs.

Using the constructed YouTube API, 1,710 laptop review videos and 710 beer review videos have been collected. Of all the collected videos, we have manually classified each product review video by review type. In the next step, we decide to randomly select the 100 videos from each category and crawl all the comments in the videos; thus the total number of comments is 19,598.

4.2. Data Preprocessing

In the video comments, every single punctuation and space has been taken from the text. In addition to that, the comments that were gathered include Unicode and other languages than English. Because there is certain text that does not need to be analyzed, such as emoji, special characters, and words with just two or three letters, we needed to build a function in Python that would do text preprocessing. Then, tokenization was required for entire words, which implies that texts must be split down into individual linguistic units. Tokenization is the process cutting the string based on each compiler word. For instance, if the comment says, “I would prefer macbook over all the laptops,” it is separated as “I”, “would”, “prefer”, “macbook”, “over”, “all”, “the”, “laptops”. Stopwords removal is also needed to remove less important words on documents. Python module provides frequent stopwords dictionary, so that we can eliminate stopwords such as “if”, “I”, “would”, “over”, “of”, “the”, and so forth. Next, to extract the basic type of a word, we perform the process of lemmatization. In this process, each word can be removed or replaced into its basic form.

4.3. Topic Modeling: LDA (Latent Dirichlet Allocation)

The process of separating many meaningful topics from a vast volume of text is known as topic modeling. In other words, topic modeling is the method of narrowing the corpus dimension down to a meaningful topic. LDA (Latent Dirichlet Allocation), developed by Blei, Ng, and Jordan (2003) is the most widely used topic modeling technique. LDA is structured in such a way that each text is described by a combination of topics, and topics are represented by a mix of terms. When applying LDA to text results, researchers should choose the number of topics to extract topics from text data. Exploring the optimal number of topics is a critical role in establishing the validity and appropriateness of the classification. And, a minimal number of topics, according to Calheiros et al. (2017), helps prevent word repetition between topics and maintain systemic validity. Westerlund et al. (2018) said that researchers can select the number of topics based on trial and error in order to prevent term duplication and ensure that the topics are interpretable. Consequently, when the optimum number of topics is determined solely by trial and error, and the terms appearing in documents do not overlap, the analysis is conducted. In this study, we first set the number of topics (from 2 to 5) in advance to apply topic modeling and check the results, then find the best number of topics by changing it. Since there are two products, we do topic modeling twice for each product's review video. In both product reviews, the optimal number of topics was found to be four. In Figure 2 and 3, the words for each topic can be checked.

```
Topic #1:
good screen bad price gaming best cheap performance battery great love

Topic #2:
please make buy suggest better comment recommend what help budget want

Topic #3:
review thank nice thanks watch keep lot much performance know keep

Topic #4:
white gen amd hey dash every ing student reply dash avita helios
```

Figure 2. Topics Found in Laptop Review Videos

```
Topic #1:
beer good try one cheap taste great know better best cheap outstanding

Topic #2:
know review give want continue drink rank do make look get keep

Topic #3:
much time drunk expert awesome nice see watching funny channel amazing

Topic #4:
vid man est pretty glass wine dude wrong name rolling que shit piss
```

Figure 3. Topics Found in Beer Review Videos

With this result, the following topics could be derived from review videos of both products: "evaluation", "request", "channel-related", and "meaningless". Since these topics were found, we classified the comments into those three topics. Thereafter, we perform a manual coding process that classifies the comments of the video designated as samples into the aforementioned topics. However, in this process, we would see meaningless comments – those not including all topics – thus, they should also be considered as a variable. After this process, we visualized the words using a Word Cloud which is a collection of words depicted in different sizes (Figure 2). The bigger and bolder the word appears, the more often it is shown in comments of review videos. This helps us to see if the results are consistent with those of the topic modeling by showing which words are frequently seen in the comments.

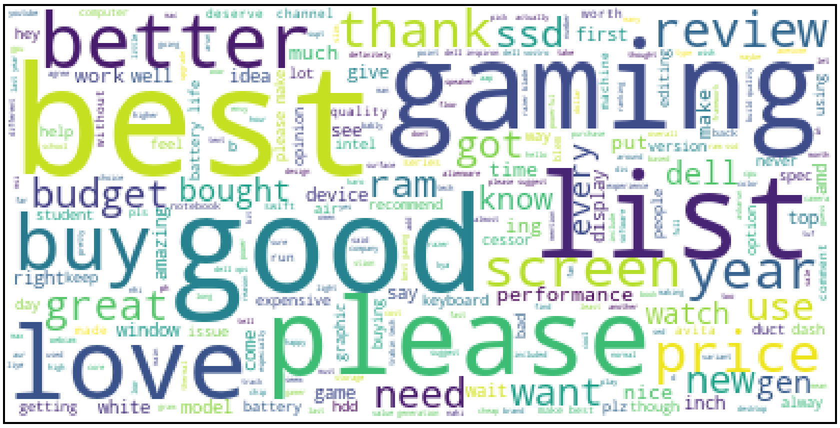

Figure 4. Common Words on Comments in Laptop Review Video

Figure 5. Common Words on Comments in Beer Review Video

4.4. Description of Variables

In order to analyze the comment patterns in review videos, we use three types of variables: dependent and independent variables and moderators. The dependent variable is “comment patterns” which are divided into two types: “product evaluation” and “request about product.” Initial ideas for comment types are given in previous research (Jansen et al., 2009 & Park et al., 2008). It revealed a number of specific categories linked to marketing and branding on Twitter by providing categories such as “positive comment and negative comment” or “recommendation and request.” The independent variables are two different review types: “attributed-based review” and “attitude-based review.” To test the effect on the comment pattern by the interaction between each review type and product type, “product type” is designated as a moderator.

The variables used in the study are described in the following table.

No.	Variables		Description
1	**Dependent** Comment Patterns	Evaluation comment	Comments that contain content related to an individual's subjective assessment of the product.
2		Request comment	Comments about the product that require additional information.
3	**Independent** Review Types	Attributed-based	A review video that contains reviews based on the attributes of the product, such as classifying different brands around attributes within the same category of product
4		Attitude-based	A review video that contains reviews based on the person's attitude toward the product, including detailed

			categorization of one type of product by various criteria
5	**Moderator** Product Types	High-involvement	A product type that goes through a relatively diverse process of individual decision making when making a purchase decision for a product
6		Low-involvement	A product type that goes through a relatively simple comparison process and an individual decision-making process when making a purchase decision about a product

Table 2. Descriptions of Variables

CHAPTER 5. ANALYSIS AND RESULT

5.1. Descriptive Statistics

Table 3 shows the descriptive statistics of each variable. As shown in Table 3, we can see the mean, standard deviation, minimum, and maximum of total comments and those of each type of comments in the review video for each product according to the property of review.

Summary Statistics		**Attributed-based**		**Attitude-based**	
		Laptop	Beer	Laptop	Beer
Total Comments	Mean	211	177.16	255.44	140.32
	SD	101.17	102.31	92.09	109.36
	Min	33	21	89	23
	Max	412	490	453	460
Evaluation Comments	Mean	47.36	45.08	123.24	65.24
	SD	26.41	24.66	50.10	56.98
	Min	10	5	37	17
	Max	120	96	236	265
Request Comments	Mean	104.16	82.08	60.32	28.60
	SD	58.42	65.86	24.90	24.49
	Min	12	9	22	2
	Max	235	325	119	97

Channel-related Comments	Mean	33.16	30.16	39.76	25.24
	SD	20.32	18.97	17.91	22.62
	Min	5	4	5	0
	Max	72	71	80	85
Meaningless Comments	Mean	26.32	19.84	32.12	21.24
	SD	15.49	14.91	22.41	23.92
	Min	4	2	3	0
	Max	71	58	92	79

Table 3. Descriptive Statistics

To conduct a regression analysis, we first converted the number of each comment pattern to the ratio within the total comments. Then, we start with the base model where we try to see the attributed-based review affects the ratio of comments related to request about product.

5.2. Result from Naïve Bayes Classifier

After manual coding, reliability verification is needed to make sure that manual coders agree. So, this process uses the alpha value of Krippendorff, which is a common way to check the reliability of manual coding. Inter-coder reliability is important for content analysis, but there doesn't seem to be a standard way to test and report inter-coder reliability, even though scholarly papers give a number of metrics. This lack of uniformity isn't so much because academics can't agree on which metric is best, but because they don't have enough information about inter-coder reliability testing, how it is done, and how the results should be interpreted. Hayes and Krippendorff (2007) say that it is clear that Krippendorff's alpha (also called KALPHA) should be used as the main measure.

The Krippendorff alpha value ranges from 0 to 1 and is considered an acceptable reliability value when the alpha value is greater than 0.8. According to the Naïve Bayes classifier, of the laptop reviews, the measure of feature 1 (request) is 0.8715 and feature 2 (evaluation) is 0.8209 as shown in Table 4. This indicates that the reliability for each feature is approximately 87% and 82% respectively, which can be determined to be the result of manual coding. In addition, in the beer review, reliability was acceptable with alpha values of 0.8348 for request and 0.9067 for evaluation. However, in the channel-related comment feature 3, both reviews show low alpha values and cannot accept reliability. Therefore, in this analysis process, the research was conducted by excluding channel-related comments and meaningless comments.

KALPHA	Feature 1 (request)	Feature 2 (evaluation)	Feature 3 (channel-related)
Laptop	0.8715	0.8209	0.3250
Beer	0.8348	0.9067	0.5351

Table 4. Krippendorff's α from manual coding

5.3. Regression Results

In order to test hypotheses, we conducted regression analysis twice by capturing the dependent variable as ratio of evaluation comments and of request comments in a review video.

	Model 1		Model 2	
	Coef.	S.E	Coef.	S.E
Review type	0.240 ***	0.016	-0.238 ***	0.023
Product type	-	-	0.040	0.023

*Review type * Product type*	-	-	-0.003	0.032
Constant	0.457 ***	0.011	0.437 ***	0.016
R^2	0.690		0.708	
$Adjusted\ R^2$	0.687		0.699	

Note: *p < .1, **p < .05, ***p < 0.01
Dependent variable: ratio of request comments

	Model 3		**Model 4**	
	Coef.	S.E	Coef.	S.E
Review type	0.236 ***	0.017	0.220 ***	0.025
Product type	-	-	-0.036	0.025
*Review type * Product type*	-	-	0.031	0.035
Constant	0.483 ***	0.012	0.265 ***	0.017
R^2	0.652		0.659	
$Adjusted\ R^2$	0.648		0.649	

Note: *p < .1, **p < .05, ***p < 0.01
Dependent variable: ratio of evaluation comments

Table 5. Results of Regression Models

The results of the regression models are shown in Table 5. In Model 1 and 2, we verify the effect of review property on the ratio of evaluation comments and the moderating effect of product type, and the effect on the ratio of evaluation comments is validated in the same way in Model 3 and 4.

As shown in Table 5, Model 1 shows that the regression coefficient is significant with 0.240 ($p<0.01$), thus H1 is supported. Model 3 is a result of supporting H2 that attitude-based review is positively related to evaluation comment ratio in review videos, and the regression coefficient is significant at 0.236 ($p<0.01$). In Model 2 and 4, an analysis was conducted to prove whether the product type exhibited a moderating effect on the review pattern, and as a result, it was found that there was no effect when review type interacting with the moderator (product type) as well as product type itself. The regression coefficients are 0.040 and -0.003 in Model 2 and -0.036 and 0.031 in Model 4, respectively. Thus, H3 is not supported. As a result, it can be seen that consumers' comment patterns vary depending on certain review properties rather than the product types. After all, regardless of the product type, we can see that consumers want to get more information about a particular product in a review video comparing different characteristics – attributed-based reviews – and that comments from a review video of a single product shows more opinions about the product than more information about that product – attitude-based reviews.

CHAPTER 6. DISCUSSION AND CONCLUSION

6.1. Discussion and Implication

This study aims to analyze the relationship between the attributes of the review video and the patterns of the review video comments to examine the difference in comment patterns by attributes. The review videos were selected based on the number of views and divided by the video attributes to analyze the contents of comments. We concluded that there was a significant difference in the pattern of comments in the review video according to the attributes of the review video. In addition, the type of product did not significantly affect the comment pattern.

By analyzing the pattern of comments between the review video with attribute-based attributes and the review video with attitude-based attributes, there was a significant difference in the pattern. Through this, the following implications can be derived. First, in the review video with attribute-based attributes, comments related to requests for content such as additional information about the product accounted for a high proportion. This implies that the companies can examine the curiosity of consumers about their products and the additional contents to highlight them. On the other hand, comments related to the evaluation of the product itself accounted for a high proportion within the review video with attributes based on attitude. The analysis of this study provides a holistic view of the public's image of the products to the company. In addition, based on the evaluation of the products in the review video, firms can consider fixing or changing their marketing approach.

In theoretical implications, this research analyzed the correlations between the property and the comments pattern of review video. Since there is a significant difference in the pattern of comments in the review video, if research on the attributes of these review videos is further subdivided, we can discover various other factors factors that affect the pattern of comments in the review video. Moreover, the product line did not significantly affect the comment pattern, thus the results of this study can be useful for studies analyzing the factors affecting the comment pattern rather than the product line and review property.

6.2. Limitation

Since only one product video was selected per product, instead of comparing by product line or by various products within the product line, there may be a lack of consistency. A lack of consistency might lead to different conclusion. Thus, process of comparison could not be enough to make a conclusion. To overcome this limitation, some processes should be included later. For example, multiple products within the same product family or each of the different products within various products needs to be studied.

Moreover, we collected review videos that contains less than 1,000 comments, thus analysis on review videos with more than 1,000 comments has not been conducted. This is because we could manually label a limited number of comments, which also relates to the limitation of manual labeling process. If we analyzed videos with more than 1,000 comments, more diverse relationship may be identified.

In addition, the comments are classified manually to analyze the pattern of the comments. Therefore, due to the nature of such manual labeling, individual subjective opinions may be included. Subjective opinions might lead to different conclusion by individual. Even though the labels of the comments have been cross-checked, subjective opinion by individuals can be reflected.

6.3. Future Research

In this study, we analyzed the attributes of the review video and the pattern of comments in the review video. Additionally, we examined how the product line can affect this process. Since analysis of review video has not been conducted on various product categories, effects on the product type by large number of the product category can be further analyzed in the future. This is because different results can be derived when analyzing significant effects on the product line by increasing the category of products.

In addition, research on other factors affecting the attributes of the review video and the pattern of comments in the review video can be conducted. Also, in the process of analyzing the pattern of review video comments, research on classifying the pattern of comments in more detail can be conducted. Through this process, comments from review videos that were not covered in this study can be handled at the same time, thus in future research, additional classification criteria for the pattern of comments can be created to enable more detailed analysis of the pattern of comments.

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국문초록

유튜브의 사용이 점차 늘어나면서 유튜브에 게시되는 영상물의 범주도 매우 다양해졌다. 이러한 영상물의 범주 가운데, 어떤 제품을 구매할 때, 제품에 대한 정보를 수집하기 위한 수단으로 사용되는 영상물도 매우 많아졌다. 이 제품들에 대한 리뷰 내용을 담고 있는 영상물 내 댓글은 또 다른 정보를 공유하는 수단으로 간주 할 수 있다. 따라서, 제품을 구매하기 전, 많은 사람들이 유튜브에서 리뷰 비디오를 찾아보는 과정에서 해당 영상물 내 댓글을 참고한다. 본 연구는 유튜브의 리뷰 영상을 중심으로 연구를 진행하는 것을 목표로 한다. 이때, 리뷰 영상의 속성 뿐만 아니라 영상의 댓글 패턴도 파악하여 리뷰 영상의 속성과 댓글 패턴의 관계를 살펴보고자 한다. 더 나아가, 리뷰 비디오의 제품 유형이 리뷰 영상의 속성과 영상의 댓글 패턴 간의 관계에 어떤 영향을 미칠지 이해해보고자 한다.

주요어 : 유튜브, 온라인 리뷰 동영상, 제품군, 댓글 분석, 토픽 모델링
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