Asia Pacific Journal of Information Systems
Vol. 33 No. 1 (March 2023), 153-170

ISSN 2288-5404 (Print) / ISSN 2288-6818 (Online)
https://doi.org/10.14329/apjis.2023.33.1.153

# The Effect of Electronic Word of Mouth from Different Sources on Movie Success in the Context of Video-on-Demand Services

Lin Wang[a], Jeongha Kim[b], Dongwon Lee[c,*]

[a] *Researcher, KONAN Technology, Korea*
[b] *MS/PhD Student, Korea University Business School, Korea*
[c] *Professor, Korea University Business School, Korea University, Korea*

## ABSTRACT

Electronic word of mouth (eWOM), such as consumer ratings, reviews, and comments, is an important information source influencing consumers' behavior and purchase decisions. Prior studies about the effects of eWOM on movie success focus on box office revenue and DVD sales. As the video-on-demand (VOD) market has been growing rapidly in terms of revenue and number of users, research on movie success that focuses on this context is imperative. In addition, prior research concentrates on a single eWOM source and neglects the importance of the relative impact of different eWOM sources. Using eWOM data and movie ranking data of 111 unique movies over three months period, this research analyzes the relative impact of eWOM from internal vs. external sources and professional vs. general users on movie success in the context of VOD industry. Results suggest that eWOM from external sources has a significant impact on movie success at the VOD platform. Moreover, the general audience's opinion is more influential on movie success compared with movie critics' opinions. The findings demonstrate that eWOM from external sources and general users plays a critical role in the information search and behavior of consumers and movie success.

*Keywords:* Electronic Word of Mouth, eWOM Source, Movie Success, User-generated Content, Video on Demand

## Ⅰ. Introduction

Video-on-demand (VOD) is a media distribution system that allows users to access videos at any preferred time (Van den Broeck et al., 2007). There exist three different types of VODs differentiated by their transactional type: subscription VOD (SVOD), transactional VOD (TVOD), and ad-based VOD (AVOD). iTunes (and its subordinate "hobby-product" Apple TV) is a primarily TVOD-based streaming service where users can purchase or rent TV shows or movies they wish to enjoy. Due to Apple's enormous success

*Corresponding Author. E-mail: mislee@korea.ac.kr

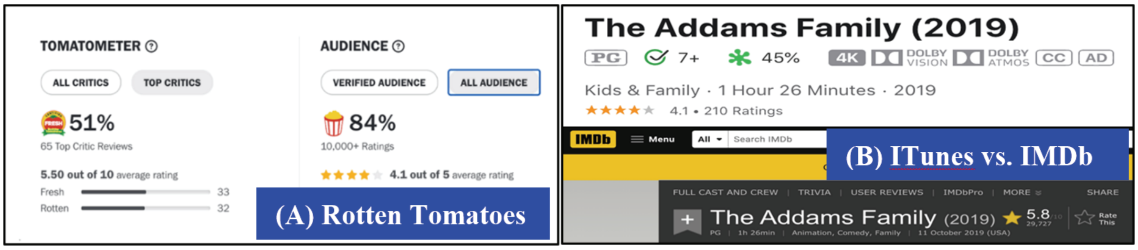
in personal technology (mobile phones, computers, software, and tablets), the company has an install base that matches very few companies around the world. The VOD industry has been growing rapidly, especially with the impact of the COVID-19 pandemic. The data from Statista (2020) demonstrates how fast the VOD industry develops. The revenue in the VOD segment was $45.78 billion in 2017 and is projected to reach more than double the revenue, which is $95.98 billion in 2025. The number of users of TVOD is growing steadily. The number of users of streaming TVOD is predicted to increase dramatically from 882 million in 2020 to 1.34 billion in 2025 (Statista, 2020).

Many factors contribute to the development and growth of the VOD industry. First, the ever-increasing Internet penetration and mobile devices in developing economies such as China offer a great opportunity for VOD providers (Valuates Reports, 2020). Second, the convenience of VOD service is another reason for its proliferation. The integration of various contents across different devices provides consumers the convenience of watching video content wherever and whenever they want on every device (Ramachandran, 2021). Third, technological innovation such as 5G broadband contributes to the growth of the VOD market. Moreover, the unexpecting outbreak of the COVID-19 pandemic has greatly influenced the VOD market due to the lockdown all over the world. According to Statista (2021), during the COVID-19 pandemic, on the weekend of March 13 and 14, 2020, consumers in different countries have increased their time spending on streaming TV and video, with around 40% growth of the time spent for users in Austria and Spain. To effectively cope with the pandemic, governments across the globe have shut down or executed operational restrictions on movie theaters, which contribute to the unprecedented growth of online content viewing. All of the figures and numbers of the VOD market indicate that VOD is a promising and fast-growing industry which deserves scholarly attention.

According to the report from FMI (2021), North America is the most lucrative region in the global VOD service market, and the trend is likely to continue. Within North America district, the US is the dominant market and is expected to remain in its position. FMI also reports that the market size of the VOD industry is expected to double in 2024, compared with the market size in 2019. Among all the regions, North America accounts for 40% of the market share, so the US market is important to explore. Hence, we decided to use the US market as our research target since iTunes provide services in many different countries.

Many websites provide rating and review information regarding various movies. For example, Rotten Tomatoes provides audience and critic ratings for movies, as shown in <Figure 1(A)>. For the movie *The Gentlemen*, the average audience rating is 4.1 out of 5; however, the top critics rating is only 5.5 out of 10. Big discrepancies are noted between ratings from different sources. Another example is the discrepancy of general audience ratings from different movie rating sources, as shown in <Figure 1(B)>. The audience rating for the movie *The Addams Family* on iTunes is 4.1 out of 5, whereas the audience rating on IMDb is only 5.8 out of 10. The inconsistent information regarding movie quality from different movie rating sources makes it ambiguous about which movie-related information source is more influential on movie success.

As discussed earlier, the VOD market is developing rapidly, especially during the pandemic when people spend most of their time at home. Time spent on watching videos or movies online is increased as a




<Figure 1> Audience vs. Critic Ratings (Rotten Tomatoes) and Audience Rating (IMDb)

result, so investigating what makes digital content (e.g., movies) successful in the context of VOD service is necessary. Furthermore, consumers search for product-related information to reduce the risk associated with purchase and consumption (Stigler, 1961). Electronic word-of-mouth (eWOM) is an important information source that influences human behaviors (Filieri et al., 2018) and product sales (Tang et al., 2014). In addition, the role of information is especially crucial for experiential goods because the quality of experiential goods is difficult to assess before the actual consumption (Eliashberg and Sawhney, 1994). Therefore, it is reasonable to assume eWOM can play an important role in influencing movie success. However, many eWOM sources exist. For example, well-known third-party movie review websites such as Rotten Tomatoes and IMDb provide information related to movie reviews and ratings. VOD platform such as iTunes also provides movie rating information. In reality though, the movie rating information is not always consistent across different sources. Discrepancies and inconsistencies exist, so the answer to which eWOM source is more influential on movie success is ambiguous. With these ideas in mind, this study aims to shed light on the following research questions:

- What are the factors that affect movie success in the VOD context?
- Which eWOM source is more influential on movie success? How do various eWOM sources affect movie success differently?

This study shows the exploratory effort to analyze the relative impact of eWOM from internal vs. external sources and general audience vs. (professional) critics on movie success in the context of the VOD industry. This study uses eWOM data from a well-known movie review platform (i.e., Rotten Tomatoes) and movie ranking data of 111 unique movies from iTunes over three months period. Our study finds that eWOM from external sources has significant and positive impacts on movie success. Furthermore, the general audience's opinion is more influential on the movie success compared with movie critics' opinions. The findings demonstrate that eWOM from external sources and the general audience plays a critical role in the information search and movie success in the VOD context.

The rest of this paper is organized as follows. Section 2 reviews the related literature and proposes the research model. Section 3 presents the data and variables, along with summary statistics. Research methodology is presented along with analysis results in section 4. Section 5 concludes the study, providing implications and limitations of this research.

# Ⅱ. Theoretical Foundations and Research Model

## 2.1. Effect of eWOM on Sales

When consumers have limited knowledge about a product, they will put effort to reduce this uncertainty to minimize the risks and maximize the outcome value (Berger and Calabrese, 1974). Eliashberg and Sawhney (1994) claim that the role of information is especially critical for experiential goods because the pre-consumption quality of experiential products is difficult to assess before actual consumption. Consumers read online reviews and not only they understand the value differences between favorable and unfavorable news, but they also focus on information such as the reviewers' reputations and exposures (Hu et al., 2008).

eWOM is one of the features consumers look for before they purchase. eWOM is defined as "the dynamic information exchange process between consumers regarding a product, service, brand, or company, which is available to a multitude of individuals and institutions via the Internet" (Ismagilova et al., 2017). Many studies demonstrate that eWOM is an important factor that influences human behaviors (Filieri et al., 2018; Floyd et al., 2014; Nam et al., 2020), product sales (Tang et al., 2014; Xiong and Bharadwaj, 2014), and consumer purchase decisions (Baber et al., 2016; Jeong and Koo, 2015). Some studies find that the valence of eWOM (i.e., rating) plays an important role on affecting product sales. Using the rating data from Amazon and Barnes and Noble, Chevalier and Mayzlin (2006) find that a book's online ratings influence its sale. Lower valence has a greater impact than higher valence of rating. Gopinath et al. (2014) posit that the valence of recommendation via eWOM has a direct impact on sales and that the volume of eWOM does not significantly affect sales. Other research finds the critical role of eWOM volume on product sales. For instance, Liu (2006) claims that the volume of eWOM significantly affects the box office revenue of movies. Gopinath et al. (2014) find that the intensity of music sampling is positively associated with the number of customer reviews on Amazon. On the contrary, several studies demonstrate that volume of eWOM has no significant impact on sales (e.g., Gopinath et al., 2014). Tang et al. (2014) find that the effects of positive and negative eWOM on sales are moderated by different types of neutral user-generated content (UGC). Some research addresses the effects of reviewer identity (Forman et al., 2008) and consumer characteristics (Ho-Dac et al., 2013) on the relationship between eWOM and product sales.

## 2.2. Sources of eWOM: Internal vs. External eWOM

eWOM can be generated from different sources. For example, a movie, as an experiential product, is difficult to evaluate unless watched. Usually before watching a movie, people search for information such as ratings and reviews of the movie to reduce the chance of choosing a bad movie (i.e., the risk related to the product). Many websites provide movie rating information such as IMDb, Rotten Tomatoes, iTunes, and so on. In addition, the ratings and reviews are given by people with different levels of knowledge of movies (i.e., movie critics vs. general audience). All the diversities within the rating and review sources can affect people's behavior of choosing movies. Sussman and Siegal (2003) develop a model called information adoption model, which explains how individuals adopt information and thus change their intentions and behaviors within computer-mediated

<Table 1> eWOM and Movie Industry

| Research | Research Context | eWOM Source | Type of eWOM Source | Main Findings |
|---|---|---|---|---|
| Liu (2006) | Movie Box- Office Revenue | Consumer Reviews on Yahoo! Movies | External General users | Volume of eWOM affect box-office revenues, but valence of eWOM doesn't have impact |
| Dellarocas et al. (2007) | Movie Box- Office Revenue | Consumer Reviews on Yahoo! Movie | External General users | Consumer reviews positively relates to movie box office |
| Duan et al. (2008a; 2008b) | Movie Box- Office Revenue | Consumer Reviews on Yahoo! Movie | External General users | Number of online reviews affect movie box office, but user ratings do not |
| Sun et al. (2014) | Movie Box- Office Revenue | Douban.com and Sina Weibo | External General users | The volume of microblogging eWOM and the Douban.com eWOM rating positively affect box office |
| Kim and Kim (2017) | VOD Market in Korea | Naver Movie | External General users | Higher box office and shorter holdback have significant impact on VOD performance |
| Kim et al. (2019) | Movie Box- Office and DVD Sales | Rotten Tomatoes | External Professionals | The volume of eWOM has stronger explanatory power of movie box office and DVD sales than valence of eWOM |

communication platforms. In this model, source credibility serves a critical role in influencing information usefulness and information adoption. Source credibility refers to consumers' overall perception regarding the credibility of an eWOM and perceived trust towards the source of information (Ohanian, 1990). Source credibility is considered as a basic factor that helps individuals judge eWOM communications (Akyuz, 2013). In addition, two major factors influence the credibility of information, which are source expertise and source trustworthiness (Applbaum and Anatol, 1972; Ismagilova et al., 2019).

Source expertise refers to the extent of skillfulness, authoritativeness, competence, and qualification a source has about the specific knowledge (Applbaum and Anatol, 1972; Whitehead, 1968). Casalo et al. (2008) claim that source expertise is a main mechanism in reducing the uncertainty of using eWOM communications in decision making. Source trustworthiness is considered an important predictor of the persuasiveness of eWOM communications (Cheung et al., 2009; Hu et al., 2008). Information from a reliable review site is more credible and may change reviewers' perceived risk (Wu, 2013). In addition, Ohanian (1990) posits that information from an expert source is more persuasive and positively affect how the information changes the receiver's attitude. Many other studies find that source trustworthiness can influence consumer behavior and purchase intention (e.g., Lis, 2013; Saleem and Ellahi, 2017). Saleem and Ellahi (2017) find that trustworthiness of the message provider affects the buying intention on social media websites in the context of fashion products.

<Table 1> summarizes the research regarding the effect of eWOM in the movie industry. Most studies focus on one source of eWOM (i.e., eWOM from external sources and general users). Using the review

<Table 2> Sources of eWOM: Internal vs. External eWOM

| Research | Research Context | eWOM source | Source of eWOM | Main Findings |
|---|---|---|---|---|
| Chevalier and Mayzlin (2006) | Book Sales on Amazon and Barnes & Noble | Consumer Reviews on Amazon and Barnes & Noble | Internal | The improvement of customer reviews can increase the product sales |
| Chen et al. (2007) | Book Sales on Amazon | Consumer Reviews on Amazon | Internal | More helpful reviews from the community have stronger impact on book sales |
| Forman et al. (2008) | Book Sales on Amazon | Consumer Reviews on Amazon | Internal | Internal eWOM source with identity information positively affect the online product sales |
| Park et al. (2009) | Digital Camera Products from Amazon | Amazon and Third-Party Websites | Internal and External | Third-party eWOM has a stronger impact on retail sales than retailer-hosted eWOM |
| Park et al. (2012) | Digital Camera Products from Amazon | Amazon and CNet | Internal and External | Valence of eWOM positively interacts with the volume at both internal and external eWOM sources |
| Gu et al. (2012) | Retailer Sales of High-Involvement Products | Amazon.com, CNet, DpReview, and Epinions | Internal and External | Third-party eWOM have a stronger impact on the sales of high-involvement products comparing to a retailer's internal eWOM |
| Zhou and Duan (2016) | Software Program | Amazon and a Third-Party Website download.com | Internal and External | Less dispersed eWOM leads to more sales; More consistent consumer evaluations across different websites lead to more positive online purchase decisions |

data from Yahoo! Movie, Dellarocas et al. (2007) demonstrate that consumer reviews from external source are positively related to movie revenues. One research studies movie success in the context of VOD (i.e., Kim and Kim, 2017). However, eWOM information is only from one source, which lacks the comparison between the effects of different eWOM sources.

Many prior studies investigate the effect of different eWOM sources (i.e., internal vs. external eWOM) on product sales and consumer purchase decisions. Some of these studies demonstrate that eWOM from internal source affect retail sales. For instance, Chen et al. (2007) examine the books sales on Amazon and demonstrate that internal eWOM has a significant impact on sales and the more helpful reviews have a stronger impact. Forman et al. (2008) also find that internal eWOM with identity information (i.e., high trustworthiness) positively affects online product sales. Chevalier and Mayzlin (2006) claim that the improvement of internal customer reviews can increase product sales using book review information from Amazon and Barnes and Noble. On the contrary, many studies indicate that eWOM from external sources significantly impacts product sales. Some studies compare the effects of eWOM from internal and external sources. For example, Park et al. (2009) compare how the eWOM from Amazon and a third-party website affect digital camera sales and find that third party-hosted eWOM has a significant impact on retail sales, whereas retailer-hosted eWOM (i.e., from Amazon) has less impact on its own sales. Gu et al. (2012) investigate the effect of eWOM on the sales of high-involvement products

<Table 3> Quality of eWOM in Movie Industry: General Users vs. Professionals

| Research | Research Context | eWOM source | Quality of eWOM | Main Findings |
|---|---|---|---|---|
| Moon et al. (2010) | Movie Revenues and New Movie Ratings | Yahoo! Movies and Rotten Tomatoes | Audiences & Critics | Critics' ratings significantly influence the movie revenues in the opening; Audience ratings influence movie revenues in the following week |
| Chakravarty et al. (2010) | Pre-release Movie Evaluation | Yahoo! Movies and 14 Popular Movie Critics | Audiences & Critics | eWOM (especially negative WOM) has stronger effect on audience who watch movie less frequently; The effect of negative eWOM is lasting even if the critic rating is positive |
| Kim et al. (2013) | Theatrical Movies' Box Office Success | IMDb and Rotten Tomatoes | Audiences & Critics | The volume of audience eWOM and the valence of critic reviews significantly influence box office performance |
| Ahmed and Sinha (2016) | Movie Box-Office and DVD Sales | IMDb and Rotten Tomatoes | Audiences & Critics | Critics' ratings positively influence both box-office and DVD sales; General audience ratings only positively affect box-office performance |

(i.e., digital camera). They find that eWOM on the retailer website has less impact on the sales of high-involvement products, whereas eWOM from third-party sources has stronger and significant influence on product sales. As shown in <Table 2>, internal and external eWOM have a significant influence on product sales under various research contexts. This research aims to tease out the relative impact between internal and external eWOM on movie success in the context of VOD service.

## 2.3. Quality of eWOM: General Users vs. Professionals

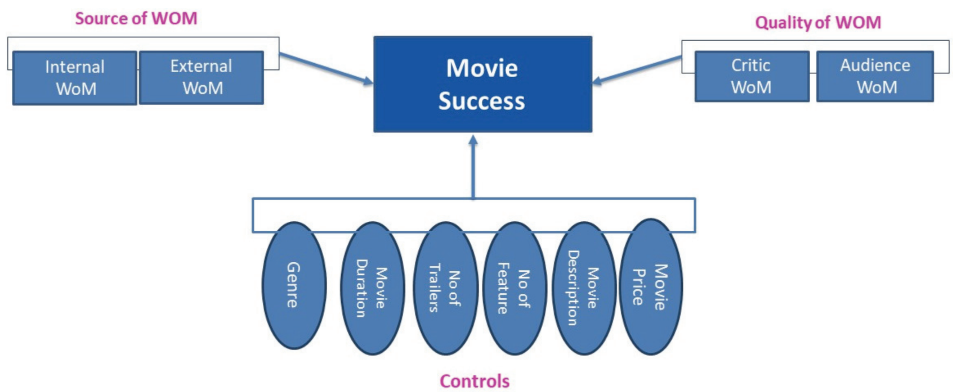
In the context of the movie industry, the two types of message sources are from moviegoers (i.e., general audience) and professionals (i.e., movie critics) (Chakravarty et al., 2010). The general audience's opinion and evaluation of a movie represent the "mass" tastes (Holbrook, 1999). The eWOM of the general audience is often relevant to personal emotions and opinions, and it intends to encourage or discourage the audience to watch a movie. On the contrary, movie critics typically have the expertise and in-depth knowledge about movies and tend to focus more on the technical or artistic aspects of the movie (Goldenberg et al., 2006; Holbrook, 2005).

Prior research indicates that the effects of eWOM and expert reviews on movie box office revenues are somewhat different (see <Table 3>). Ginsburgh and Weyers (1999) find that experts and the general audience value different attributes of movies by differentiating quality movies judged by the two groups. Moreover, movie critics have more knowledge of movies and can be considered with more expertise and credibility (Kim et al., 2013), therefore, they may be more influential. Studying the effect of eWOM on movie box office and DVD sales, Ahmed and Sinha (2016) find that critics' ratings positively affect box office and DVD sales. General audience ratings only have a positive and significant effect on box office performance.

## 2.4. Research Model

Critics may focus more on artistic values than on market values (e.g., fun factor), which are more important to ordinary people (Kim et al., 2013). In addition, although professionals have more profound knowledge and general consumers can obtain useful information from professionals, the two groups sometimes have different opinions and tastes because of certain fundamental differences between them in terms of experiences and preferences (Chakravarty et al., 2008; Holbrook, 1999; Wanderer, 1970). Therefore, consumers consider the general audience's opinion more convincing and often follow similar amateurs' opinions in various ways (Moon et al., 2010). Given the abovementioned various research results, the present study explores how the quality of the eWOM (i.e., eWOM from professionals vs. general users) affects product success (i.e., movie success) differently.

Determining the relevant features that play a role in movie success is integral in planning out the marketing of the movie of interest. Since the advent of online marketing, it has been easier for researchers to identify these features using tools that can extract relevant information from millions of online data sources. Features, such as the price of movie tickets (Ulker-Demirel et al., 2018), number of words in the scripts (Eliashberg, 2014; Eliashberg et al., 2007), movie features (Borghol et al., 2012), number of online trailers (Karray and Debernitz, 2017), duration since debut (Chiou, 2008), and movie genre (Kim and Kim, 2017) play an important role in movie success. For example, in a study that analyzed the impact of movie ticket prices on customers' purchasing intent, movie theatres' different ticket pricing and promotional strategies influence customers' viewership of the movie (Ulker-Demirel et al., 2018). The number of words in the script also has an impact on the movie success. By extracting basic features of the movie script, such as genre and content, semantics, and bag-of-word variables, Eliashberg et al. (2014) show that word specificity significantly has predictive power of box office performance. Naturally, the movie feature (e.g., resolution, etc.) is positively correlated with the popularity of YouTube videos (Borghol et al., 2012). With regard to how the number of trailers influences movie success, consumers react more strongly toward the first trailer compared with the follow-up trailers, implying that the successive release of movie trailers returns a lower cost-efficient advertisement of movies (Karray and Debernitz, 2017). In addition, a pre-release buzz of movies and video games, measured by a number of online articles, trailer videos, and social media engagements, significantly predicts the performance of the product (Xiong and Bharadwaj, 2014).




<Figure 2> Research Model

Our research model is presented in <Figure 2>.

# Ⅲ. Data and Variables

## 3.1. Data Collection

The analyses are conducted using panel data and aggregated data of daily movie ranking from the *US iTunes Chart* and eWOM data from an internal source (i.e., *iTunes*) and an external website (i.e., *Rotten Tomatoes*). Rotten Tomatoes is a well-known review-aggregation website that provides film and TV program-related information such as ratings, reviews, and other movie-related information. People have been relying on Rotten Tomatoes to find movie reviews and ratings since its launch in 2000. However, this website seems to matter even more after Fandango acquired Rotten Tomatoes in 2016 because its scores started to appear next to the movie listings (Wilkinson, 2017). In particular, Rotten Tomatoes offers eWOM information (i.e., rating score) from both general audience and critics, which provides the necessary data for comparing the different effects of eWOM among general users and professionals. In addition, the data such as movie prices and the number of features are collected from iTunes.

This study originally collected 788 unique movie titles from the iTunes daily list of the top 100 movie rentals chart for three months from December 1, 2020, to February 28, 2021. Many movies were released on iTunes before December 1, 2020 when we started to collect eWOM related data (e.g., ratings, number of ratings, etc.) and movie ranking information. It would cause a left-censoring issue if we include movies that were released before December 1, 2020, since we are not able to measure their performance on iTunes. To account for the left censoring issue, this research only included the movies released after December 1, 2020, on iTunes, reducing the number of unique movies to 111.

Data regarding the movie genre were collected from The Numbers website. Information such as movie release date on the big screen and the date for collecting movie ranking was also used to account for the movie age. In Rotten Tomatoes website, there are 11 movies that did not contain rating information during the data collection period (i.e., 2020 World

<Table 4> Descriptive Statistics of the Variables

| Variable | Description | Mean | StDev | Min | Max |
|---|---|---|---|---|---|
| *iTunesRate* | iTunes rating score | 7.45 | 1.45 | 2.32 | 10.00 |
| *RTAudienceRate* | Rotten Tomatoes average rating score by audience | 7.19 | 1.43 | 2.54 | 9.79 |
| *RTCriticRate* | Rotten Tomatoes average rating score by critics | 6.04 | 1.29 | 3.00 | 8.80 |
| *iTunesNumRate* | Number of ratings on iTunes | 3.08 | 1.21 | 0.46 | 5.97 |
| *RTAudienceNumRate* | Number of audience ratings on Rotten Tomatoes | 4.57 | 1.36 | 1.79 | 9.21 |
| *RTCriticNumRate* | Number of critic ratings on Rotten Tomatoes | 3.66 | 1.05 | 1.61 | 6.04 |
| *PriceRatio* | The price ratio (movie rent/buy) of the movie | 0.50 | 0.19 | 0.10 | 1.00 |
| *NoofWord* | Number of words in the movie description section | 87.01 | 41.39 | 5.00 | 281.00 |
| *NoofFeature* | Number of features provided for the movie on iTunes | 2.53 | 1.14 | 1.00 | 6.00 |
| *NoofTrailer* | Number of trailers on iTunes | 1.07 | 0.26 | 1.00 | 2.00 |
| *MovieAge* | Days since the earliest movie release date on big screen | 89.00 | 173.58 | 3.00 | 1431.50 |

Series Champions: Los Angeles Dodgers, A Stone in the Water, American Dream (2020), Behind the Try: A Try Guys Documentary, Boonie Bears: Blast Into the Past, Gap Year, Guitar Man, Ip Man: Kung Fu Master, Savage State, The House That Rob Built, The Last Blockbuster). During the analysis process, the movies without rating information were excluded.

### 3.2. Dependent Variable

The objective of this research is to investigate the relative influence of eWOM from internal vs. external sources and general users vs. professionals on movie success in the context of VOD service. The dependent variable is *the ratio between the number of times the movie was ranked in the chart and the total days since the movie was released on iTunes*. Suppose the movie was released on iTunes on December 31, 2020. Since the last day of data collection was February 28, 2021, the total days would be 60 days. The dependent variable is the ratio which takes the movie release dates into consideration.

### 3.3. Independent Variables

The key explanatory variables of this research are eWOM information from internal vs. external sources and general users vs. professionals. In this study, we focus on eWOM valence (i.e., movie rating). In a survey conducted in 2008, 90% of moviegoers confirmed that their decisions are affected by online ratings (Oh and Chon, 2008). Chung and Hwang (2012) claim that online ratings have important impact on the theatrical and VOD market. Therefore, online rating is taken as a crucial factor contributing to higher movie performance. To estimate the eWOM variable, we use the *average rating scores* as an indicator for eWOM valence. In addition, we use movie price; the number of movie features provided by iTunes; movie age, which is measured by the days difference from the movie release date to the date movie ranking data is collected; and movie genre as control variables. <Table 4> provides the description and summary statistics of the variables used in this study. Out of the full score rating, which is 10, the average rating is 7.45 for iTunes, which is the highest, followed by the average rating for Rotten Tomatoes audience rating, which is 7.19, and critic and top critic ratings.

## Ⅳ. Methodology and Empirical Estimation

### 4.1. Grouped Logit Model

The main objective of this study is to examine how various eWOM sources affect movie success. One way to measure movie success is to check whether the movie is ranked in the top 100 charts. This can be modeled with the *grouped logit model*. This model is similar to the models such as logit, probit and logistic regression, which are used for analyzing binary variables. The grouped logit is a method that uses data representing proportions of observations to estimate individual-level units, where the dependent variable is a binary variable, and the independent variables are attributes of the unit of analysis. Specifically, the effects of internal eWOM vs. external eWOM and general audience rating vs. critic rating on movie success are explored using a grouped logit model, which is an appropriate model for analyzing proportions data (Lee et al., 2009). In the grouped logit model, the dependent variable is the proportion of the total number of positive responses and the total population. In the case of this research, the probability

<Table 5> Results from Group Logit Model

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| *iTunesRate* | -.111<br>(.106) | -.137<br>(.132) | | | | -0.150<br>(.145) |
| *RTAudienceRate* | | .277**<br>(.110) | .223*<br>(.120) | | .312**<br>(.138) | .276**<br>(.124) |
| *RTCriticRate* | | | | -.123<br>(.142) | -.278*<br>(.162) | .020<br>(.145) |
| *Ln(iTunesNumRate)* | .863***<br>(.155) | .901***<br>(.168) | | | | .856***<br>(.185) |
| *Ln(RTCriticNumRate)* | | | | .549**<br>(.216) | .562**<br>(.228) | .100<br>(.201) |
| *PriceRatio* | .646<br>(.739) | .687<br>(.752) | 1.362<br>(.923) | .424<br>(.894) | .817<br>(.919) | .702<br>(.770) |
| *NoofWord* | -.002<br>(.004) | -.0003<br>(.004) | .003<br>(.005) | -.001<br>(.004) | .004<br>(0.005) | .000<br>(0.004) |
| *NoofFeature* | .312**<br>(.132) | .203<br>(.131) | .553***<br>(.155) | .441***<br>(.166) | .292<br>(.178) | .163<br>(.151) |
| *NoofTrailer* | -1.468**<br>(.708) | -1.336**<br>(.799) | -1.437*<br>(.788) | -1.925**<br>(.800) | -1.423*<br>(.813) | -1.339*<br>(.733) |
| *MovieAge* | 0.001<br>(0.001) | 0.001<br>(0.001) | 0.000<br>(0.001) | .000<br>(0.001) | 0.000<br>(.001) | 0.001<br>(0.001) |
| *Genre* | Y | Y | Y | Y | Y | Y |
| *Constant* | -2.197<br>(1.317) | -4.118***<br>(1.464) | -3.074**<br>(1.428) | -1.237<br>(1.097) | -3.221**<br>(1.442) | -4.294***<br>(1.570) |
| *No. of Obs* | 88 | 79 | 80 | 82 | 77 | 76 |
| $R^2$ | 0.4296 | 0.4384 | 0.2390 | 0.2789 | 0.2893 | 0.4417 |

of a movie being ranked in the chart is the proportion of the number of times the movie is ranked in the chart and the total days since the movie was released on iTunes. This follows a binomial distribution.

The probability that a movie will be in the chart is defined as $P(InChart = 1) = \frac{e^Z}{1+e^Z}$, where $Z$ is a linear equation of the variables that may affect movie performance at the VOD platform. $P_i = E(Inchart = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}} = \frac{1}{1+e^{-Z}} = \frac{e^Z}{1+e^Z}$, $Z = \beta_0 + \beta_1 x_1 + \beta_2 x_2$, where $x_1$ denotes the eWOM information from different sources, and $x_2$ denotes the control variables. The odds ratio is $P_i/(1 - P_i)$, which indicates the ratio of the probability that a movie will be ranked in the chart to the probability that it will not be. $L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + u_i$.

## 4.2. Empirical Estimation and Results

In the main analysis, the grouped logit model is used to estimate the effects of eWOM from different sources on movie success. The dependent variable is the proportion of the number of times the movie is ranked in the chart and the total days since the movie was released on iTunes. The coefficients of iTunes rating are negative and insignificant, whereas the coefficient of the external eWOM (i.e., Rotten Tomatoes audience rating) is positive and significant. In Model 2, when comparing iTunes rating with Rotten Tomatoes audience rating, the coefficient of the former is negative and insignificant, but the coefficient of the latter is 0.277, which is positive and significant. Model 5 examines the different effects of eWOM on the general audience and critics. The coefficient of Rotten Tomatoes audience rating is positive and significant, whereas the coefficient of the critic rating is negative and marginally significant. The possible explanation of the marginally significant negative coefficient of the critic rating could be that critics have more depth knowledge about the movie and could appreciate the different aspects of the movie compared to the general audience, as mentioned above in the literature review part. Therefore, the general audience may not like movies critics value. Model 6 includes the eWOM from internal and external sources as well as critics. The results are consistent with other models' specifications. The coefficient of Rotten Tomatoes audience rating is 0.276, which is positive and significant. The coefficients of iTunes rating and Rotten Tomatoes critic rating are marginally significant. These results indicate that external eWOM (i.e., Rotten Tomatoes audience rating) is more influential than internal eWOM (i.e., iTunes rating) on movie success in the VOD context. Moreover, the eWOM from the general audience is relatively more influential than that from critics.

## Ⅴ. Discussion and Conclusion

To summarize, this research analyzes the relative impact of eWOM from internal vs. external sources and critics vs. the general audience on movie success in the VOD context. The results demonstrate that eWOM from external sources has a significant impact on movie success on the VOD platform. Moreover, the general audience's opinion is more influential on the movie success than movie critics' opinion.

The findings of this study have several important theoretical implications. First, to our best knowledge, this study is the first to investigate and compare the relative effect of eWOM from internal vs. external sources and critics vs. the general audience on product sales. The results help identify the important role of eWOM from external sources and general users in the information search and consumer behaviors. The findings also help researchers develop a more comprehensive understanding of the effect of eWOM. Second, the findings of this research are based on the VOD context, which differs from prior research that is based on theater movie and DVD context. VOD services exhibit different characteristics compared with movie theaters and DVDs in that they are more convenient and allow the audience to access whenever and wherever. The VOD environment provides the convenience for the audience to access movie-related information, encourages the audience to engage in information searching, and reduces the time between the information searching and the behavior of watching a movie. The characteristics of VOD highlight the importance of investigating information search behavior and its effect on consumer behavior in this context. Lastly, the results of this study reconfirm the importance of source credibility and source trustworthiness in information search and adoption. In addition, this study suggests the importance of similar perspectives when evaluating a product. eWOM from the general audience is more influential on movie success because the majority of consumers are general audiences without in-depth and professional knowledge of the movie.

The results of this study also have practical implications. First, the results identify the factors influencing movie success in the VOD context, which can be important to movie makers and marketers. The movie industry is highly competitive with many products being produced every year. This study helps movie companies and VOD platforms to better understand what factors contribute to movie success in the VOD context for them to better manage and make more profit. Second, the results indicate that WOM from external sources and general users is valuable to movie success. For movie companies and movie marketers, the results provide direction regarding what to work on for them to make successful and popular movies. Hence, our findings imply that if movie companies or movie markets aim to achieve success in the platforms, they could allocate more resources (e.g., time, money) to movies that are highly rated by ordinary audience instead of professional movie critics. In addition, instead of focusing on the internal WOM of the movies internally (i.e., VoD platform), movie companies and marketers should put more effort in order to generate better WOM from external influential movie review communities (e.g., Rotten Tomatoes). Moreover, for VOD platforms to bring movies that will be successful on the VOD platforms, they could take the WOM of the general audience from influential third-party movie review websites/communities as one of the measurements/indicators when they evaluate the movie before making decisions of whether or not to include the movie in the platform. Moreover, our study emphasized that movies can be categorized as high-involvement products. Hence, movie directors and producers can have a dynamic and competitive environment since the VOD market is rapidly growing, and many movies have been released through these services. Therefore, movie directors and producers need to develop optimal operations and business strategies to manage it by considering general audience rating more. Since our analysis is conducted using data of daily movie ranking from the US iTunes chart, movies listed on this website has already been released in the theater then has been updated through VOD services. Referring to Moon et al. (2010), critics' ratings affect movie revenues significantly when the movie is available whereas audience ratings influence movie revenues in the following weeks. Therefore, our finding suggests that general audience rating is more influential, and marketers should put more effort on external eWOM.

This research has several limitations. First, the data collection period is only three months, so accounting for the seasonality factor is difficult. Furthermore, due to the limited availability of the data collection period, our sample size is comparatively small. Hence, the result can be differed if one includes more samples. Future studies can generalize the results by analyzing the data for a longer period. Second, the research only accounts for the static factor of movie success (i.e., the number of times in the chart). Future studies can utilize more data to investigate how different eWOM sources affect the duration a movie can survive in the chart or how fast a movie is ranked on the chart using survival analysis. Third, this research only focuses on one country (i.e., the United States) and one VOD platform (i.e., iTunes). Future studies can examine other countries and other platforms such as Netflix and YouTube to identify the country-specific and platform-specific heterogeneities. Lastly, the movie is an experiential product, so the results should be interpreted with caution when applied to other product categories such as retailer products.

## <References>


[1] Ahmed, S., and Sinha, A. (2016). When it pays to wait: Optimizing release timing decisions for secondary channels in the film industry. *Journal of Marketing*, *80*(4), 20-38.

[2] Akyuz, A. (2013). Determinant factors influencing eWOM, *Mediterranean Journal of Social Sciences*, *4*(11), 159-166.

[3] Applbaum R. F., and Anatol, K. W. E. (1972). The factor structure of source credibility as a function of the speaking situation. *Speech Monographs*, *39*(3), 216-222.

[4] Baber, A., Thurasamy, R., Malik, M. I., Sadiq, B., Islam, S., and Sajjad, M. (2016). Online word of-mouth antecedents, attitude and intention to purchase electronic products in pakistan. *Telematics and Informatics*, *33*(2), 388-400.

[5] Berger, C. R., and Calabrese, R. J. (1974). Some explorations in initial interaction and beyond: Toward a developmental theory of interpersonal communication. *Human Communication Research*, *1*(2), 99-112.

[6] Borghol, Y., Ardon, S., Carlsson, N., Eager, D., and Mahanti, A. (2012). The untold story of the clones: Content-agnostic factors that impact YouTube video popularity. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1186-1194.

[7] Casalo, L., Flavián, C., and Guinalíu, M. (2008). The role of perceived usability, reputation, satisfaction and consumer familiarity on the website loyalty formation process. *Computers in Human Behavior*, *24*(2), 325-345.

[8] Chakravarty, A., Liu, Y., and Mazumdar, T. (2008). Online user comments versus professional reviews: Differential influences on pre-release movie evaluation. *MSI Reports*, Working Paper Series, Report No. 08-105, 115-137.

[9] Chakravarty, A., Liu, Y., and Mazumdar, T. (2010). The differential effects of online word-of-mouth and critics' reviews on pre-release movie evaluation. *Journal of Interactive Marketing*, *24*(3), 185-197.

[10] Chen, P., Dhanasobhon, S., and Smith, M. D. (2007). An analysis of the differential impact of reviews and reviewers at Amazon.com. In *Proceedings of the 27th International Conference on Information Systems (ICIS-2007),* Montreal, Canada.

[11] Cheung, C. M. K., Lee, M. K. O., and Thadani, D. R. (2009). The impact of positive electronic word-of-mouth on consumer online purchasing decision. In *Proceedings of the 2nd World Summit on the Knowledge Society: Visioning and Engineering the Knowledge Society*, September 16-18, 2009, Crete, Greece.

[12] Chevalier, J. A., and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345-354.

[13] Chiou, L. (2008). The timing of movie releases: Evidence from the home video industry. *International Journal of Industrial Organization*, *26*(5), 1059-1073.

[14] Chung, K., and Hwang, Y. (2012). Differential factors contributing to movie viewing on ppv service of satellite broadcasting and in the movie theater. *Broadcasting & Communication*, *13*(2), 45-90 (In Korean).

[15] Dellarocas, C., Awad, N., and Zhang, X. (2007). Exploring the value of online reviews to organizations: implications for revenue forecasting and planning. *Journal of Interactive Marketing*, *21*(4), 23-45.

[16] Duan, W., Gu, B., and Whinston, A. B. (2008a). The dynamics of online word-of-mouth and product sales: An empirical investigation of the movie industry. *Journal of Retailing*, *84*(2), 233-242.

[17] Duan, W., Gu, B., and Whinston, A. B. (2008b). Do online reviews matter? an empirical investigation of panel data. *Decision Support Systems*, *45*(4), 1007-1016.

[18] Eliashberg, J., Hui, S. K., and Zhang, Z. J. (2007). From story line to box office: A new approach for green-lighting movie scripts. *Management Science*, *53*(6), 881-893.

[19] Eliashberg, J., Hui, S. K., and Zhang, Z. J. (2014). Assessing box office performance using movie scripts: A kernel-based approach. *IEEE Transactions on Knowledge and Data Engineering*, *26*(11), 2639-2648.

[20] Eliashberg, J., and Sawhney, M. S. (1994). Modeling goes to hollywood: Predicting individual differences in movie enjoyment. *Management Science*, *40*(9), 1151-1173.

[21] Filieri, R., Raguseo, E., and Vitari, C. (2018). When are extreme ratings more helpful? empirical evidence on the moderating effects of review characteristics and product type. *Computers in Human Behavior*, *88*, 134-142.

[22] Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., and Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. *Journal of Retailing*, *90*(2), 217-232.

[23] FMI (2021), Video on Demand (VOD) Service Market. Retrieved from https://www.futuremarketinsights.com/reports/video-on-demand-market

[24] Forman, C., Ghose, A., and Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research*, *19*(3), 291-313.

[25] Ginsburgh, V., and Weyers, S. (1999). On the perceived quality of movies. *Journal of Cultural Economics*, *23*, 269-283.

[26] Goldenberg, J., Donald R. L., Daniella S., and Michal M. B. (2006). The role of expert versus social opinion leaders in new product adoption. *Marketing Science Institute Report*, No. 06-124. MA: Cambridge.

[27] Gopinath, S., Thomas, J. S., and Krishnamurthi, L. (2014). Investigating the relationship between the content of online word of mouth, advertising, and brand performance. *Marketing Science*, *33*(2), 241-258.

[28] Gruenwedel, E. (2022, May 9). Report: Rotten tomatoes named best movie rating database. *Media Play News*. Retrieved from https://www.mediaplaynews.com/report-rotten-tomatoes-named-best-movie-rating-database

[29] Gu, B., Park, J., & Konana, P. (2012). Research note—the impact of external word-of-mouth sources on retailer sales of high-involvement products. *Information Systems Research*, *23*(1), 182-196.

[30] Ho-Dac, N. N., Carson, S. J., and Moore, W. L. (2013). The effects of positive and negative online customer reviews: Do brand strength and category maturity matter? *Journal of Marketing*, *77*(6), 37-53.

[31] Holbrook, M. (1999), Popular appeal versus expert judgements of motion pictures. *Journal of Consumer Research*, *26*(2), 144-155.

[32] Holbrook, M. (2005), The role of ordinary evaluations in the market for popular culture: Do consumers have 'Good Taste'? *Marketing Letters*, *16*(2), 75-86.

[33] Hu, N., Liu, L., and Zhang, J. J. (2008). Do online reviews affect product sales? the role of reviewer characteristics and temporal effects. *Information Technology and Management*, *9*(3), 201-214.

[34] Ismagilova, E., Dwivedi, Y., Slade, E., and Williams, M. (2017). *Electronic Word-of-Mouth in the Marketing Context: A State-of-the-Art Analysis and Future Directions*. Springer.

[35] Ismagilova, E., Slade, E. L., Rana, N. P., and Dwivedi, Y. K. (2019). The effect of electronic word of mouth communications on intention to buy: A meta-analysis. *Information Systems Frontiers*, *22*(5), 1203-1226.

[36] Jeong, H. J., and Koo, D. M. (2015). Combined effects of valence and attributes of e-wom on consumer judgment for message and product: The moderating effect of brand community type. *Internet Research*, *25*(1), 2-29.

[37] Karray, S., and Debernitz, L. (2017). The effectiveness of movie trailer advertising. *International Journal of Advertising*, *36*(2), 368-392.

[38] Kim, E., and Kim, S. (2017). Online movie success in sequential markets: Determinants of video-on-demand film success in Korea. *Telematics and Informatics*, *34*(7), 987-995.

[39] Kim, S. H., Park, N., and Park, S. H. (2013). Exploring the effects of online word of mouth and expert reviews on theatrical movies' box office success. *Journal of*

*Media Economics*, *26*(2), 98-114.

[40] Kim, K., Yoon, S., and Choi, Y K. (2019). The effects of eWOM volume and valence on product sales: an empirical examination of the movie industry. *International Journal of Advertising*, *38*(3), 471-488.

[41] Lee, D., Kauffman, R. J., and Bergen, M. E. (2009). Image effects and rational inattention in internet-based selling. *International Journal of Electronic Commerce*, *13*(4), 127-166.

[42] Lis, B. (2013). In eWOM we trust. A framework of factors that determine the eWOM impact. *Business & Information Systems Engineering*, *5*(3), 129- 140.

[43] Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74-89.

[44] Moon, S., Bergey, P. K., and Iacobucci, D. (2010). Dynamic effects among movie ratings, movie revenues, and viewer satisfaction. *Journal of Marketing*, *74*(1), 108-121.

[45] Nam, K., Baker, J., Ahmad, N., and Goo, J. (2020). Dissatisfaction, disconfirmation, and distrust: An empirical examination of value code-destruction through negative electronic word-of-mouth (eWOM). *Information Systems Frontiers*, *22*(1), 1-18.

[46] Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *Journal of Advertising*, *19*(3), 39-52.

[47] Oh, E. H., and Chon, B. S. (2008). Determinants of film critics between online users and professional reviewers. *Korea Journal of Broadcast*, *22*(6), 267-289.

[48] Park, J., Gu, B., and Konana, P. (2009). Impact of Multiple Word of Mouth Sources on Retail Sales. In *Proceedings of the 30th International Conference on Information (ICIS-2009)*, Phoenix, AZ, USA, December 15-18, 2009.

[49] Park, J., Gu, B., and Lee, H. (2012). The relationship between retailer-hosted and third-party hosted WOM sources and their influence on retailer sales. *Electronic Commerce Research and Applications*, *11*(3), 253-261.

[50] Ramachandran, N. (2021). Video on demand market: Growth, trends, and forecasts (2020-2025). Webnexs Blog. Retrieved from https://www.webnexs.com/blog/video-demand-marke-growth-trends-forecasts

[51] Valuates Reports. (2020). Video on demand (VOD) market size is projected to reach USD 88,523.67 million by 2025, September 30, 2020.

[52] Saleem, A., and Ellahi, A. (2017). Influence of electronic word of mouth on purchase intention of fashion products on social networking websites. *Pakistan Journal of Commerce & Social Sciences*, *11*(2), 597-622.

[53] Statista (2020). Video-on-demand. Retrieved from https://www.statista.com/outlook/dmo/digital-media/video-on-demand/worldwide

[54] Statista (2021). Video streaming growth worldwide: Coronavirus impact 2020. Retrieved from https://www.statista.com/statistics/1107559/video-streaming-consumption-growth-worldwide-coronavirus/

[55] Statista. (2022a, April 22). Netflix's global revenue 2021, by region. Retrieved from https://www.statista.com/statistics/1090098/netflix-global-revenue-by-region/

[56] Statista. (2022, October 19). Netflix's quarterly revenue 2013-2022. Retrieved from https://www.statista.com/statistics/273883/netflixs-quarterly-revenue/

[57] Stigler, G. J. (1961). The economics of information. *Journal of Political Economy*, *69*(3), 213-225.

[58] Sun, T., Song, T., and Huang, J. (2014). Effects of microblogging and third-party word of mouth on product sales: Empirical study based on movie box office revenue. In *Proceedings of the 2014 Pacific Asia Conference on Information Systems* (*PACIS* -2014).

[59] Sussman, S. W., and Siegel, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, *14*(1), 47-65.

[60] Tang, T., Fang, E., and Wang, F. (2014). Is neutral really neutral? the effects of neutral user generated content on product sales. *Journal of Marketing*, *78*(4), 41-58.

[61] Ulker-Demirel, E., Akyol, A., and Simsek, G. G. (2018). Marketing and consumption of art products: The movie industry. *Arts and the Market*, *8*(1), 80-98.

[62] Van den Broeck, W., Pierson, J., and Lievens, B. (2007). Video-on-demand: Towards new viewing practices? *Observatorio (OBS*)*, *1*(3), 23-44.

[63] Wanderer, J. J. (1970). In defense of popular taste: Film ratings among professionals and lay audiences. *American Journal of Sociology*, *76*(2), 262-72.

[64] Whitehead, J. L. (1968). Factors of source credibility. *Quarterly Journal of Speech*, *54*(1), 59-63.

[65] Wilkinson, A. (2017). Rotten tomatoes, explained, Vox. Retrieved from https://www.vox.com/culture/2017/8/31/16107948/rotten-tomatoes-score-get-their-ratings-top-critics-certified-fresh-aggregate-mean

[66] Wu, P. F. (2013). In search of negativity bias: An empirical study of perceived helpfulness of online reviews. *Psychology & Marketing*, *30*(11), 971-984.

[67] Xiong, G., and Bharadwaj, S. (2014). Prerelease buzz evolution patterns and new product performance. *Marketing Science*, *33*(3), 401-421.

[68] Zhou, W., and Duan, W. (2016). The sales impact of word-of-mouth distribution across retail and third-party websites. In *Proceedings of the 37th International Conference on Information (ICIS-2016)*, Dublin, Ireland, December 11-14, 2016.

## ◆ About the Authors ◆

**Lin Wang**

Lin Wang received her first Master's degree in Human Resources Management at Rutgers, The State University of New Jersey, and received her second Master's degree in Management Information System at Korea University, South Korea. She received her B.S. degree in economics at Beijing Jiaotong University, China. Her research interests include social media, electronic commerce, and AI & big data analytics.

**Jeongha Kim**

Jeongha Kim is a MS-PhD student of Management Information Systems at Korea University Business School. She received her B.S degree in economics from University of Melbourne in Australia. Her research interests include metaverse, mobile business, economics of IT, digital marketing and platform in Information Systems.

**Dongwon Lee**

Dongwon Lee is a Professor of MIS at Korea University Business School and the co-president of KrAIS (Korean Chapter of Association for Information Systems). He earned his Ph.D. from University of Minnesota, his MS from University of Arizona, and BBA and MBA from Seoul National University. His research interests are e-business pricing, social media, big data analytics, mobile business, and platform business. His work has been published in *Information Systems Research*, *Journal of Consumer Research*, *Journal of AIS*, *Journal of MIS*, *Review of Economics & Statistics*, *Information & Management*, *International Journal of Electronic Commerce*, *Data Base*, *Communications of AIS*, *Information Systems Frontiers*, *Journal of Business Research*, and others.

Submitted: April 12, 2022; 1st Revision: August 12, 2022; 2nd Revision: October 30, 2022; Accepted: December 5, 2022