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A Study of Message Framing and Content Popularity on Online Video Reviews :An Empirical Analysis on YouTube Contents

메시지 프레이밍과 리뷰 컨텐츠의 조회 수에 관한 연구:
유튜브 영상 리뷰를 중심으로

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경영학과 경영정보전공

이 규 연

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이 논문을 경영학석사 학위논문으로 제출함

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ABSTRACT

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ABSTRACT

The demand for video reviews is growing continuously, with more consumers searching for product information in video platforms and marketers increasingly incorporating video marketing into their digital strategy. Despite the growing prominence of video reviews, few studies have examined the topic in Information Systems studies. The purpose of our study is to gain a better understanding of content popularity in online video reviews. Drawing upon the dual-process theory, we investigate the relationship between positive and negative message framing in video reviews and the viewership of the reviews. We also compare the reviews of search and experience products and evaluate whether the product type influences the relationship. 341 search product reviews and 384 experience product reviews were collected via the YouTube API, and the transcripts of each video were extracted and preprocessed for sentiment analysis. Our results suggest that framing the title of a review, either with positive or negative words, is associated with higher view counts. Although the degree of sentiment used in the content of the review did not have a significant association with content view counts, the product type had a moderating effect on this relationship. We believe that our research could contribute to the field of analyzing video content using natural language processing and give practical implications for content marketing strategies.

Keywords: Video Reviews, User-Generated Content, Content Popularity
Student Number: 2018-25288

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CHAPTER 1 INTRODUCTION

1.1. Research Background and Motivation

It is well known that online opinions and reviews are widely read when making purchasing decisions. By helping people acquire information about a product, customer reviews affect consumer decision making and, consequently, product sales. As social media has gone through rapid expansion and growing importance, so have online reviews. YouTube (www.youtube.com), the world's largest video sharing website with 2 billion monthly active users in Q2 2019 (Salim 2019), has newly emerged as a review platform. Customer reviews in the form of video content are increasing in number, with more customers watching video reviews in the first step of their shopping procedure (Google/Ipsos 2017). In a poll held by Google, 64% of consumer electronics shoppers replied that they watch electronic product video reviews on YouTube before their purchase (Jarboe 2014). Furthermore, the number of product review videos uploaded to YouTube has increased by 50 percent over the study year (2014-2015) (Google data 2016).

The increasing use of YouTube and video content as a reviewing modality warrants new investigations. Compared to the massive amounts of information online, attention is arguably the most valuable but short supplied resource on the Internet (Shen et al. 2015). For content creators, the

possibility of gaining attention is one of the major benefits of producing online reviews. Users compete for attention by providing with contents people are most interested in and most likely to be attracted to. As product video reviews contribute significantly to consumers' decision-making processes, it is essential to understand the task of receiving attention.

There has been a growing interest in YouTube as a source of product information and reviews in recent years. For example, Ren (2015) investigated the causality loop between video reviews and sales – that online reviews drive sales and reflect on sales. Wiegard et al. (2017) developed a model for automatically extracting features from the comments of product video reviews. In their work, it was proven that comments on product-related YouTube videos could be identified as a reliable data source comparable to review data from Amazon. These studies have demonstrated that YouTube data can be a valuable source of product reviews and customer opinions. Little is, however, known about the content popularity of video reviews.

Meanwhile, many studies have examined the classic theory of search and experience goods in the product review literature. The classification of search and experience goods is concerned with the availability of information about product attributes before its purchase and usage (Nelson 1970). Search goods are those products whose attributes can be evaluated before the purchase, while experience goods are products whose quality can be

evaluated once after they are consumed. Previous studies have examined how the impact of review factors is moderated by the product types (Mudambi and Schuff 2010; Pan and Zhang 2011; Huang et al. 2013). We also attempted to understand the interacting effects of product types and video review factors.

In this paper, we examine the relationship between the contents of a video review and its popularity. As YouTube hosts both search and experience products in one platform, we will compare reviews of both product types. One of the significant difficulties of this topic is the hardship of analyzing unstructured video data. Text embedded in a video can be a valuable resource when summarizing the video content. Past studies have retrieved the speech transcripts in a video and used it in indexing and summarizing video content (Nemrava et al. 2008; Kucuk and Yazici 2011). In our study, we analyzed video data by extracting the transcript of each video and pre-processing them available for natural language analysis.

1.2. Research Goals and Research Questions

Drawing on the dual-process theory on persuasion, we focused on message framing in reviews of each search and experience products. We will compare reviews that are framed with positive and negative sentiment and reviews that are not framed with such sentiment. Our study investigates the degree of

sentiment used in reviews of search/experience products and proposes the following research questions:

- Is the degree of sentiment spoken by the reviewer associated with the viewership of a video review?
- Are there differences in the relationship between the degree of sentiment and viewership in search and experience product reviews?
- Is the degree of sentiment in the front portion of the video most strongly associated with the viewership of a video review?

The remainder of the paper is structured as follows: We will begin by introducing previous research on product reviews and video content popularity. Then we will discuss the theories used in our study and develop the hypotheses. Next, we will present the data and methodology of our research, which will be followed by the results of our analysis. Lastly, we will conclude with the findings and discussions of our work.

CHAPTER 2 LITERATURE REVIEW

2.1. Online Content Popularity

2.1.1. Previous Research on Consumer Video Reviews

Online reviews are delivered primarily in two different modalities: text reviews and video reviews (see Figure 1). Written reviews are still the most common format of online reviews, typically accompanied by a numerical rating that indicates the satisfaction of the product being evaluated.

Factors of review popularity also have been investigated mostly in the context of textual reviews, while few attempts have been made to identify the factors of content popularity in the context of video reviews. The main factors that account for content popularity in written reviews can be classified into two broad categories: review related factors and reviewer related factors. Review related factors include review length (Salehan and Kim 2016), review rating (Yin et al. 2016), and the total number of reviews of the product (Forman et al. 2008). Reviewer related factors refer to the characteristics of the person who writes the review such as information disclosure of the reviewer (Einar et al. 2015), the number of friends of the reviewer (Yin et al. 2014), and the number of reviews written by the reviewer (Park and Nicolau 2015).

In IS literature, a few studies have investigated the video format of online reviews. Xu et al. (2015) examined the influence of the presentation format of online reviews on consumer perceptions. They demonstrated the significant role of presentation format and product type on consumer perceptions. Their results indicated that compared to text reviews, video reviews have a significant impact on purchase intentions while there is an interaction effect of the product type. Alsharo et al. (2016) investigated online video reviews on YouTube to address the most commonly reviewed product categories and the factors that contribute most to video review helpfulness. They reported that the most reviewed categories were video game reviews (77%), movie reviews (12%), technology reviews (9%). Considering this result, we will also focus on the aforementioned categories.

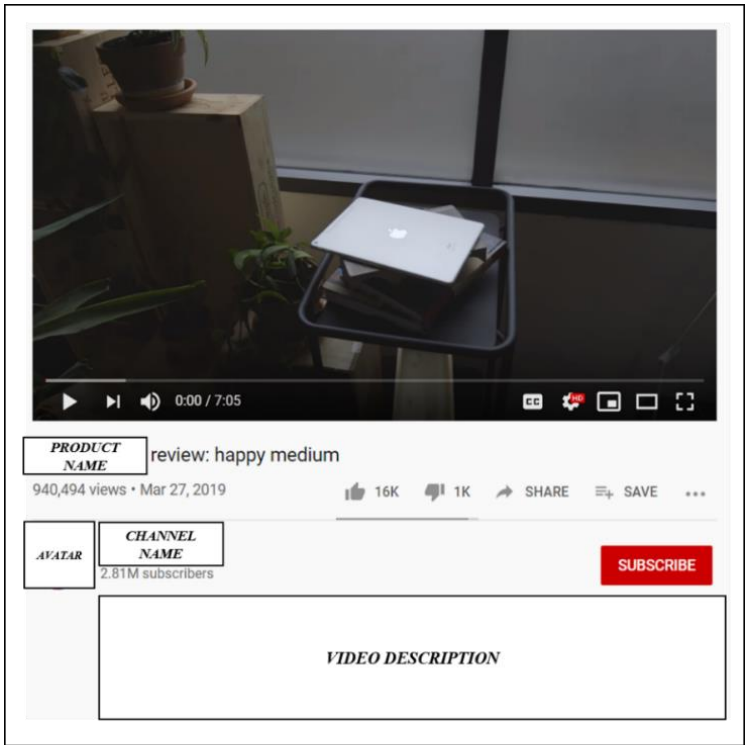

Figure 1. Example of a Product Video Review

2.1.2. Previous Research on Content Popularity

In the context of written product reviews, popularity is mostly measured by the number of helpfulness votes received by other users. Most review platforms such as Amazon.com provide a sorting mechanism based on the number of helpfulness votes of the reviews. In the case of popular products with a considerable number of reviews, most consumers rely on top-ranked reviews with high helpfulness scores since those reviews are sorted at the top of the webpage.

On the other hand, the popularity of video content is evaluated by different measures, but typically includes most viewed, most favorited, most responded, and most discussed (Burgess and Green 2018). Our study measures popularity with view count, which most closely resembles the measurement for the aggregated amount of attention used by the mainstream media.

Although the exact algorithm of view counts on YouTube is not disclosed, it is generally agreed that viewers have to watch a considerable portion of the video to be counted as a view (Wyzowl 2018). YouTube defines a view as a "playback requested by an actual user who got what they were intending to get," (Von Baldegg 2012) as they consider views as the new "currency" of the web. The view counting algorithm does not calculate a view based on the loading of a video page but considers the actual watch time of the video (van Es 2019). In order to prevent artificial views, YouTube filters out views reloaded by a single user, views auto-played by the website, and views that are seemingly played by programmed bots. Therefore, in our study, we treat the view counts of content as the number of people who actually watched the video through to completion.

Many studies have tried to identify the properties that contribute to video view counts. Feroz Khan and Vong (2014) examined the virality of videos based on two essential determinants: user characteristics (user's

subscriber count, join date) and video characteristics (video publish date, duration, and category). Borghol et al. (2012) observed a robust linear 'rich-get-richer' model of popularity growth, meaning that a video will draw new views at a proportional rate to the number of views already obtained. These studies focused on the relationship between user/video statistics and video popularity. Both of these works revealed that other than the number of subscribers, the aggregated view count of previous videos and video age account for video popularity.

There also exists research that evaluated the characteristics of the content *per se* and their impact on video popularity. Lewinski (2015) analyzed videos of social media campaigns from commercial banks and focused on the nonverbal communication of the speakers. They examined the facial expressions of bankers and concluded that the lack of facial emotions contributed to video popularity. The authors explained that this could be because people do not expect bankers to show affiliative emotions. Schoeffler and Herre (2014) measured the audio quality of music videos and tried to identify its influence on user ratings. Unlike what they expected, there was no significant correlation between audio quality and high-rated videos. We carry out our research by analyzing the speech of the reviewers, using the subtitles obtained via the YouTube Data API. Applying a natural language processing (NLP) algorithm, we attempt to capture the effect of the degree of

sentiment on video popularity.

2.1.3. Product Type and Online Reviews

The classification of search and experience goods first introduced by Nelson (1970) is one of the most broadly used notions of product types in marketing. Search and experience goods are categorized by the ease of obtaining product quality information before purchase. Search goods are defined as products whose attributes can be acquired before purchase, while attributes of experience goods cannot be known until the purchase and use of the product (Nelson 1970).

The search/experience product classification has been investigated by many studies in the assessment and comprehension of online consumer reviews (Huang et al. 2013; Zhang et al. 2014). These research on product type and online reviews typically discuss the moderating effect of product type on review ratings (Xia et al. 2008; Purnawirawan et al. 2015). In his work, Purnawirawan et al. (2015) demonstrated that consumers would respond more strongly to valence (positive or negative messages of reviews) for experience goods than for search goods. This is explained by the intangible attributes of experience products and the corresponding increase in uncertainty of evaluation before purchasing experience goods. The

moderating effect of product type on review helpfulness was also frequently identified by previous researchers (Senecal and Nantel 2004; Park and Lee 2009, Baek et al. 2012). For example, the experimental results of Senecal and Nantel (2004) showed that people were more likely to be influenced by the recommendation of others when purchasing an experience good than a search good. Park and Lee (2009) showed that the negative eWOM effect is higher for experience goods than for search goods.

However, there are contradictory findings regarding the validity of search/experience classification. Many researchers (Alba et al. 1997; Peterson et al. 1997; Huang et al. 2009; Cho et al. 2018) have argued that search and experience goods became less distinguishable. This is partly due to the ubiquity of the Internet, which enables consumers to learn from the purchasing experiences of others and collect information easily before purchase, unlike in offline settings. An analysis of the browsing behavior of U.S. consumers indicated that consumers spend a similar amount of time online on gathering information on search goods and experience goods before their purchase (Huang et al. 2009). Accordingly, most attributes became 'searchable,' and the boundary between search and experience goods is no longer viable. Some researchers argue that search and experience goods became less distinguishable (Klein 1998), while others state that the change does not seem significant (Nakayama et al. 2010). In the interim, Baek et al.

(2012) indicated the different situations in which consumers refer to online reviews. They pointed out that consumers search for others reviews of experience goods mainly because they cannot obtain necessary information from the supplier. This finding indicates that the different situations by using online reviews of different product types should also be taken into account.

The findings of previous literature about the moderating effect of product types are also limited to the cases of text reviews, while little attention is paid to video reviews. In this regard, we considered the moderating role of product type on the relationship between video review factors and video popularity.

2.2. Dual-Process Theory and Message Framing

The dual-process theory, referring to the two different types of systems (System 1 and 2) in reasoning, have been long supported in psychological and economic literature (Tversky and Kahneman 1974, Sloman 1996, Kahneman and Frederick 2002, Evans and Stanovich 2013). Heuristic, or System 1 thinking, is described as automatic, associative, rapid, and intuitive, while analytic, or System 2 thinking, is described as controlled, normative, and result-oriented in decision making. For tasks that are less important and risky, mental shortcuts, or heuristics, are used by System 1 to simplify the reasoning process (Kahneman 2011). In this case, System 1 thinking connects the new

information with already known patterns and experiences. On the other hand, System 2 thinking recalls information from past experience, adds on rational judgment, and engages in correcting biases from the outcomes made by System 1.

Although their tasks are different, these systems work together when making a decision (Chaiken and Ledgerwood 2011). The correction models of human judgment suggest that individuals attempt to comprehend a stimulus primarily based on their subjective experience (System 1). Only, if there are enough time and energy available, System 2 corrects the previous assumptions by considering other more rational factors to understand the objective properties of the stimulus (Gilbert and Gill 2000).

The framing effect refers to the cognitive bias where different presentations of an identical issue can result in different decisions (Tverski and Kahneman 1981). In his book, Entman (1993, p. 52) described that "to frame is to select some aspects of the perceived reality and make them more salient." Prior research has suggested that emotions can act as frames (Nabi 2003; Entman 1993). The framing effect could be overcome when individuals carefully scrutinize their options. However, this deliberate process takes up cognitive resources and, being a "cognitive miser," the human brain attempts to conserve mental effort through heuristics, hence leading to the cognitive bias that we observe (Fox and Cooper 1984).

In our study, we suggest that in online customer reviews, subjective information conveying emotion can act as frames. Positively framed reviews may emphasize the beneficial aspects of the product, while negatively framed reviews may discuss more the loss of a purchase (Kahneman and Tversky 1979). We try to discover a relationship between the message framing of a video and its view count. Each video on YouTube has a title and body content. In our work, we will explore the framing effects of both the title and the content of a video review. We believe that the degree of emotionally framed messages in a product review is effectively demonstrated by the number of sentiment terms used. And the more emotionally framed messages the review contains, the more likely it is for the viewer to continue watching the video review.

2.3. Hypotheses Development

In linguistic studies, language intensity is defined as a "stylistic feature of language that is conveyed through the properties of emotionality." (Hamilton and Hunter 1998). The intensity of a message can differ by language usages, such as using emotion-laden words or precise language. Positively or negatively framing a message can influence the extent of message persuasion (Smith and Petty 1996). Thus, messages with a high degree of sentiment can

be effectively processed by listeners. Whether it be a positively or negatively framed review, reviews that convey more subjective information are likely to be more persuasive and more continued to be played by viewers. Thus, we hypothesize:

Hypothesis 1: The degree of sentiment expressed in the content of a video review is positively associated with its number of views.

Hypothesis 2: The product type moderates the relationship between the degree of sentiment expressed in the content of a video review and its number of views.

We extract the sentiment of both the title and body of the review. The titles are especially important in YouTube videos since they are the 'first impression' of content and users depend largely on titles when deciding whether to watch the content or not. We expect that titles that are framed with emotions are more appealing to users and will attract more users to the video content. Therefore, we hypothesize:

Hypothesis 3: The degree of sentiment expressed in the title of a video review is positively associated with its number of views.

Previous studies on subjective information and review popularity focus mostly on textual reviews. Researchers have conducted opinion mining on the review content and showed that both objective and subjective information could influence review popularity (Cao et al. 2011). However, text and video reviews show fundamental dissimilarities stemmed from the difference in medium. Reading is self-paced while watching a video is done at a pace determined by the producer. Video reviews may offer better browsability through real-time audio and visual cues, which can take less effort for processing information. Because viewers do not invest much in the video review as much as readers of a text review do, we assumed that they would be less tolerant of the low amount of sentiment terms in the front part of the video. Consequently, we hypothesize the following:

Hypothesis 4: The degree of sentiment expressed in the front part of the video review is positively associated with its number of views.

When testing H5 and H6, we tried to find the relevant time slot of a video in which the amount of sentiment holds significant influence over video viewership.

CHAPTER 3 METHODOLOGY

3.1. Data Collection and Variables

The paper uses three sets of data: video statistics, channel statistics, and video content data. These data were collected via the open API, 'YouTube Data API' using Python. First, we collected video reviews of search product reviews using three keywords ('laptop review,' 'smartphone review,' 'tablet review'), and of experience product reviews using three keywords ('movie review,' 'game review,' 'book review'). The YouTube search engine displays the results arranged by their relevance to the search query. Our sample videos were also collected in this order.

Secondly, we obtained factors such as 'view counts,' 'channel(publisher) ID,' 'publication date,' and 'video duration in seconds' for each video review. YouTube channels refer to the publishers of a video. Based on the channel IDs of each video, we collected the channel information. The channel data we collected involves 'aggregated view count,' 'number of subscribers,' and 'number of videos published.'

Lastly, the review factors of each video were collected: the title and subtitles of each video. Subtitles were collected in SubRip file formats (.SRT). SRT files display (1) the sequential count of subtitles, (2) the timecodes in the

format of hours, minutes, seconds, and milliseconds (HH:MM:SS, MIL), and (3) the text of the subtitle. Figure 2 shows an example of an SRT file. Not all videos have subtitles, so we had to discard some of the videos in which transcripts were not available. As many of the subtitles were not punctuated, we used an automatic punctuator[1] (Tilk and Alumäe 2016) before analyzing the data.

In our study, we collected 150 videos for every six keywords, and after removing the videos without transcripts, 725 videos from 417 different channels were left and to be analyzed.

```
1
00:00:04,580 --> 00:00:09,870
Alright guys, it's finally time to follow up on my unboxing of the <product name>.

2
00:00:09,869 --> 00:00:13,549
This tablet was sent to me by the company to review, but

3
00:00:13,550 --> 00:00:15,980
obviously, all opinions in this video are my own.
```

Figure 2. Example of an SRT File

Sentiment analysis (SA) is the field of study that examines the

[1] Source code is available at https://github.com/ottokart/punctuator2

emotions, attitudes, and sentiments towards entities such as products, issues, and topics. In our study, we use a Python package called 'TextBlob' to detect the level of sentiments in video transcripts (Loria et al. 2014). TextBlob uses a Naïve Bayes classifier to identify words that carry sentiment. Then, it determines whether the sentence is more subjective or objective and offers a subjectivity measure. We use this measure of subjectivity, which ranges from [0, 1] with 0, meaning that the sentence is completely objective and 1, completely subjective.

For the content of a video, we performed a sentence-level sentiment analysis of each video and measured the emotional valence by adding up all the sentence-level sentiment scores. Then, we divided the sentiment score by the length of the video because some videos may have more amount of sentiment terms due to their long length (content subjectivity score). Figure 3 shows a brief overview of the sentiment analysis process.

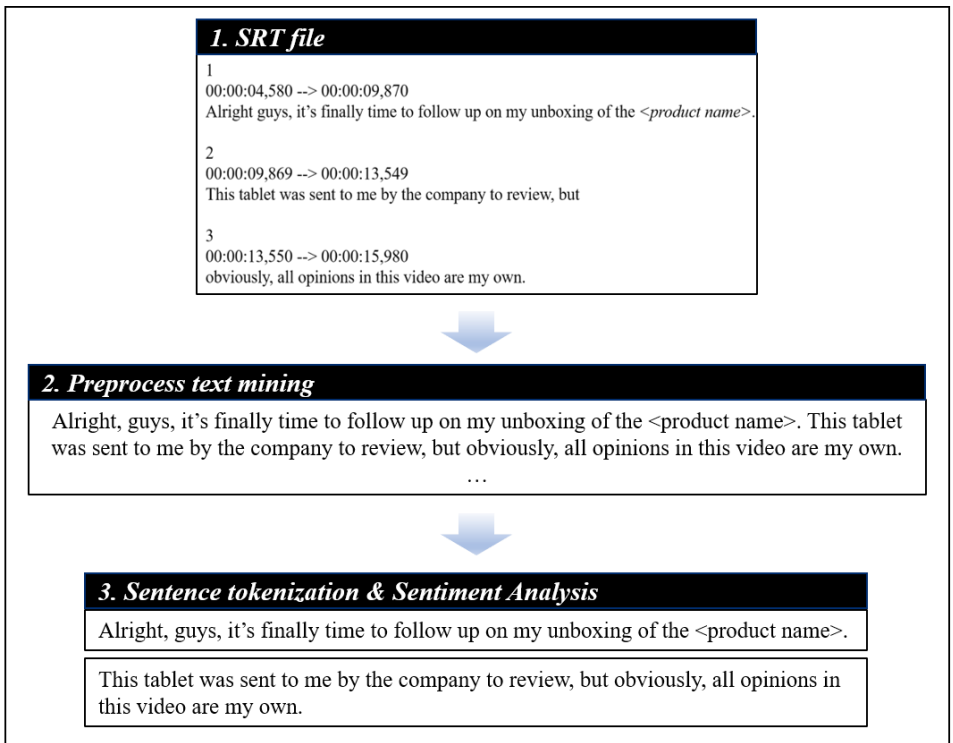

Figure 3. Overview of Text Analysis

The key variables of our study is as follows:

1) *Subscribers*: The number of subscribers of the channel which uploaded the review content.
2) *Days*: The number of days past since the video was uploaded.
3) *Number of Videos:* The number of videos uploaded by the channel owner of the review content.
4) *Video Duration:* The length of the review content in seconds.
5) *Title Sentiment Score:* The degree of sentiment of the title of the review content. Sentiment scores were measured by a Naïve Bayesian-based analysis tool.
6) *Content Sentiment Score:* The degree of sentiment of the content of the video. The transcripts of the video contents were extracted, and we did a sentence-level sentiment analysis on these transcripts.
7) *SEARCH_GOOD:* A dummy variable coded as 1 for reviews of search products, 0 for reviews of experience products.
8) *Sentiment Score Until N Minute:* The degree of sentiment expressed within the first *N* minute of the video review.

Prior research on YouTube showed that the number of subscribers, aggregated view counts of the channel, age of the video (days), and the length of the video (duration) contribute to video popularity (views). We will use

these variables for our base model. Because of the high collinearity between the number of subscribers and aggregated view counts of the channel, we only applied the former into our model. We created a dummy variable (SEARCH_GOOD) to see if there are any interactions between the main variable and the product types.

In order to discover the time window of a video in which the degree of sentiment detected has a significant correlation with over video viewership, we divided each video into several time windows. Accordingly, variables such as *Sentiment Score Until N Minutes* were added. These variables refer to the amount of sentiment within the first *N* minutes of the review, where *N* increases by 1. For example, *Sentiment Score Until 1 Minute* refers to the number of sentiment terms within the reviewer's speech in the first 1 minute of the review.

3.2. Model

The study of popularity of YouTube videos based on meta features has been implemented using several types of parametric models. Text-based features including titles, tags, and description of videos are mostly plugged in multivariate linear regression models in the context of video popularity measurement (Cheng et al. 2008; Pinto et al. 2013).

We used Multiple logarithmic regression after checking the collinearity between variables. The ranges of YouTube video statistics are large and distributions are right-skewed, therefore we had to normalize and log transform the data. Due to the nonnormality of variables, we log-transformed the dependent variable (view count) and independent variables. The variables had low variance inflation factors, indicating that there are no multicollinearity issues.

CHAPTER 4 RESULTS

4.1. Descriptive Statistics

Table 1 shows the descriptive statistics of each variable. Analysis of the targeted 725 videos showed that the average view count of each content is 11.096, the average number of days since the video was uploaded is 6.180, and the average duration of the video is 6.276 seconds. The data of 417 channels showed that the average number of subscribers of a channel is 11.338, and the average number of videos of a channel is 6.080. The average sentiment score of a review title is 0.1073 with minimum=0 and maximum=1. For the sentiment score of a review content, the average score is 508.78, with minimum=56.38 and maximum=1622.61. Finally, the average sentiment score until the first minute of the video is 3.344.

Table 1. Descriptive Statistics

Variable		N	M	SD	Median	Min	Max
Dependent Variable	*(Ln)Views*$_i$	725	11.096	2.164	11.393	5.707	17.094
Independent Variables	*(Ln)Subscribers*$_i$	725	11.338	2.942	11.898	.6931	18.441
	(Ln)Days$_i$	725	6.180	1.528	6.494	.000	8.387
	(Ln)Number of Videos$_i$	725	6.080	1.552	6.277	.0000	9.865
	(Ln)Video Duration$_i$	725	6.276	.5911	6.244	3.829	9.144
	Title Sentiment Score$_i$	725	.1073	8.972	.000	.000	1.000
	Content Sentiment Score$_i$	725	508.78	.232	461.92	56.38	1622.61
	Sentiment Score Until 1 Minute$_i$	725	3.344	1.514	3.212	.000	8.688

Table 2 is a description of the sentiment score of each time window. As mentioned above, the Sentiment Score until N Minutes refers to the amount of sentiment within the first *N* minutes of the review. The variance of the sentiment scores of each time window increases gradually, as shown in Figure 4.

Table 2. Description of Time Window Variables

	Sentiment Score (SS) Until 1 Min.	SS Until 2 Min.	SS Until 3 Min.	SS Until 4 Min.	SS Until 5 Min.	SS Until 6 Min.	SS Until 7 Min.
Min.	0	1.473	2.648	3.706	4.031	4.031	4.031
Median	2.685	5.917	9.331	12.813	15.886	18.794	21.920
Mean	2.829	6.248	9.633	13.127	16.143	19.006	21.657
Max.	8.128	15.989	23.410	28.332	35.956	42.511	48.920

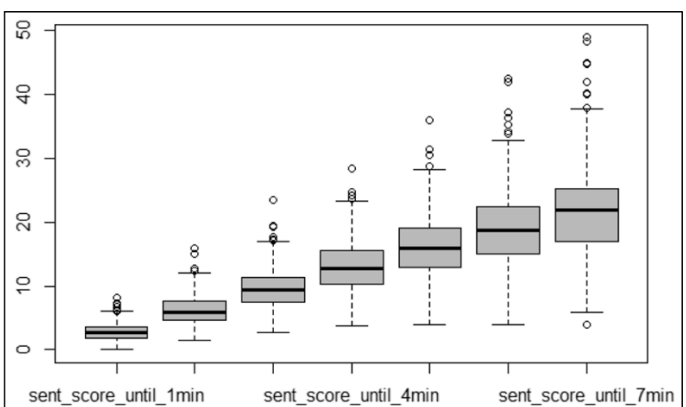

Figure 4. Boxplot of Sentiment Score of Time Windows

4.2. Results

Table 3 shows the results of our regression models. We started with the base model (Model 1), where we plugged in the factors that are previously known

to affect the view count of a video (Borghol et al. 2012; Broxton et al. 2013; Feroz Khan and Vong 2014). Our base model accounts for 58.9% of a video's view count. The total number of videos previously uploaded by the user had a significant negative effect on view count (B=-.434, p<.001). The results indicate that as the number of total videos posted by a channel increases, the view count of a video posted by the channel decreases proportionally. This is consistent with the literature regarding video virality (Cha et al, 2007; Feroz Khan and Vong 2014) which suggest that users interested in earning a lot of view counts should avoid posting a lot of videos.

Subsequently, we introduced the sentiment score of the titles (B=.793, p<.05) (Model 2). The relationship between the degree of sentiment expressed in the title of a review and its view counts were positive and significant, regardless of the product type of the reviewed product. The results indicate that more sentiment expressed in the title of the review is significantly associated with higher view count. Our expectation that titles framed with more vivid emotions would bait the users more compared to title messages that are not framed. Thus, Hypotheses 3 is supported.

Onto Model 3, we introduced the sentiment score of the content of the video reviews. In Model 3, we also tested for interaction effects and introduced the moderating variable of product types. The relationship between the degree of sentiment expressed in the content of a review and its

view counts were not found, but the interaction term SEARCH_GOOD x Content Sentiment Score was positive and statistically significant (B=.015, p<.01). This shows that for search goods, the degree of sentiment expressed in the content of a review is positively associated with the view count of the review, but for experience goods, it is not (Model 3). Thus, the results do not support H1, but support H2. Although not previously hypothesized, the video review samples in our data demonstrate that search product reviews tend to have higher views than experience product reviews. Previous research (Alsharo et al. 2016) showed that experience products such as video games and movies are the most reviewed categories covering 89% of all review videos in YouTube, however our results indicate that search product reviews are more likely to have higher view counts.

We also tried to find the relationship between the amount of subjective information in a specific time window, and the view counts. Our plan was to first add the sentiment score of each time window and see if the sentiment score of any such window shows significant correlation with the view count of the content. If a certain time window had shown significancy, we would compare the results with a model including the sentiment score of the rest of the video (sentiment score from *N* minutes to the end of the video). We added the sentiment score of the first (Model 4), second, and third minute of the video (p=.05) to the base model, but the main effects and the interaction

effect were not significant. Though the Sentiment Score until fourth minute of the video started to show significancy to the view count, we could not consider this time window as the front part of the video. Thus, H5 and H6 were not supported.

Table 3. Results of Multiple Regression

	Model1		**Model2**		**Model3**		**Model4**	
	B	SE	B	SE	B	SE	B	SE
(Ln)Subscribers$_i$	.713 ***	.037	.717 ***	.027	.717 ***	.027	.709 ***	.027
(Ln)Days$_i$	.297 ***	.036	.298 ***	.036	.301 ***	.035	.299 ***	.036
(Ln)Number of Videos$_i$	-.434 ***	.051	-.436 ***	.051	-.446 ***	.051	-.432 ***	.051
(Ln)Video Duration$_i$	.259 ***	.091	.229	.092	.246 ***	.154	.274 ***	.092
Title Sentiment Score$_i$			.793 *	.389				
Content Sentiment Score$_i$					.-.001	.006		
SEARCH_GOOD			.101	.119	-.448 *	.217	-.042	.268
*SEARCH_GOOD * Title Sentiment Score*$_i$			-.823	.488				
*SEARCH_GOOD * Content Sentiment Score*$_i$					.015 **	.006		
Sentiment Score Until 1 Minute$_i$							.031	.050
*SEARCH_GOOD * Sentiment Score Until 1 Minute*							.041	.074
VIF	1.67		2.04		3.19		3.00	
R^2	.589		.592		.593		.590	
Adjusted R^2	.587		.587		.589		.586	

※ Dependent variable: *(Ln)Viewsi*
Note: * *p<0.05*, ** *p<0.01*, *** *p<0.001*

CHAPTER 5 DISCUSSION AND CONCLUSION

5.1. Discussion

The influence of user-generated online reviews on marketing has been long acknowledged in various industries. The fast-growing trend toward video reviews can be explained partly by their effectiveness in delivering quality information. When interpreting a video review, customers do not have to rely on their imagination, as video clips present reviews by showing the product images and the whole process of how a product can be used. While written reviews are often supported by pictures attached to the reviews, video reviews are provided with more dynamic color and movements, richening the reviewer's experience. In this study, we investigate the messages delivered throughout a video review and their relation to review viewership.

First, we found that the reviews with titles expressing more sentiment are likely to have more view counts. This may be due because customers decide whether to watch the video based on the title, and the more sentiment it expresses, the more likely it is for one to be persuaded to click the content. Figure 5 shows an example of titles with a high/low degree of sentiment. Reviews with a high degree of sentiment expressed in the title are likely to have more views.

[Titles with high degree of sentiment]

- <*Product*> Review After 2 Months - Almost Perfect Laptop
- I Ditched My <*Product A*> for the <*Product B*> 6! (But Only Made It A Week!)
- Awesome Microphone - <*Product*> Review!

[Titles with low degree of sentiment]

- <*Game*> (2018) Review (Wii)
- Book Review - <*Book*> - Reviews and Recommendations
- <*Product*> Review with Pros & Cons

Figure *5*. Example of titles with high/low degree of sentiment

Secondly, we found that for search products, the degree of sentiment expressed in the content of a video is positively related to the view counts of the content. Figure 5 displays an example of search product reviews with a high/low degree of sentiment. The review on the left is more likely to have higher view counts than the review on the right. Lastly, we could not find a relationship between the degree of sentiment expressed in the front part of the content, and its view counts, unlike what we expected.

[Review with high level(amount) of sentiment]	[Review with low level(amount) of sentiment]
People sometimes ask why would you buy a gaming laptop when you can just build a custom PC for like $7? This is why: This is the new 15-inch *<product>* and it is one of the best-looking laptops I've seen this year. The design has changed quite a bit, the corner radius is a little bit smaller slightly more boxier shape, and I think it looks really good. (…)	The *<product>* gaming laptop has been refreshed with the new advanced model, which now features *<company>*'s latest RTX graphics. Starting with the specs my unit has an Intel i7-8750H CPU, 90 watt *<company>* RTX 2080 Max-Q graphics, 16GB of memory running in dual channel, a 15.6 inch 1080p 144Hz IPS screen and a 512GB M.2 NVMe SSD. (…)

Figure 6. Example of Reviews with a High/Low Level of Sentiment

5.2. Theoretical and Managerial Implications

Our analysis may have both academic and managerial implications. The process and results of our analysis may contribute to online review literature and also guide relevant researchers who are interested in analyzing the sentiment of video transcripts.

In the IS literature, studies on written reviews were of the main concern. Our study is one of the few works to extend the current studies of textual reviews to audiovisual reviews and explore the relationships between review factors and video popularity. Previous works that have analyzed video contents by text mining the transcripts are mostly done with a focus on video indexing and tagging. Our research quantifies textual data and makes an attempt to identify its relationship with video viewership. Our work may contribute to online review literature and also guide relevant researchers who are interested in analyzing the sentiment of video transcripts.

Second, the present findings can inform content creators. Users who upload content show interest in ways to gain viewership because they maximize revenue based on the traffic to the content views. Understanding the message of video content becomes a necessary step in identifying the determinants of viral viewership. Video creators can gain practical guidance in designing the factors of a video review. Our results may have managerial implications also for company sponsors. Nowadays, companies sponsor content creators, anticipating marketing effects of collaborating with 'influencers,' or 'digital content creators'. Our study can help companies set the guidelines to propose to their partners and maximize their performance in digital marketing strategies.

5.3. Limitations and Future Research

There are several limitations to our study. First of all, the popularity of the product itself is not considered in our preliminary analysis. The view count of the video is very likely to be related to the reputation of the product. Collecting reviews of a specific product may help control the impact of the popularity of the product. Also, Videos are technically multimedia, as they contain a combination of different forms such as text, image, metadata, visual, and audio. Therefore, such features should be considered when analyzing a video. Flattening video contents into text may be problematic since the overall

nuance of the video can be overlooked. Although our research may be useful when simplifying the process of content analysis, other features of the video should be considered as well for further analysis.

The results of Model 3 that exhibit the moderating effect of product types led us to develop further insights on the purpose of watching video reviews on YouTube, as Baek et al. (2012) stated in their paper that the situations of searching for online reviews might differ by product type. According to our results, for search product video reviews, it is likely for reviews with more degree of sentiment to have more views while it is not for experience product reviews. We suspect that users in YouTube watch reviews of search and experience goods in different stages; most people who watch reviews of experience goods do so in a post-purchase stage as YouTube reviews are very likely to contain spoiler information (see Figure 7), while people who watch search product video reviews tend to do so at the pre-purchase stage. Therefore, we assume there would be differences in review consuming behavior in search and experience products on YouTube and that it is necessary for further research to clarify the models by considering the intentions of watching a video review.

[Example of a Search Product Video Review]

<company name>'s basic *<product name>* has been updated for 2019 and while I'm still a little bit disappointed with it for a couple of reasons, it's actually still the best choice for people who need a basic but very reliable tablet. The one thing *<company name>* always upgrades with each *<product name>* update is the processor. So I was honestly shocked when I heard it's packing the same A10 fusion chip from last year's *<product name>* but then I started to think about why *<company name>* would do this and has started to make more sense to me. I'll explain why in a minute. Now if you guys saw my video titled "Do not buy the new 10.2 inch *<product name>* ", I want to explain the two reasons why I said that. First off, the A10 chip (…)

[Example of an Experience Product Video Review]

Hey. Let's talk about a *<company name>* movie. To follow up to the surprisingly successful first film, this movie finds Anna Elsa Kristoff Olaf and Sven as they travel to an ancient and enchanted land. They set out to find the origin of Elsa's powers in order to save their kingdom and try to lift a spell that has entrapped too many people inside an enchanted forest. People have to remember that when *<movie name>* came out nobody was anticipating the level of success that it had. So seeing the movie for the first time I thought "Hey this is actually not too bad," and I still think the first *<movie name>* is actually okay. It's a pretty good animated movie although over time the songs were so overplayed on the radio that they made my ears bleed (…)

Figure 7. Example of Search/Experience Product Video Reviews

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국문 초록

메시지 프레이밍과 리뷰 컨텐츠의 조회 수에 관한 연구: 유튜브 영상 컨텐츠를 중심으로

영상 콘텐츠를 소비하는 시장이 빠른 성장세를 보이면서 구매 과정에서도 영상 리뷰에 대한 수요가 지속적으로 증가하고 있다. 제품 정보를 검색할 때 비디오 플랫폼을 활용하고 있는 소비자는 많아진 반면 정보시스템 분야에서 해당 주제에 대한 연구는 부족하다. 본 연구는 영상 리뷰 콘텐츠의 인기에 대한 이해를 목적으로, 영상리뷰의 요인과 영상의 조회 수의 관계를 분석한다. 이중 프로세스 이론을 바탕으로, 영상 리뷰에 사용된 긍정적/부정적인 메시지 프레이밍과 영상의 조회 수의 관계를 살펴보고, 제품 유형의 조절효과에 대해서도 확인하였다. 유튜브 API를 통해 725개의 영상리뷰를 수집하고, 각 영상의 자막을 추출하여 감정분석을 시행하였다. 분석 결과, 긍정적/부정적 단어로 프레이밍이 된 제목의 경우 조회 수와의 상관관계를 확인할 수 있었다. 리뷰 내용의 프레이밍에 대해서는 조회 수와 유의한 상관관계를 찾아볼 수 없었지만, 제품 유형에 대해서는 조절효과를 가지는 것으로 나타났다. 이 연구는 영상 리뷰의 자막을 자연어 처리 기술로 분석하고 실무자의 콘텐츠 마케팅 전략에 활용될 수 있는 시사점을 제안한다는 점에서 학문적, 실무적으로 기여한다.

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