經營學博士學位論文

The Effect of Electronic Word of Mouth on Movie Sales:

Focusing on Time, Channel, and Value

온라인 口傳이 映畵 賣出에 미치는 影響:

時期, 媒體, 價値를 中心으로

2013年 2月

서울大學校 大學院

經營學科 經營學專攻

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Focusing on Time, Channel, and Value

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이 논문을 경영학 박사학위논문으로 제출함
2012 년 10 월

서울대학교 대학원
경영대학 경영학 전공
백 현 미

백현미의 경영학박사 학위논문을 인준함
2012 년 12 월

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ABSTRACT

THE EFFECT OF ELECTRONIC WORD OF MOUTH ON MOVIE SALES:

FOCUSING ON TIME, CHANNEL, AND VALUE

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With the rapid spread of social media, numerous things never imagined before are being realized. Many changes are evident in every corner of society because of the effects of social media. The current situation indicates a recent upsurge of interest in eWOM from various social media channels. This study overcomes the limitations of the existing research that could not present a unified interpretation of electronic word of mouth (eWOM). Thus, this study aims to analyze the impact of eWOM from three aspects of eWOM, namely, the time when eWOM is written, the social media channel that eWOM is written, and the value of eWOM. Our detailed research questions are as follows:

- Does the difference between pre- and post-consumption eWOM (disconfirmation) have an impact on movie revenue?
- How does the impact of eWOM on movie revenue change depending on the difference of social media channels on which eWOM is written?
- Is the impact of a valuable eWOM stronger than other forms of eWOM? If so, what is a valuable eWOM?

This study collects eWOM information on movies from February to August 2012 from Twitter, Yahoo! Movies (online review site), blog, and YouTube (free video sharing site) on a daily basis from two or three weeks before opening to closing. This study also collects the sales information on the movies on a weekly basis from BoxOfficeMojo.com. Using text mining analysis, this study classifies tweets into four, namely, intention tweet, positive tweet, neutral tweet, and negative tweet. Additionally, to examine the value of eWOM, 15,059 online reviews on various products in Amazon.com are randomly collected. Based on these data, three studies are conducted to answer the research questions.

The first study on time of eWOM investigates the impact of pre- and post-consumption eWOM on sales based on expectation confirmation theory. Consequently, the disconfirmation in the number of tweets before and after opening has a negative impact on the film sales. This premise suggests that forming a higher expectation than the substantial value does not always bring about positive results, in the current situation that the eWOM on the substantial value of movies spreads rapidly.

The second study is a comparative analysis of eWOM channels on how the impact of eWOM on movie sales differs on the social media channel where eWOM is written. Based on Rogers's innovation diffusion model, this study analyzes whether the impact of each social media on innovators and imitators is significantly different. The study also analyzes whether the impact in the initial and in the late stage of opening is significantly different. The result indicates that Twitter is relatively influential on the innovators in the initial stage of opening because of its mass media characteristic of spreading information rapidly in real time. On the other hand, Yahoo! Movies, one of online review sites, is found to be relatively influential on the imitators in the late stage of opening because of its interpersonal communication characteristic, showing a strong persuasion by collective intelligence. This study is academically significant because this is the first work that attempts to classify social media channels from the perspective of the "impact of social media" using actual eWOM data. Moreover, this study is expected to be utilized as basic data to present strategic directions from the corporate perspective in which social media is utilized by period or by purpose. This study also suggests the future direction of social media evolution.

The third study on the value of eWOM reveals that all forms of eWOM do not have the same influence, and determines which eWOM is valuable. The existing research could not draw consistent conclusions on the relationship between rating extremity and review helpfulness. The current study explores these reasons from the perspective of collective intelligence. Online review information from Amazon.com is utilized in this study, and the response surface methodology is used to demonstrate that when the individual review ratings are more consistent with the product average ratings, the helpfulness of reviews increases. In other words, most consumers tend to believe the reviews that are close to product average rating which is a kind of collective intelligence is more helpful. This observation can be interpreted to show that collective intelligence, which plays a major role in forming consumer attitudes toward product quality, is an important factor to determine review helpfulness. The findings of this study are expected to help draw a strategy that is available to reduce the information overload on consumer purchase decision and make online marketers understand the characteristics of helpful reviews.

This study has three contributions. First, the study contributes from the research methodology perspective. For this analysis, eWOM is collected as panel data from Twitter, Yahoo!Movies, YouTube, and blog. Text mining is utilized to collect the information on the contents of eWOM as quantified variables. eWOM information from

various social media channels is utilized, and a more extensive analysis is applied compared to the existing research. Second, the study contributes from the theoretical perspective. This study is significant in that the disconfirmation between pre- and post-consumption eWOM on the movie has a negative impact on the movie sales based on expectation confirmation theory. This study also determines that social media is divided into the media that has the characteristic of mass media or interpersonal communication based on the innovation diffusion model. Third, this study contributes from the practical perspective. The study is expected to present strategic directions for corporate eWOM management. Based on the findings from this study, a company is expected to identify eWOM characteristics by period and by media, and consider the differentiation of valuable eWOM that can be utilized to reveal more efficient eWOM management.

Keywords: Electronic Word of Mouth (eWOM), Social Media, Expectation Confirmation Theory, Innovation Diffusion Model, Collective Intelligence

Student Number: 2008-30155

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CHAPTER 1 INTRODUCTION

1.1 Research Background and Motivation

With the rapid spread of social media, various chan14ges are taking place across all sectors of society. Many changes are evident in every corner of society because of the effects of social media, such as promotional strategies using social media including YouTube by the stars of Hallyu, declaration of war through Twitter, and utilization of social media for an election campaign. The landscape of film has also significantly changed with the spread of social media into the movie world.

Social media plays a role in facilitating customer purchase decisions, as it expands the spread of word of mouth (WOM). Electronic word of mouth (eWOM) plays an important role as a reliable information source for consumers. This consumer-oriented information is helpful in making purchase decisions because it provides indirect product experiences (Park and Kim 2009). Consumer-oriented information may have greater credibility and relevance compared to seller-oriented information (Bickart and Schindler 2001). The existing studies have proved that eWOM is utilized as an important information source for consumers when they make purchase decisions (Basuroy et al. 2003; Chen et al. 2008; Chevalier et al. 2006; Dellarocas et al. 2007; Duan et al. 2008; Rui et al. 2011). Recently, with the important role of eWOM and the appearance of various social media channels, numerous studies on the impact of eWOM on sales have been conducted. However, the scope of published studies on the impact of eWOM is quite broad, and the studies appear relatively fragmented and inconclusive (Cheung and Thadani 2010). The limitations of existing studies are summarized in the following paragraphs.

First, studies on the impact of eWOM on revenue did not consider the time of writing the eWOM. The existing studies have investigated the impact of post-consumption eWOM on movie revenue after opening week (Duan et al. 2008; Rui et al. 2011; Qin 2011; Basuroy et al. 2003), or have attempted to show the impact of pre-consumption eWOM on opening week revenue (Asur et al. 2010; Dellarocas et al. 2007; Versaci 2009). Comprehensive studies on the impact of eWOM on movie revenue from before to after the release of movie are scarce.

Second, previous studies did not consider the eWOM channels. In the online review context (Dellarocas et al. 2007; Duan et al. 2008; Liu 2006), Twitter (Asur et al. 2010; Bughin 2011; Rui et al. 2011; Shin et al. 2011; Zhang et al. 2010), blogs (Qin 2011), and many other social media channels, studies on the impact of eWOM have been conducted. However, no comparative analysis on the impact of eWOM on sales depending on different social media channels has been performed although many studies consider the impact of eWOM from each social media channel.

Third, the findings of existing studies on the valuable eWOM especially on the aspect of rating extremity are inconclusive. Forman et al. (2008) reported that moderate book reviews are less helpful than extreme book reviews. Mudambi and Schuff (2010) pointed out that no significant relationship exists between review extremity and review helpfulness for search goods, and that review helpfulness for experience goods increases when the rating is moderate.

1.2 Research Goals and Research Questions

To overcome the limitations in the existing studies, this study aims to analyze the impact of eWOM by dividing the eWOM into three dimensions, namely, time, channel, and value of eWOM.

The first dimension is on the time of eWOM, the moment or period when eWOM is written. To perform a more in-depth analysis of the impact of eWOM on revenue, this study considers pre-consumption eWOM (eWOM before movie release) and post-consumption eWOM (eWOM after movie release) as influence factors on movie revenue, and investigates the interaction between the two from the perspective of expectation confirmation theory (ECT). According to Oliver (1980), consumers usually have some expectations from a particular product before they consume. Such expectations compare with their perception formed after they consume. The consumer satisfaction level is formed by the difference between expectation and performance (i.e., disconfirmation) and expectation. In this respect, this study focuses on how movie revenue is influenced by the difference between the eWOM regarding the expectation before movie release and the eWOM regarding perceived performance after movie release. This study will draw implications to demonstrate that forming higher expectations than actual values in the situations where the eWOM on the actual values of movie rapidly spreads does not always bring good results.

The second dimension is on the channels of eWOM. No studies have been made on whether the eWOM characteristics would depend on the social media channel. However, information searchers obtain information on the same subject from various social media channels, such as Twitter, online boards, YouTube, and blogs. Nevertheless, do they recognize the information or data obtained from various social media channels in the same manner? Treating each social media channel identically is problematic. Thus, identifying the differences of impact among social media channels is necessary. Based on Rogers's diffusion of innovation model, innovators are greatly affected by mass media, whereas imitators by interpersonal communication (Rogers 2003). Therefore, the current study investigates how the influence of eWOM from each social media channel, such as Twitter, online review site, YouTube, and blog, differs by period. Many companies are able to measure the communication among consumers and provide multifarious ways to market their products or services with the appearance of various social media channels (Hennig-Thurau et al. 2010). Thus, companies need to figure out how the eWOM from each social media channel is influential in consumer purchase decision by period. Hence, this study can provide implications that a company should find a way to manage eWOM by period through social media channel. Moreover, the study is expected to draw the evolving direction of social media channel to expand the influence of eWOM.

The third dimension is on the value of eWOM. In the existing studies, the relationship between the valuable eWOM (helpfulness of online review) and the message sidedness of eWOM (rating extremity of online review) is inconclusive. The existing studies have attempted to identify the relationship between review helpfulness and rating extremity without consideration of consumer attitude toward product quality. Mudambi and Schuff (2010) attempted to identify the reason for the inconsistent findings of not considering product type (search good versus experience good). However, the present study aims to analyze why these mixed findings have been drawn from the collective intelligence perspective. This study demonstrates that the reason for the inconsistent findings is the non-consideration of the collective intelligence (majority attitude toward a product), rather than the product type.

Thus, the study attempts to answer the following research questions:

- Does the difference between pre- and post-consumption eWOM (disconfirmation) have an impact on movie revenue?
- How does the impact of eWOM on movie revenue change depending on the difference of social media channels on which eWOM is written?
- Is the impact of a valuable eWOM stronger than other forms of eWOM? If so, what is a valuable eWOM?

This study attempts to collect the daily eWOM on over 145 movies released from February to August 2012. The panel data on eWOM are collected from Twitter, Yahoo! Movies, YouTube, or blogs, two or three weeks before the release until after the release. This study also collects movie information such as MPAA rating, genre, and weekly movie revenue data from BoxOfficeMojo.com. Based on the collected data, the study attempts to find an answer for each research question.

As the research domain, movie is selected for two reasons. First, movie is an experience good that an individual cannot see how good it is before he or she purchases. For experience good, eWOM is considered as an important information source. Second, eWOM and revenue information about movie are relatively easy to obtain. For most of the items, revenues are unknown. For example, book sales are reversely calculated through sales ranking in a previous study (Chen et al. 2004).

The current study has several contributions. From the first study on time of eWOM, forming the expectations appropriate for the actual movie values is important. The findings of this study are also expected to help a company's strategic decision making by increasing the accuracy of its revenue forecasting.

From the second study on channel of eWOM, the social media channels can be classified based on the actual data from the perspective of social media impact. This study also suggests that the social media can be explained by the characteristics of mass media and interpersonal communication from Rogers's perspective of innovation diffusion model. These findings are expected to provide some suggestions in which social media channel is appropriate for use according to the purpose of eWOM management.

From the third study on value of eWOM, this study serves as a starting point in developing new perspectives on the effects of consumer attitude toward product quality on the relationship between review rating and review helpfulness. The findings of this study are expected to be helpful for drawing a strategy to reduce the information overload for consumers as online market owners come to understand the characteristics of helpful online reviews.

CHAPTER 2 LITERATURE REVIEW

This chapter is a literature review on eWOM, expectation confirmation theory, innovation diffusion theory, and collective intelligence.

2.1. Electronic Word of Mouth

2.1.1 Definition of eWOM

Traditional word of mouth (WOM) is defined as "informal, person-to-person communication between a perceived noncommercial communicator and a receiver regarding a brand, a product, an organization, or a service" (Anderson 1998; Harrison-Walker 2001). WOM has evolved into electronic word of mouth (eWOM) communication because of the growth of the Internet. eWOM is defined as "any positive or negative statement made by potential, actual, and former customers about a product or a company via the Internet" (Cheung and Thadani 2010).

The existing studies suggest that eWOM differs from WOM in various aspects. First, generating eWOM has no restrictions on time and space (Lee 2009). Anyone who can use the Internet can generate and utilize eWOM. Information seekers are able to find numerous pieces of eWOM information if they are online at any time. Second, eWOM transmitted in the form of written text via Internet bulletins does not disappear. Thus, the diffusion rate is faster and the scope is broader (Sung et al. 2002).

Aside from these advantages, eWOM has a few disadvantages. First, most of eWOM are created by anonymous strangers, not by acquaintances. For this reason, determining the reliability of eWOM is difficult (Nakayama et al. 2010). Second, giving an immediate feedback in eWOM than in WOM is challenging (Sung et al. 2002), whereas individuals can communicate in real time in WOM.

2.1.2 Social Media as eWOM Channels

Social media is defined as “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user generated content (UGC)” (Kaplan and Haenlein 2010). Social media channels have various kinds (e.g., social networking, text messaging, shared photos, podcasts, streaming videos, wikis, blogs, discussion groups), such as Facebook, Twitter, LinkedIn, YouTube, online review sites, and blogs (Hanna et al. 2011).

Social media itself grows like a sort of organism: users voluntarily participate, share information, and create contents by making the most of interactivity. Social media has an advantage in terms of cost compared to the existing media. Anyone can obtain information or write with no time and space constraints. Social media has radically changed the ways of interacting.

Discerning the types of social media channels is not easy (Hanna et al. 2011). Few studies classify the types of social media (Kaplan and Haenlein 2010; Kietzmann et al. 2011). Kaplan and Haenlein (2010) mentioned six different types of social media, namely, collaborative projects (e.g., Wikipedia), blogs and microblogs (e.g., Twitter), content communities (e.g., YouTube), social networking sites (e.g., Facebook), virtual game worlds (e.g., World of Warcraft), and virtual social worlds (e.g., Second Life). The six different types of social media are divided by social presence and self-presentation. Kietzmann et al. (2011) provided a framework to classify social media using seven functional building blocks, such as identity, conversations, sharing, presence, relationships, reputation, and groups. The constructs enable researchers to understand how different levels of social media functionality can be configured (Kietzmann et al. 2011).

2.1.3 Overview of eWOM Literature

Chan and Ngai (2011) divided many eWOM studies into input, process, and output of eWOM, from the IPO (input-process-output) perspective. "Input of eWOM"-related studies have mostly focused on writer's motivation, reader's motivation, and marketer's motivation (Chan and Ngai 2011). "Process of eWOM"-related studies have concentrated on eWOM platform, system, interface/site design, message characteristics, and eWOM information interpretation/processing (Chan and Ngai 2011). "Output of eWOM"-related studies, which occupy the largest portion in eWOM studies, have focused on the impact of eWOM on consumer purchase decisions and sales (Chan and Ngai 2011). The present study mainly belongs to the "output of eWOM" category, because it aims to analyze the impact of eWOM on movie revenue. Therefore, this study summarizes the existing studies related to the impact of eWOM.

Existing studies have focused on various kinds of products to examine the impact of eWOM on revenue. Movie (Dellarocas et al. 2007; Duan et al. 2008a; Duan et al. 2008b; Liu 2006; Qin 2011), book (Chen et al. 2004; Chevalier et al. 2006), stock (Zhang et al. 2010), brand image (Bughin 2011; Zhang et al. 2011), hotel (Ye et al. 2010), music album (Morales-Arroyo and Pandey 2010), and many other products have been investigated in existing studies. Existing studies have also focused on various kinds of social media channels as eWOM sources. In the context of online review (Dellarocas et al. 2007; Duan. et al. 2008; Liu 2006), Twitter (Asur et al. 2010; Bughin 2011; Rui et al. 2011; Shin et al. 2011; Zhang et al. 2010), blog (Qin 2011) and many other social media channels, studies on the impact of eWOM have been conducted.

In the movie context, many studies have investigated the impact of eWOM from online review sites on movie revenue (Dellarocas et al. 2007; Duan et al. 2008a; Karniouchina 2010; Liu 2006; Moon et al. 2010). Liu (2006) observed that the volume of eWOM has a positive impact on box-office revenue, but eWOM valence does not have a significant impact on box-office revenue. Dellarocas et al. (2007) presented a model that can be used to predict box-office revenue in the opening weekend concerning 80 films, based on innovation diffusion model. They revealed that the early volume of online review could be used as a proxy for early sales. They also revealed that the valence of user review could predict the coefficient of internal influence of movie and the rate of decay of a movie's coefficient of external publicity. Duan et al. (2008a) investigated daily review and daily movie revenue data for two weeks after 71 films had been released. They found that user rating does not have a significant impact on movie revenue (persuasive effect), whereas the volume of reviews has a significant positive impact on movie revenue. Karniouchina (2010) suggested that movie buzz has a positive impact on box-office revenue during the entire theatrical release of the movie, but star buzz has its positive impact mainly on the opening week. Moon et al. (2010) examined the impact of the movie ratings from professional critics, amateur communities, and viewers themselves on the movie performance. As a result, they found that high early movie revenue is related to subsequent movie ratings, and the high advertising spending on movies with high ratings maximizes movie revenue.

Recently, several studies have examined the impact of eWOM from Twitter on movie revenue (Asur and Huberman 2010; Rui et al. 2011). Asur and Huberman (2010) predicted the opening week box-office revenue using the tweet rate in the pre-release week (the number of tweets referring to a particular movie per hour). They revealed that the explanatory power is higher when considering sentiments presented in tweets. Rui et al. (2011) indicated that the total number of tweets has a positive effect on box-office revenue. They also suggested that a tweet with many followers has a stronger impact on box-office revenue.

In the trailer site context, Versaci (2009) found that three-week pre-release forms of eWOM, such as trailer views, message board comments, and votes, have a positive impact on the opening weekend box-office revenue. In the blog context, Qin (2011) reported a significant relationship between the volume of word-of-blog and box-office revenue.

In the book revenue context, Chen et al. (2004) found that consumer rating is not related to book sales; however, the number of consumer reviews has a significant positive impact on book sales. Chevalier and Mayzlin (2006) also investigated the impact of online reviews on the book sales from the biggest book sales sites, such as Amazon.com and Barnesandnoble.com. They noted that the volume of eWOM has an impact on book sales ranking in both book-selling sites. The impact of eWOM valence is limited, and one-star review (negative review) has a bigger impact on sales than five-star review (positive review).

Godes and Mayzlin (2004) showed that eWOM dispersion is positively related to future rating, and its impact diminishes as time goes on. On the other hand, they found that WOM volume is not significantly related to future rating. In the context of book, CD, and video, Hu et al. (2008) asserted that quantitative aspects such as review rating, and qualitative aspects such as reviewer quality and reviewer exposure, have impacts on sales. Gu et al. (2012) suggested that the impact of the retailer's internal eWOM on sales is somewhat limited in high-involvement products such as digital camera. In other words, the impact of the retailer's external eWOM on digital camera sales is stronger than the impact of the retailer's internal eWOM. Table 2-1 summarizes the existing studies on the impact of eWOM on revenue.

Table 2-1. Previous Studies on the Impact of eWOM on Product Sales

Study	eWOM sources	Research Context	Findings
Liu (2006)	Yahoo!Movies	Movie	· The volume of eWOM has a positive impact on box office revenue · The valence of eWOM does not have an impact on box office revenue · There is a high expectation of a movie before film release, but the valence of WOM is lower after film release
Dellarocas et al. (2007)	Yahoo!Movies		· The early volume of online review can be used as a proxy for early sales · The valence of online review can predict the coefficient of internal influence of movie and the rate of decay of a movie's coefficient of external publicity
Duan et al. (2008a)	Yahoo!Movies		· The rating of review does not have a significant impact on the movie revenue (persuasive effect) · The volume of review has a positive impact on the movie revenue (awareness effect)
Karniouchina (2010)	Internet Movie Database (IMDB) & Yahoo!Movies		· Movie buzz has a positive impact on box office revenues during the entire theatrical release of the movie · Star buzz has a positive impact mainly on the opening week
Moon et al. (2010)	Yahoo!Movies & Rotten Tomatoes Movie		· High early movie revenue is related to subsequent movie ratings · High advertising spending on movies with high ratings maximizes the movie revenue
Asur and	Twitter		· The tweet rate in the pre-release week (the number of tweets referring to a

Huberman (2010)			particular movie per hour) can explain the opening weekend box office revenue · The explanatory power is higher when considering sentiments presented in tweets
Rui et al. (2011)	Twitter		· The number of tweets has a positive effect on box office revenue · Tweet with many followers had a larger impact on box office revenue
Versaci (2009)	TrailerAddict, ComingSoon, Fandango& Rotten Tomatoes		· Three-week pre-release eWOM such as trailer views, message board comments, and votes has a significantly positive impact on the opening weekend box office revenue
Qin (2011)	BlogPulse		· There is a casual relationship between the volume of word-of-blog and box office revenue · Word-of-blog volume can be a predictor of movie sales and its result as well.
Chen et al. (2004)	Amazon.com	Book	· The valence of consumer rating is not related to product sales · The number of consumer reviews had a significant positive impact on sales.
Chevalier and Mayzlin (2006)	Amazon.com & BN.com		· The volume of eWOM has an impact on book sales in Amazon.com and Barnesandnoble.com · The impact of eWOM valence on book sales is limited · One-star review has a bigger impact on book sales than five-star review
Godes and Mayzlin (2004)	Usenet	TV Show	· eWOM dispersion is positively related to future rating and its impact diminishes as time goes on

			· The volume of eWOM is not significantly related to future rating
Hu et al. (2008)	Amazon.com	Book, CD, Video	· In online review, Quantitative aspects like review rating, etc and qualitative aspects such as reviewer quality, reviewer exposure, etc have positive impacts on sales
Gu et al. (2012)	Amazon.com, Cnet, DpReview & Epinions	Digital camera	· The impact of retailer's internal eWOM on sales is somewhat limited in high-involvement products such as digital camera (limited influence on its sales) · The impact of retailer's external eWOM on digital camera sales is stronger than the impact of retailer's internal eWOM

2.1.3 Dimensions of eWOM: Time, Channel, and Value

This chapter investigates existing literature on the impact of eWOM on product sales from various dimensions of eWOM, namely, time, channel, and value of eWOM.

Time of eWOM

The impact of pre-consumption eWOM (Asur and Huberman 2010; Dellarocas et al. 2004; Versaci 2009) and the impact of post-consumption eWOM (Basuroy et al. 2003; Chen et al. 2004; Chevalier and Mayzlin 2006; Duan et al. 2008a; Eliashberg and Shugan 1997; Qin 2011; Rui et al. 2011) have been analyzed independently. These studies found that for movies, pre-consumption eWOM has an impact on opening weekend revenue, whereas post-consumption eWOM has an impact on the revenue after the opening weekend.

Channel of eWOM

More studies on the impact of eWOM from each social media are actively underway with the recent developments in various social media channels. Most studies focus on the impact of eWOM from online review websites, such as Yahoo! Movies and IMDB (Duan et al. 2008a; Karniouchina 2010; Liu 2006). However, many recent studies investigated the impact of eWOM from various social media channels, such as Twitter (Asur and Huberman 2010; Rui et al. 2011), trailer site (Morales-Arroyo and Pandey 2010; Versaci 2009), and blog (Morales-Arroyo and Pandey 2010; Qin 2011).

However, few comparative studies exist on the impact of eWOM from various social media channels on product sales. Moreover, few studies considered various kinds of eWOM from various social media channels (Morales-Arroyo and Pandey 2010; Oghina et al. 2012). Nevertheless, these studies have focused on developing the revenue prediction model more accurately, not comparing the eWOM type from various social media channels. Morales-Arroyo and Pandey (2010) analyzed the impact of eWOM from various social media channels on music album revenue. They considered blog posts, YouTube comments, YouTube views, YouTube video count, MySpace postings, and MySpace listening as various kinds of eWOM. After analyzing the impact of eWOM on the 12-week album sales, they found that each eWOM content has a different impact by period, and consequently, the combination of eWOM contents best describes the music album sales. Oghina et al. (2012) maintained that eWOM is not isolated from various channels, but rather each is linked to a particular movie. They showed that if all eWOM contents from Twitter and YouTube regarding 60 films are combined, they could best describe IMDB's rating.

Value of eWOM

Several studies have reported contradictory results on the relationship between message sidedness and message effectiveness, and inconsistent findings have been observed. Several studies have indicated that two-sided messages can enhance credibility (Eisend 2006; Golden and Alpert 1987; Hunt and Smith 1987; Kamins and Marks 1987). Two-sided messages significantly enhance the perceived credibility of the source, reduce negative cognitive responses, and enhance the brand attitude and purchase intention (Eisend 2006). Golden and Alpert (1987) contended that two-sided arguments can elicit more positive perceptions of the form of communication used, including an increase in message believability. Kamins and Marks (1987) observed that the use of the two-sided reputational appeal seems to enhance the credibility of the advertiser. On the other hand, Hunt and Smith (1987) suggested that two-sided messages are less effective in promoting seller credibility and message acceptance in the personal selling context compared to one-sided messages. Several studies have also reported contradictory results in the domain of reviews. Schlosser (2005) found that two-sided reviews (one-sided review) are more credible and lead to a more positive attitude toward a movie when source ratings are moderate (extreme). Forman et al. (2008) asserted that moderate book reviews are less helpful than extreme book reviews. Mudambi and Schuff (2010) maintained that the reason for the inconsistency in the findings results from the discounting of the product type. Based on actual online reviews from Amazon.com, they implied that the extremity and depth of the review as well as the product type affect the helpfulness of the review. In their research, they concluded that no significant relationship exists between review extremity and review helpfulness for search goods, and that review helpfulness for experience goods increases when the rating is moderate.

Table 2-2 analyzes the existing studies based on three dimensions of eWOM. Each element from the first two perspectives has respective studies, but few comprehensive ones. Moreover, the findings from the existing studies in terms of valuable eWOM are inconclusive.

Table 2-2. Three Dimensions of eWOM: Time, Channel, Value

Dimensions of eWOM		Studies
Time of eWOM	Pre-consumption eWOM	Dellarocas et al. (2007); Asur et al. (2010); Versaci (2009)
	Post-consumption eWOM	Chen et al. (2004); Chevalier et al. (2006); Duan. et al. (2008); Eliashberg et al. (1997); Liu et al. (2011); Qin (2011); Basuroy et al. (2003)
Channel of eWOM	Twitter	Asur et al. (2010); Liu et al. (2011)
	Online Review Website (ex. Yahoo!Movies, IMDB, etc.)	Duan. et al. (2008); Karniouchina (2010); Liu (2006)
	Video Sharing Site (ex. YouTube, TrailerAddict, etc.)	Versaci (2009)
	Blog	Qin (2011)
Value of eWOM	Moderate eWOM	Mudambi and Schuff (2010)[1]
	Extreme eWOM	Forman et al. (2008)[2]

1. Experience good
2. Book

Other Dimensions of eWOM

Except for the three dimensions of eWOM, a number of studies attempted to understand eWOM in various aspects. Table 2-3 also summarizes the existing studies based on these dimensions of eWOM.

First, the existing studies examined the impact of various elements of eWOM on product sales. The representative characteristics of eWOM include volume, valence, and dispersion. eWOM volume means the amount of eWOM disseminated (Bin Gu 2012). eWOM valence refers to customer opinions (positive or negative) about product quality (Bin Gu 2012). eWOM dispersion is defined as the extent to which customer conversations about product quality are taking place across a broad range of communities (Godes et al. 2004). However, these research findings are mixed. Most studies have found that eWOM volume has a significantly positive impact on product sales (Asur et al. 2010; Chen et al. 2004; Chevalier et al. 2006; Duan et al. 2008; Liu 2006; Rui et al. 2011; Qin 2011; Versaci 2009), and Godes et al. (2004) maintained that eWOM volume is not related to future rating. For eWOM valence, studies that suggest valence has a significantly positive impact on product sales or is likely to do so (potential) (Chevalier et al. 2006; Dellarocas et al. 2007; Hu et al. 2008; Rui et al. 2011) have been mixed or have no impact at all (Chen et al. 2004; Duan et al. 2008; Rui et al. 2011). Yang et al. (2011) explored the impact of eWOM valence on mass movies and niche movies to determine the reason why the impacts of eWOM valence on movie revenues are mixed in the existing studies. For niche movies, eWOM valence has a significant impact, but for mass movies, it does not.

Second, WOM is both an influencer and predictor (Eliashberg et al. 1997; Basuroy et al. 2003). Eliashberg et al. (1997) demonstrated that critical reviews are stronger as predictor rather than influencer, by showing the impact that critical reviews have on box-office revenue, but the effect is temporary from the five-week data of the entire eight-week data. On the other hand, Basuroy et al. (2003) suggested that critical reviews play both roles as predictor and influencer, because critical reviews have a significant impact on the entire eight-week box-office revenue.

Third, studies have attempted to understand both the awareness and persuasive effects of eWOM (Duan et al. 2008a; Godes and Mayzlin 2004; Rui et al. 2011). Godes and Mayzlin (2004) revealed that eWOM in TV shows has a significant impact on TV show performance by showing that more dispersion to various media can increase the awareness effect. Duan et al. (2008a) suggested that as the awareness effect provides information on the existence of a product, consumers consider the product as their choice set. On the other hand, the persuasive effect forms the consumer attitude and evaluation toward the product, ultimately affecting the purchase decision. They analyzed the impact of movie reviews on movie revenue, and found that the review valence has no significant impact on movie revenue, but the volume has a significantly positive impact on it. According to Duan et al. (2008a), this outcomes indicates that online reviews have an awareness effect. Rui et al. (2011) explained that Twitter is a push mode and a suitable eWOM to be seen as an awareness effect, and demonstrated that eWOM in Twitter can have both awareness and persuasive effects.

Table 2 -3. Other Dimensions of eWOM

Dimensions of eWOM			Studies
Volume vs. Valence	Volume	Yes	Asur et al. (2010); Chen et al. (2004); Chevalier et al. (2006); Duan et al. (2008); Liu (2006); Liu et al. (2011); Qin (2011); Versaci (2009)
		No	Godes et al. (2004)
	Valence	Yes	Chevalier et al. (2006); Dellarocas et al. (2007); Hu et al. (2008); Liu et al. (2011)
		No	Chen et al. (2004); Duan et al. (2008); Liu et al. (2011)
Influencer vs. Predictor	Influencer		Basuroy et al. (2003)
	Predictor		Eliashberg and Shugan (1997); Basuroy et al. (2003)
Awareness vs. Persuasive	Awareness Effect		Duan et al. (2008a); Godes and Mayzlin (2004); Rui et al. (2011)
	Persuasive Effect		(Rui et al. 2011)

2.2 Theoretical Backgrounds

2.2.1 Expectation Confirmation Theory

Since its appearance in the early 1970s, expectation confirmation theory (ECT) has become an essential theory for the study of consumer satisfaction and dissatisfaction. According to Oliver (1980)'s ECT, the level of consumer satisfaction is formed by the difference between expectation and performance (i.e., disconfirmation) and expectation. In other words, consumers tend to expect a product to some extent before they consume, and then compare it to what they perceived after using a product or service. Consumer expectation acts as a comparison standard to compare a particular service or product performance. The level of expectation before consumption is consistent with the perceived performance after consumption determines consumer satisfaction with a particular product or service. If the perceived performance of a product or service is higher than expected, consumers form positive disconfirmation; if the perceived performance is lower than expected, they form negative disconfirmation; and if the perceived performance is the same as what they expected, they form simple confirmation. According to this theory, if expectation confirmation and disconfirmation forms, dissatisfaction ensues. The causal relationship between disconfirmation and satisfaction, as well as the direct effect between expectation and satisfaction, appears significant regardless of product, situation, and research method. Figure 2-1 schematizes the ECT in Oliver (1980).

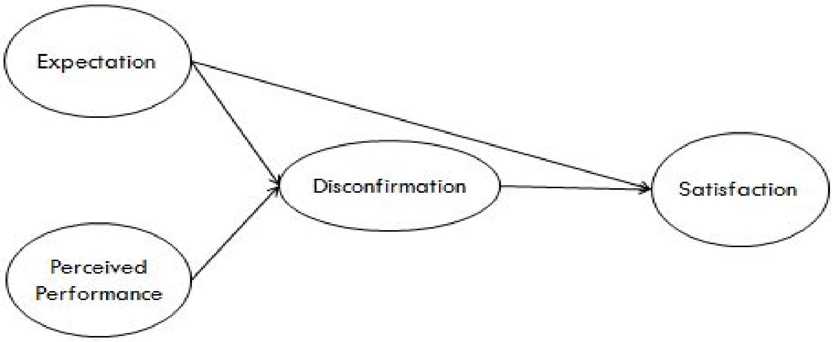

Figure　2 -1 Expectation Confirmation Theory

Tse and Wilton (1988) presented a comprehensive theoretical basis for the direct effect of perceived performance in addition to expectation and disconfirmation presented by Oliver (1980), as an influencing factor to satisfaction. Figure 2-2 schematizes the ECT presented by Tse and Wilton (1988). Expectation is defined as "individual beliefs or sum of beliefs about the levels of attributes possessed by a product/service" (e.g., Oliver and Linda, 1981; Churchill and Surprenant, 1982; Bearden and Teel, 1983). The present study views that expectation, disconfirmation, and perceived quality as preceding variables have a direct effect on satisfaction based on the expanded ECT.

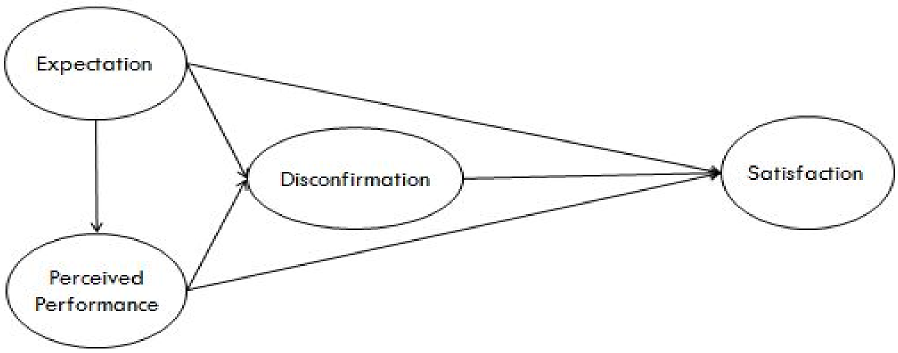

Figure　2 -2 Extended Expectation Confirmation Theory

After Bhattacherjee (2001) investigated the continuous use of online banking service, a number of IS researchers have conducted studies on the continuous use of IS using ECT (Bhattacherjee 2001; Bhattacherjee and Premkumar 2004; Hsu et al. 2004; Lee 2010; Lin et al. 2005; McKinney and Yoon 2002; Thong et al. 2006). In the IS field, the ECT is combined with various theories to explain the continuous use of IS by users. Bhattacherjee (2001) examined the continuous use of online banking service based on ECT and TAM (technology acceptance model). McKinney and Yoon (2002) explored customer satisfaction with website for long-term customer retention in e-commerce. Hsu et al. (2004) proposed that self-efficacy is a factor contributing to the continuous use of the web. Lin et al. (2005) investigated the value of including "playfulness" in ECT in explaining the continued use of a website. Thong et al. (2006) suggested perceived ease of use, perceived usefulness, perceived playfulness, confirmation, and satisfaction as explanatory variables to explain the consistent use of mobile Internet service. Lee (2010) suggested perceived usefulness, attitude, concentration, subjective norm, perceived behavior control, and confirmation as explanatory factors that affect the consistent use of e-learning. Table 2-4 summarizes the existing studies in the IS domain that have used ECT.

Various factors are considered from different perspectives and research areas; nevertheless, the common finding is that the consistent intention to use is determined by confirmation between expectation and personal experience with IS. This study verifies the hypothesis that confirmation between expectation (pre-consumption eWOM) and perceived performance (post-consumption eWOM) will have positive impacts on movie sales from the group perspective.

Table 2-4. Expectation Confirmation Theory used in IS Domain

Study	Theory	Independent Variables	Mediating Variables	Dependent Variables	Domain
Bhattacherjee (2001)	Expectation Confirmation Theory; Technology Acceptance Model	Perceived usefulness; Confirmation	Satisfaction	IS continuance intention	Online banking
McKinney and Yoon (2002)	Expectation Confirmation Theory	IQ (information quality) & SQ (system quality) expectation	IQ & SQ perceived performance; IQ & SQ disconfirmation; Web IQ & SQ satisfaction	Web customer satisfaction	Online shopping
Hsu et al. (2004)	Expectation Confirmation Theory; Social Cognitive Theory	Prior perceived disconfirmation; Internet self-efficacy	Satisfaction with prior use; Outcome expectations	WWW continuance intention	WWW application
Lin et al. (2005)	Expectation Confirmation Theory; Flow Theory	Confirmation	Perceived usefulness; Perceived playfulness; Satisfaction	Continuance intention	Web site
Thong et al. (2006)	Expectation Confirmation Theory; Technology Acceptance Model	Confirmation	Perceived ease of use; Perceived usefulness; Perceived enjoyment; Satisfaction	Continued IT usage intention	Mobile internet service
Lee (2010)	Expectation Confirmation Theory; Technology	Confirmation; Perceived ease of use; Perceived enjoyment;	Perceived usefulness; Satisfaction; Attitude	Continued Intention	e-learning

	Acceptance Model; Theory of Planned Behavior; Flow Theory	Concentration; Subjective norm; Perceived behavior control			

2.2.2 Diffusion of Innovation Model

The diffusion of innovation model, which started from several academic areas in the 1940s and the 1950s, is a persuasion model that reveals how new innovations in society or organization had spread (Rogers 2003). Specifically, the model developed several questions into one generalized model; the questions include the following: Which types of innovation spread quickly? Which members will accept the innovation sooner or later over time? How do the communication channels that members use differ? How does the diffusion of innovation differ depending on the social norm and social system? How does critical mass form in the course of diffusion? What should be the role of an opinion leader in the course of diffusion? (Rogers 2003). Such diffusion studies have been utilized in diverse academic areas, such as social psychology, communications, public relations, advertising, marketing, consumer behavior, public health, and rural sociology (Rogers 2003).

The current study investigates the meaning of diffusion and the components of innovation diffusion as defined by Rogers (2003). Diffusion refers to "the process in which an innovation is communicated through certain channels over time among the members of a social system." The four main elements of diffusion include innovation, communication channels, time, and the social system. Innovation is defined as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption." Communication channel is a means to convey innovation messages from one individual to another. Given that mass media channel is a means to inform a potential adopter of the existence of the innovation, interpersonal channel is effective in persuading others to accept a new idea. The temporal dimension of diffusion is related to the innovation-decision process, the innovativeness of an individual or other unit of adoption, and an innovation's rate of adoption in a system. As innovation-diffusion occurs in a social system, the structure of the social system affects innovation-diffusion in various aspects.

This study explores communication channels from the perspective of Rogers (2003). As stated previously, communication channels are classified into interpersonal communication and mass media in the course of diffusion. Largely, each channel plays a role to create knowledge (mass media), or to persuade individuals to change their attitude toward innovation (interpersonal communication). According to Rogers (2003), mass media channel pertains to the "means of transmitting messages that involve a mass medium, such as radio, television, newspapers, and so on, which enables a source of one or a few individuals to reach an audience of many." Mass media can reach a large audience rapidly, create knowledge and spread information, and change weakly held attitudes. On the other hand, interpersonal communication channel means communication between two or more individuals (Rogers 2003). Interpersonal communication channels can provide a two-way exchange of information, and persuade an individual to form or to change a strongly held attitude (Rogers (2003). Marketing/Management diffusion tradition has attracted more attention since the start of the 1960s, and recently expanded with the increased use of Internet for service marketing (Rogers 2003). The first purchase-diffusion models that are well-known in the field of marketing/management diffusion include Fourt and Woodlock (1960), Mansfield (1961), and Bass (1969); among these models, the most representative diffusion model is that of Bass (1969). The model proposed by Fourt and Woodlock (1960) considers only the innovative purchaser, whereas that of Mansfield (1961) considers only the imitative purchaser. In the diffusion model proposed by Bass (1969), both the innovative purchaser and imitative purchaser are considered. Bass (1969) hypothesized that the innovative purchaser would be affected by mass media communications, whereas the imitative purchaser would be affected by WOM communications before accepting new products (durable). In other words, potential purchasers are divided into two groups. Innovative purchasers are affected by external influencers such as promoting activities or marketing communications; hence, a formed early adopter-group expands; meanwhile, imitative purchasers accept new products, and are affected by internal influencers, including WOM (Bass 1969). The rate of product diffusion is determined by interpersonal communications between innovator and imitator (Rogers 2003).

A movie is a representative experience good Chung (2011). Considering that it shows no repeated purchase behavior, diffusion theory is applicable for movies. Using the diffusion model, Chung (2011) demonstrated that the initial base of movie viewers expand in the early times of film release when innovators are affected by promotion before release, and the imitators who hear about movie evaluations from them can decide to watch the movie. Therefore, the current study examines whether the diffusion model can explain the movie-accepting process. Social media is viewed as an evolved form of the existing mass media, and has the characteristics of interpersonal communication. The eWOM from each social media channel shows different degrees of convergence between mass media and interpersonal communication. Accordingly, eWOM by platform is expected to have a different influence.

2.2.3 Collective Intelligence

Collective intelligence refers to "the capacity of human collectives to engage in intellectual cooperation in order to create, innovate and invent" (Lévy 2010). Heylighen (1999) defined collective intelligence as "the ability of a group to solve more problems than its individual members." Collective intelligence is being investigated in various fields, including sociology, business administration, and computer engineering. Wheeler (1910), an entomologist, presented this concept for the first time based on his observation of the social behaviors of ants in the 1910s. Collective intelligence was defined sociologically by Russell (1983); later, the concept of collective intelligence in the cyberspace was defined by sociologists Lévy and Bonomo (1999). They argued that human society had formed the collective intelligence, sharing the ability and property of collective intelligence with scientific technology, thereby allowing us to reach the completion stage of the new evolution toward the true integration of humanity by overcoming the temporal and spatial restrictions.

Sulis (1997) suggested the following five major concepts of collective intelligence: stochastic determinism, interactive determinism, non-directed communication, non-representational contextual dependency, and stigmergy. Tapscott and Williams (2008) noted that collective intelligence is mass collaboration. The following four principles should exist to allow collective intelligence to occur: openness, peering, sharing, and acting globally.

Collective intelligence on the Internet has been actively used for a long time. Wikipedia, Google, Amazon.com's consumer reviews, CNET's product scores, Meta Blog's popular tags, and library bestseller lists exemplify the pervasiveness of collective intelligence on the Internet.

Most reviews on products and sellers in the Internet shopping malls become indispensable, and many people are making their purchase decisions by referring to these reviews. Malone et al. (2010) suggested averaging as one of important variants of group decision – voting, consensus, averaging, and prediction market – in collective intelligence. For example, anyone can rate a book from Amazon.com with a five-star scale, and this rating enables the presentation of the overall score of a book.

Furthermore, the evaluation of this collective intelligence is continuously attempted. Many online shopping malls including Amazon.com have a system to evaluate even this review. This study aims to perform an empirical analysis of whether the public relies on collective intelligence based on these evaluation data on Amazon.com reviews.

CHAPTER 3 RESEARCH MODEL

3.1. Research Model

This study investigates the impact of eWOM on product performance from various dimensions of eWOM. As shown in Figure 3-1, the impact of eWOM on product sales can be classified into three dimensions: time, channel, and value of eWOM. Based on these dimensions, the research model consists of three studies.

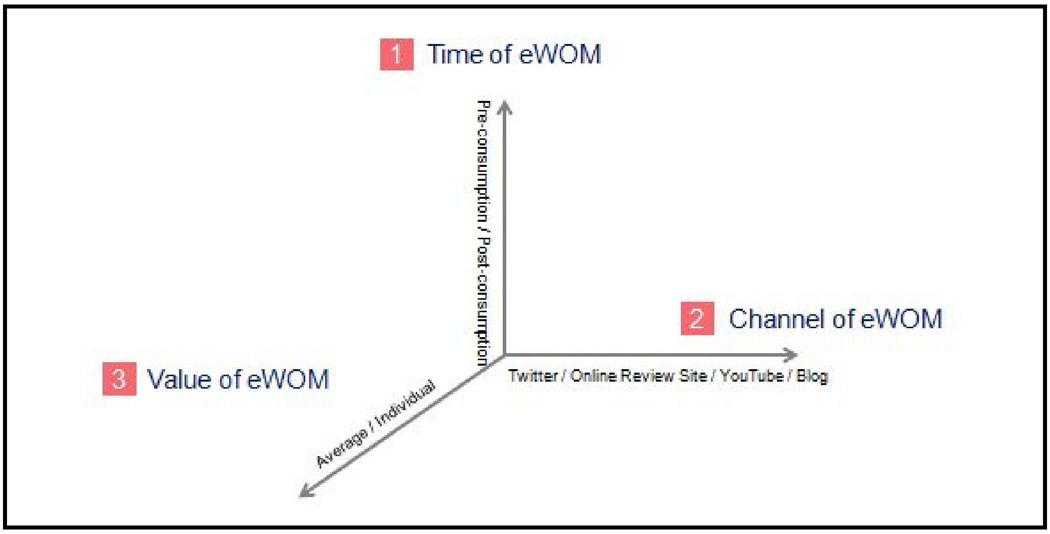

Figure 3-1. Three Dimensions of eWOM

The first study is on time of eWOM. As mentioned previously, the hypothesis that the disconfirmation between pre- and post-consumption eWOM affects movie sales according to the ECT will be verified. The impact of both pre-consumption eWOM, reflecting expectations, and post-consumption eWOM, reflecting consumer evaluations on movie revenue, will be examined.

The second study is on the channels of eWOM. A comparison of the impact of eWOM from each social media channel will be made based on the diffusion of innovation model. In this study, eWOM from Twitter, Yahoo! Movies, YouTube, and blogs will be analyzed. The impact of eWOM on innovators and imitators will be explored to determine how they differ, depending on the characteristics of eWOM from various social media channels.

The third study is on the value of eWOM. This study will investigate the impact of eWOM valence on sales by considering eWOM helpfulness. The hypothesis that the difference between the individual review rating and the product average rating is negatively related to the review helpfulness will be verified as well.

3.2 Research Hypotheses

3.2.1 Time of eWOM

The foundation of this theoretical framework is the ECT put forward by Oliver (1980). The current study proposes the following research model: expectation and disconfirmation, which is drawn from expectation and perceived quality, affect movie revenue. In other words, the research model suggests that in the movie context, eWOM, including pre-consumption eWOM, and disconfirmation between pre- and post-consumption eWOM, influences movie revenue (Figure 3-2).

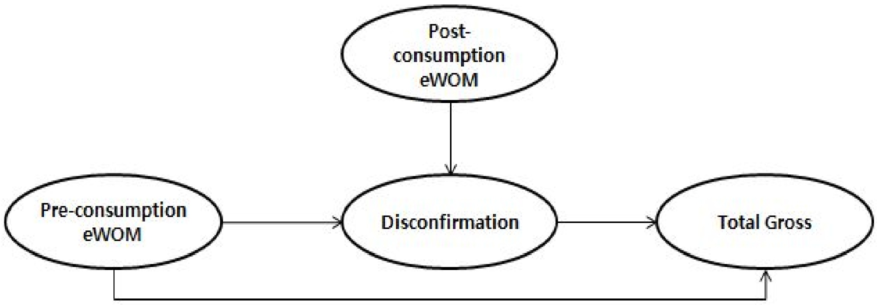

Figure 3 -2. Conceptual Research Model for Time of eWOM

Pre-consumption eWOM has a significant impact on opening weekend box-office revenue (Asur and Huberman 2010; Dellarocas et al. 2007; Versaci 2009; Yang et al. 2011). Asur and Huberman (2010) revealed that the tweet rate of pre-release week (i.e., the number of tweets referring to a particular movie per hour) can significantly affect the opening weekend box-office revenue. Dellarocas et al. (2007) presented a model to predict the opening weekend box-office revenue based on the diffusion model. Versaci (2009) revealed that three-week pre-release Internet buzz, such as trailer views, message board comments, and votes of desire, had a significant impact on the opening weekend box-office revenue.

Hypothesis 1: The volume of pre-consumption eWOM will have a positive impact on opening week movie revenue.

A number of studies suggested that eWOM regarding the experiences with purchased products or services had a significant impact on product or service sales (Asur and Huberman 2010; Chen et al. 2004; Chevalier and Mayzlin 2006; Duan et al. 2008a; Godes and Mayzlin 2004; Liu 2006; Qin 2011; Rui et al. 2011; Versaci 2009). Chen et al. (2004) revealed that the number of consumer reviews had a significant positive impact on sales. Chevalier and Mayzlin (2006) examined the impact on book sales of online reviews from the biggest book sales sites, such as Amazon.com and Barnesandnoble.com. They found that the WOM volume had an impact on marketability and ranking in both book-selling sites. Duan et al. (2008a) reported that the volume of reviews had a significant explanatory power on movie revenue. Qin (2011) cited a casual connection between volume of word-of-blog and box-office revenue. Rui et al. (2011) noted that the number of tweets had a positive effect on box-office revenue. Therefore, the present study posits the following:

Hypothesis 2: The volume of post-consumption eWOM will have a positive impact on movie revenue after opening week.

Oliver (1980) stated that the difference in the score between pre-purchase and post-purchase attitudes was significantly related to post-exposure satisfaction. In the online review context, Chung (2011) also revealed that WOM arising from expectation-performance disconfirmation had an impact on movie sales. He used netizens' pre- and post-consumption evaluations posted on the Korean movie sites as measures of movie expectation and movie quality, respectively. Therefore, the current study hypothesizes that disconfirmation between pre- and post-consumption eWOM is negatively related to total revenue.

Hypothesis 3: The volume disconfirmation between pre- and post-consumption eWOM will have a negative impact on movie revenue.

2.2.2 Channels of eWOM

Rogers (2003) asserted that mass media is one of the fastest and most efficient means of informing the presence of innovation (i.e., producing perception-knowledge), and it plays an important role among innovative users. Meanwhile, interpersonal communication is efficient means of persuading others to accept the new ideas, and it plays an important role among imitative users. In other words, the awareness effect plays an important role in the initial stage of innovation, and the persuasive effect in the later stage of innovation.

Rogers also stated that the innovation-decision process consists of knowledge, persuasion, decision, implementation, and confirmation. The current study focuses on knowledge and persuasion. In the knowledge stage, individuals mainly pursue innovative information. They want to know what innovation is, and how and why it works. Mass media panel plays a role in conveying this information effectively. In the persuasion stage, individuals look for evaluation information on the innovation to reduce the uncertainty of the results expected from the innovation. The interpersonal communication network is likely to convey evaluation information on the innovation. In this stage, mass media channel is relatively unimportant. Mass media message is essentially universal, whereas individuals who decide whether to adopt innovation or not want to know information in more detail.

Rogers presented the following characteristics to distinguish mass media from interpersonal communication.

The characteristics of mass media:

1. Mass media can reach a large audience rapidly (immediacy).
2. Mass media can produce knowledge and spread information (diffusibility).
3. Mass media can cause small changes toward the existing attitudes (persuasion).

The characteristics of interpersonal communication:

1. Information is exchanged in two directions (two-way communication).
2. Interpersonal communication can form strong attitudes in users, or help change their attitudes (persuasion).

Therefore, this study conducts a survey of the characteristics of social media channels based on the characteristics of mass media and interpersonal communication presented by Rogers (2003). The present study considers four social media channels as main sources of eWOM: Twitter, a representative social networking service (SNS) and microblog service; Yahoo! Movies, an online review site; YouTube, a free video sharing site; and blogs, in which users upload and share personalized posts. The existing studies have also focused on these sites, which represent noticeable eWOM activity sites (Asur and Huberman 2010; Dellarocas et al. 2007; Duan et al. 2008b; Gu et al. 2012; Hu et al. 2008; Qin 2011; Rui et al. 2011; Versaci 2009; Yang et al. 2009). Twitter, an online

SNS and microblog service, was launched in March 2006. In social media, users can see their connections with others, or show their social networks to others. Twitter enables users to share their tweets or microblogging postings that are limited to 140 characters. In March 2012, Twitter reported that its network has 140 million active users and hosts 340 million tweets a day.[1] YouTube, which was created in February 2005, is a website on which users can upload, watch, and share video clips. According to YouTube, its viewers watch three billion videos every day, and spend 23 minutes per day on the site.[2] Yahoo! Movies is an online discussion board for movies. Created in May 1998, Yahoo! Movies provides a large collection of information on movies such as trailers, clips, box-office information, show times, and movie theater information. Users are allowed to read and write reviews and ratings in this website. Blogs are defined as "websites that contain online personal journals with reflections by the writers and the opportunity for visitors to comment" (Thorson and Rodgers 2006). Blogs, which are periodically updated, include text, images, audio, video, and their combinations (Vickery and Wunsch-Vincent 2007). Interactive communication is possible as users can write their comments or replies on blogs or use trackbacks.

The possible classification of these four social media channels according to the characteristics of mass media and interpersonal communication is shown in Figure 3-3. A seven-point Likert scale survey of 17 experts was conducted to determine if each social media channel is closer to either mass media or interpersonal communication. As measures to differentiate mass media from interpersonal communication, the following four measures are utilized (Rogers 2003; Pavlik et al. 2011): immediacy, diffusibility, persuasion, and two-way communication.

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[1] http://mashable.com/2012/03/21/Twitter-has-140-million-users/

[2] http://www.youtube.com/advertise/watching.html

The factor loading values of the measures to classify mass media and interpersonal communication presented by Rogers (2003) were analyzed. As a result, two-way communication appeared to be inappropriate as the criterion for media classification from social media channels (Table 3-1). Hence, only immediacy, diffusibility, persuasion were used to classify mass media and interpersonal communication.

Table 3-1. Factor Loadings for Measure of Mass Media

Factor Loadings	
Immediacy	.953
Diffusibility	.879
Persuasion	.659
Two-way communication	-.364

The inter-rater reliability value obtained through Cronbach's alpha was 0.953. The characteristic of mass media appeared most strongly in Twitter, followed by YouTube, blog, and Yahoo! Movies (Figure 3-3).

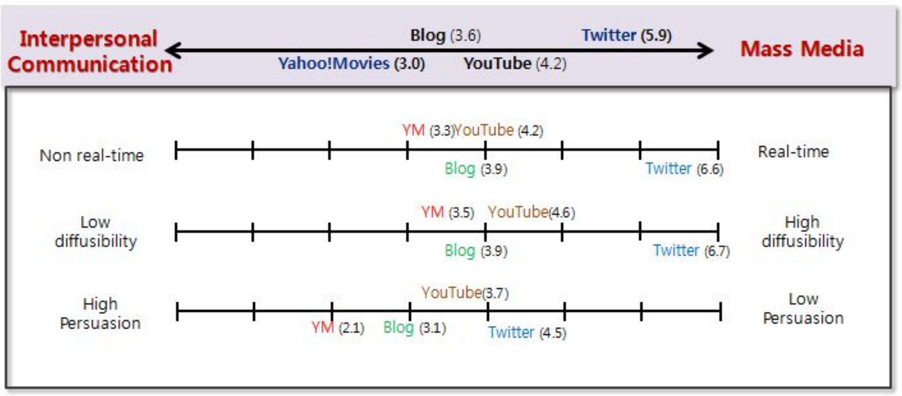

Figure 3-3. Characteristics of Various Social Media

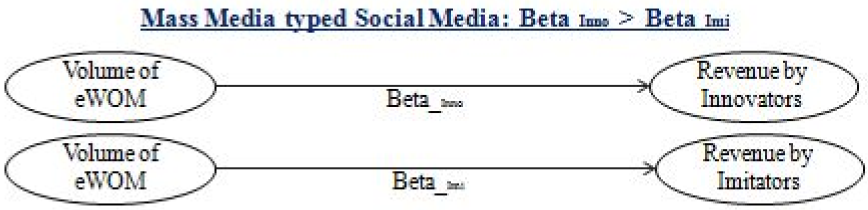

Figure 3 -4. Impact of Mass Media type of Social Media

According to the survey presented previously, Twitter showed a strong aspect of mass media. Rogers (2003) asserted that mass media, as one of the fastest and most efficient means of informing the presence of innovation, plays an important role to innovative users. Thus, Twitter is expected to have a stronger impact on innovators than on imitators (Figure 3-4). Rui et al. (2011) noted that online review sites mainly have persuasive effects, whereas Twitter has awareness effects in addition to persuasive effects. Awareness effect refers to “the function of spreading basic information about the product among the population” (Rui et al. 2011). As Twitter has a much stronger awareness effect than the other social media channels, it is expected to have more characteristics of mass media compared to other social media channels (Rogers 2003). Kwak et al. (2010) stated that Twitter had the characteristics of news media from the social network. In conclusion, Twitter is predicted to be more influential on innovators than imitators. Therefore, I hypothesize that Twitter is expected to have a stronger impact on innovators (revenue in the initial stage) than on imitators (revenue in the later stage).

Hypothesis 4a: The volume of tweets from Twitter (mass media type of social media) will have a stronger impact on innovators than on imitators.

Hypothesis 4b: The volume of tweets from Twitter (mass media type of social media) will have a stronger impact on movie revenue in the initial stage than the later stage.

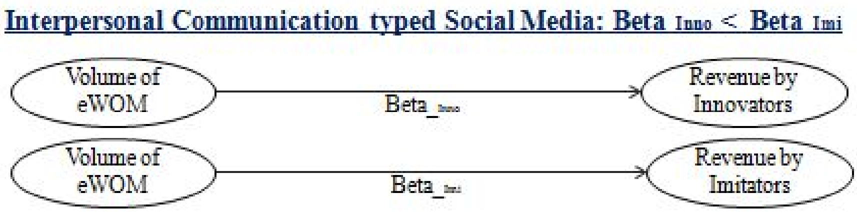

Figure 3 -5. Impact of Interpersonal Communication type of Social Media

Online review site, as presented above, is a channel that shows the aspect of interpersonal communication. Rogers (2003) asserted that interpersonal communication is effective in persuading imitators to accept the new ideas. Therefore, online review sites such as Yahoo! Movies are expected to have a stronger impact on imitators than on innovators (Figure 3-5). In addition, Rui et al. (2011) maintained that online review sites are dominated by persuasive effects. The persuasive effect plays an important role in the later stage of innovation (Roger 2003). Therefore, the current study hypothesizes that online review sites such as Yahoo! Movies are expected to have a stronger impact on imitators (revenue in the later stage) than on innovators (revenue in the initial stage).

Hypothesis 5a: The volume of ratings from Yahoo! Movies (interpersonal communication type of social media) will have a stronger impact on imitators than on innovators.

Hypothesis 5b: The volume of ratings from Yahoo! Movies (interpersonal communication type of social media) will have a stronger impact on movie revenue in the later stage than in the initial stage.

3.2.3 Value of eWOM

Several studies have found that reviews that are considered more helpful by consumers have stronger effects on consumer purchase decision than other reviews (Chen et al. 2008; Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2011). In addition, McKnight and Kacmar (2006), and Cheung et al. (2009) have indicated that the most important factor in eWOM adoption is eWOM credibility. Therefore, the present study hypothesizes that the impact of helpful reviews on movie revenue will be stronger than other reviews (Figure 3-6).

Hypothesis 6: The valence of helpful reviews will have a stronger impact on movie revenue than non-helpful reviews.

Figure 3-6. Moderating Effect of Review Helpfulness

Several studies on the effects of the consistency of existing messages on message reliability have been conducted (Cheung et al. 2009; Schlosser 2005; Zhang and Watts 2003). Zhang and Watts (2003) reported that the consistency of existing messages positively affects knowledge adoption in the communities of practice. Schlosser (2005) also revealed that two-sided reviews (one-sided review) are more credible and lead to a more positive attitude toward a movie when source ratings are moderate (extreme). Cheung et al. (2009) proved that the extent to which the current eWOM recommendation is consistent with other contributors' experiences concerning the same product is positively related to the credibility of eWOM in online consumer discussion forums.

An average rating for a particular product can be considered an overall opinion from other reviewers, which is a type of collective intelligence (Malone et al. 2010). Consumers place higher trust on an online review with a rating that is comparable to the average review rating. Thus, the current study hypothesizes that rating inconsistency, which is the difference between the review star rating and the product average rating, is negatively related to review helpfulness (Figure 3-7).

H7. The difference between the review star rating and the product average rating is negatively related to review helpfulness.

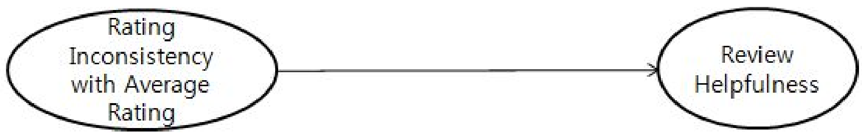

Figure 3-7. Relationship between Rating Inconsistency and Helpfulness

CHAPTER 4 RESEARCH METHOD

This chapter covers the overview of data collection, variables, and analytical methods for testing the model and hypotheses.

4.1 Data Collection

This study collected eWOM and sales information on 145 films released from February to October 2012 as daily panel data (weekly sales information), two or three weeks before the release until after the release. eWOM information was collected from Twitter, Yahoo!Movies, YouTube, and blogs. Movie and sales information was collected from BoxofficeMojo.com.

The study collected tweet information from Twitter (http://www.Twitter.com), online review information from Yahoo!Movies (http://www.movies.yahoo.com), trailer information from YouTube (http://www.youtube.com), blog posting information from Yahoo blog search API, and weekly sales and movie information data from BoxOfficeMojo.com (http://www.boxofficemojo.com). Table 4-1 presents previous studies using the same data sources in the current study.

Table 4 -1. Previous Studies Using Same Data Sources in the Research

Source of Data	Studies
Yahoo!Movies	Duan et al. (2008a); Duan et al. (2008b); Karniouchina (2010); Liu (2006)
Twitter	Asur et al. (2010); Rui et al. (2011)
YouTube	Morales-Arroyo et al. (2010)
Blog	Morales-Arroyo et al. (2010); Qin (2011)
BoxOfficeMojo	Asur and Huberman (2010); Dellarocas et al. (2007); Duan et al. (2008a); Duan et al. (2008b); Rui et al. (2011); Qin (2011)

Twitter

Following Rui et al. (2011), the present study used Twitter's open application programming interface (API) to develop a program to collect daily tweet and user information for the target movies. Previous research used data from Twitter to investigate the impact of eWOM on box-office revenue (Asur and Huberman 2010; Rui et al. 2011). Figure 4-1 shows a snapshot of Twitter search results, and Table 4-2 presents data collected from Twitter.

Figure 4-1. Snapshot of Twitter Search Results

Table 4-2. Data Collected from Twitter

Data Collected		Definition	Instrumentation
Movie level	Volume	A number of tweets per a day for a movie	Numerical Value (Scale)
Tweet level	Contents	Contents of a tweet	Textual Description
	Date	Date when a review is written	Numerical Value (Scale)
User level	Follower Number	Number of followers	Numerical Value (Scale)

Figure 4-2 is a snapshot of the process of crawling tweet.

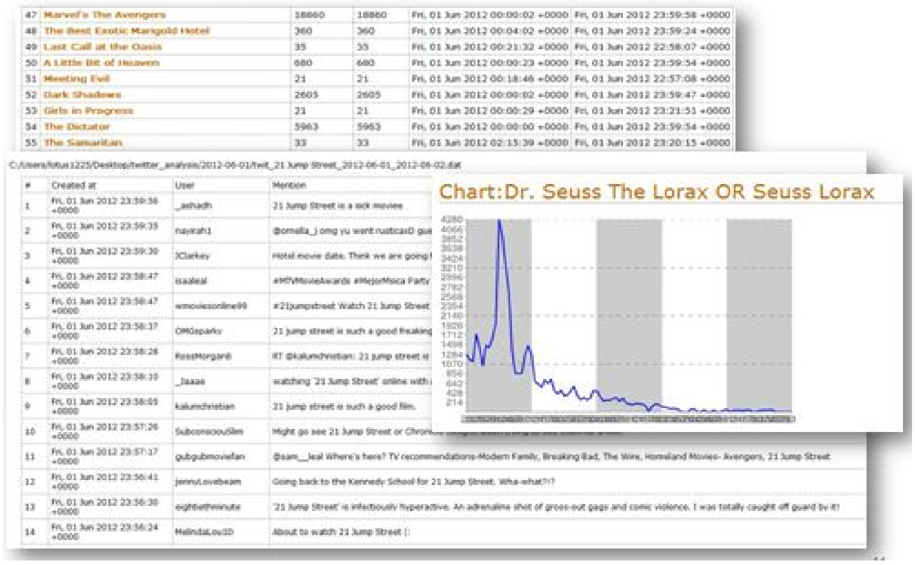

Figure 4 -2. Snapshot of Process of Crawling Tweet

Yahoo!Movies

This study collected actual online review data for target movies from Yahoo! Movies, which is one of the famous online review websites for movies. In this research, a crawler developed using Python 2.6 was utilized to download web pages of reviews from Yahoo! Movies. Another Python-based system was developed to parse HTML web pages into a database.

Yahoo! Movies was selected as the source of online review data because it is the most popular movie review website, has a well-organized design, and is relatively easy to collect information from, thus optimally reducing data collection errors (Liu 2006). Previous research used data from Yahoo! Movies to investigate the impact of eWOM on box-office revenue (Dellarocas et al. 2007; Duan et al. 2008a; Liu 2006; Moon et al. 2010).

Figure 4-3 shows a snapshot of online reviews in Yahoo! Movies, and Table 4-3 presents data collected from Yahoo! Movies.

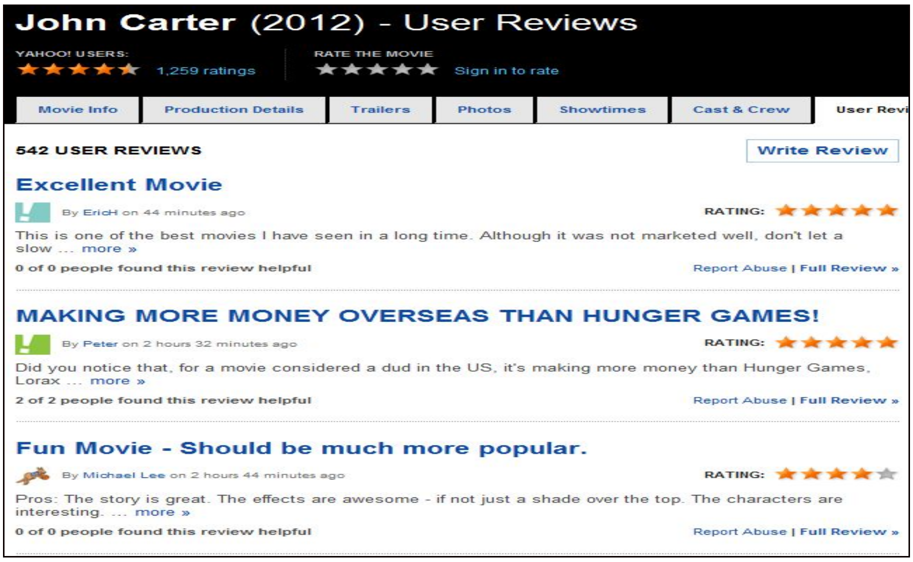

Figure 4 -3. Snapshot of Online Reviews in Yahoo!Movies

Table 4 -3. Data Collected from Yahoo!Movies

Data Collected		Definition	Instrumentation
Movie level	Average Rating	Average star rating on the movie	Numerical Value (Scale)
	Number of Ratings	A number of cumulative existing ratings per movie	Numerical Value (Scale)
	Average Review Rating	Average star rating on the movie (text review)	Numerical Value (Scale)
	Number of Reviews	A number of cumulative existing reviews per movie (text review)	Numerical Value (Scale)
Review level	Review Rating	A star rating value on a review	Numerical Value (1, 2, 3, 4, 5)
	Contents	Contents of a review message	Textual Description
	Date	Date when a review is written	Numerical Value (Scale)
	Helpfulness	Proportion of positive answers to total answers to question asking if the review is helpful	Numerical Value (Scale)

YouTube

Previous research used data from YouTube to investigate the impact of eWOM on opening week box-office revenue (Morales-Arroyo and Pandey 2010). The current study collected daily trailer information (number of views and comments) for the target movies from YouTube.

To collect data from YouTube, a few problems needed to be resolved. The selection of a representative trailer to measure people's interest in a movie trailer is a matter of choice, considering that a particular movie has more than one trailer. Thus, 10 official trailers were selected in the order of most frequently viewed counts, two or three weeks before film release. Figure 4-4 shows a snapshot of a trailer in YouTube, and Table 4-4 presents the data collected from YouTube.

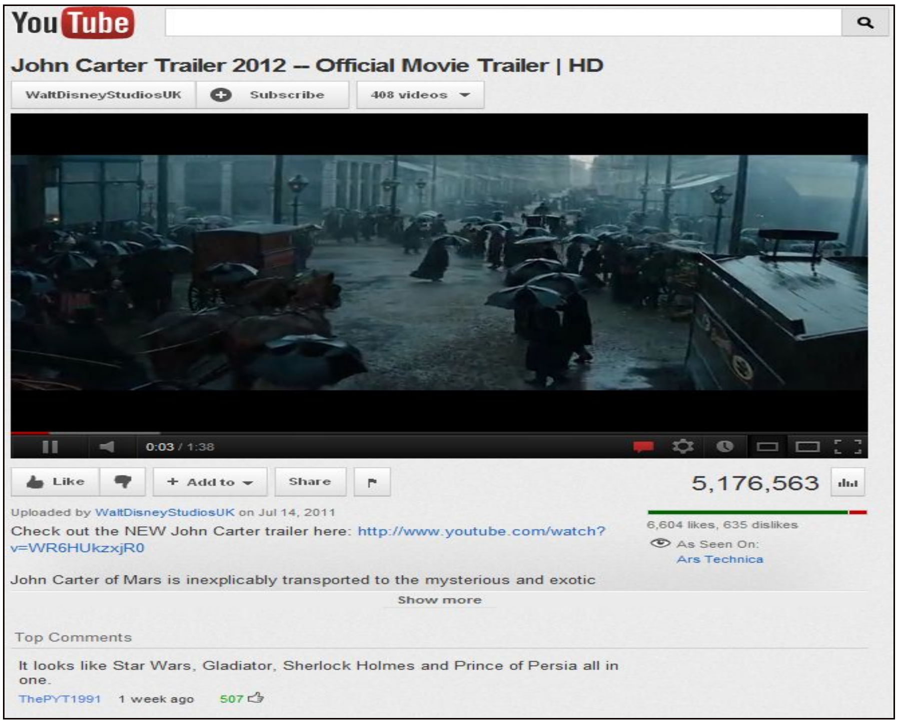

Figure 4 -4. Snapshot of a Trailer in YouTube

Table 4-4. Data Collected from YouTube

Data Collected		Definition	Instrumentation
Movie level	Number of Trailers	A number of trailers per movie	Numerical Value (Scale)
Trailer level	Number of Views	Average number of view counts in several trailer	Numerical Value (Scale)
	Number of Counts	Average number of cumulative existing reviews in several trailers	Numerical Value (Scale)

Blog

This research collected daily blog posts for the target movies using Yahoo! blog search (http://blogsearch.yahoo.com). Previous studies used Google blog search and BlogPulse to investigate the eWOM impact on product sales. However, as of January 2012, BlogPulse is no longer available. Moreover, Google blog search provides wrong information if the number of blogs is more than 64. Although Yahoo! blog search offers relevant blogs in less number than Google blog search, it is considered as more reliable than Google blog search. Blog search aggregates the number of blogs containing the word "movie" with the movie title from Jan. 1, 2012 to Oct. 6, 2012 on a daily basis. Table 4-5 shows the data collected from blogs.

Table 4-5. Data Collected from Blog

Data Collected		Definition	Instrumentation
Movie level	Number of Blog Posts	A number of blog posts per movie	Numerical Value (Scale)
Blog level	Date	Date when a review is written	Numerical Value (Scale)

BoxOfficeMojo.com

Previous research used data from BoxOfficeMojo.com to investigate the impact of eWOM on box-office revenue (Asur and Huberman 2010; Dellarocas et al. 2007; Duan et al. 2008a; Qin 2011; Rui et al. 2011).

The current study collected data on film-specific weekly revenue, genre, MPAA rating, number of screens, and the presence of a sequel from BoxOfficeMojo.com (see Table4-6). Figure 4-5 shows a snapshot of BoxOfficeMojo.com.

Table 4 -6. Data Collected from BoxOfficeMojo.com

Data Collected		Definition	Instrumentation
Movie level	Weekly Revenue	Weekly revenue for a movie	Numerical Value (Scale)
	Genre	Genre of a movie	Dummy Variable
	MPAA Rating	MPAA Rating of a movie	Dummy Variable
	Release Date	Date when a movie is released	Numerical Value (Scale)
	Number of Screens	Number of screens for a movie	Numerical Value (Scale)
	Sequel	Whether or not a movie is sequel	Dummy Variable

Figure 4 -5. Snapshot of BoxOfficeMojo.com

4.2 Variables

For this study, the independent variables are eWOM volume and valence information from each social media channel, and the control variables are general movie characteristics. Dependent variables are weekly movie revenue, revenue from innovator, and imitator by period. Table 4-7 summarizes the independent, control, and dependent variables.

Independent Variables

This study uses eWOM volume and valence obtained from Twitter, Yahoo! Movies, YouTube, and blogs, as independent variables. (1) Twitter considers the number of tweets, including both the number of weekly tweets and the number of followers about the movie. (2) Yahoo! Movies uses the average rating and volume of rating reviews (reviews with rating only), and the rating and volume of text reviews (reviews with both text and rating). (3) YouTube considers view count and number of comments as independent variables. In existing studies, view count (Morales-Arroyo and Pandey 2010; Oghina et al. 2012), number of comments (Morales-Arroyo and Pandey 2010; Oghina et al. 2012), and like-dislike percentage (Oghina et al. 2012) had been used for YouTube eWOM. (4) Blogs use the number of blog posts regarding a movie.

Control Variables

Existing studies on movie box-office factors have been continuously conducted in the marketing area. Dellarocas et al. (2007) analyzed the existing studies to summarize the movie revenue-affecting factors, namely, star power, movie genre, MPAA ratings, media advertising, timing of release, and professional critic reviews. Moon et al. (2010)

considered movie genre, sequel, MPAA ratings, running time, production time as the factors to affect movie revenue. Yang et al. (2011) considered movie genre, number of screens, and MPAA rating as the factors to affect movie revenue. Therefore, the present study considered movie genre, MPAA ratings, and sequel as control variables.

Dependent Variables

Movie revenue is regarded as a dependent variable. This study also considers the coefficient of innovation and coefficient of imitation calculated from movie sales as dependent variables.

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Table 4 -7. Variables in Research Model

Variables		Data Source	Definition
Independent Variables	Tweet Number	Twitter	A number of tweets per a daily for a movie
	Number of Tweet Audience		A number of tweets considering number of followers
	Average Rating (rating review)	Yahoo!Movies	Average star rating on the movie (Rating review)
	Volume (rating review)		A number of cumulative existing ratings per movie (Rating review)
	Average Rating (text review)		Average star rating on the movie (text review)
	Volume (text review)		A number of cumulative existing reviews per movie (text review)
	Number of Views	YouTube	Number of view counts in a trailer
	Number of Comments		A number of comment counts p4er trailer
	Number of Blog Posts	Blog	A number of blog posts per movie
Control Variables	Genre	BoxOfficeMojo	Genre of a movie
	MPAA Rating		MPAA Rating of a movie
	Release Date		Date when a movie is released
	Number of Screens		Number of screens for a movie
	Sequel		Whether or not a movie is sequel
Dependent variables	Weekly Revenue	BoxOfficeMojo	Weekly revenue for a movie

4.3 Analysis Method

Based on the formula above, multiple regression analysis (specifically, hierarchical regression analysis) is used. The hierarchical regression model is used to support a researcher's hypothesis, and individual variable inputs may be used depending on the research purpose.

First, the Hausman test is used to determine whether a fixed or random effects model is appropriate. In panel data analysis, the nature of the unobserved effect (individual heterogeneity) should be considered (Wooldridge 2001). The unobserved effect is an analogous term that is applied to cross-sectional units (Wooldridge 2001). The unobserved effect can be treated as a random effect if it is viewed as a random variable, and it can be treated as a fixed effect if it is viewed as a parameter to be estimated for each cross-section observation (Wooldridge 2001). If the present research has to treat the unobserved effect as a fixed effect, then (1) dummy variables will be added as independent variables (least square dummy variable, or LSDV), or (2) within transformation will be applied to consider fixed effects.

Second, if an endogeneity problem exists, two-stage least square (2SLS) analysis or lagged independent variables will be used in this study. Variable X is endogenous if it is correlated with the model error term. Endogeneity has three causes: correlated missing regressors, measurement error, and reverse causality. 2SLS is a kind of generalized least square analysis (i.e., if a correlation exists between error term and explanatory variable), which controls endogeneity using simultaneous equation. Instrumental variables in 2SLS have to be correlated with explanatory variables, but uncorrelated with the model error term.

Third, another aspect to consider is multicollinearity between variables. Multicollinearity refers to a violation of the assumption that no independent variable is a linear combination of other independent variables. If multicollinearity exists in multiple regression model, (1) the estimated regression coefficients are largely changed when an independent variable is added or deleted, or (2) no significant regression coefficients emerge despite the high explanatory power. To detect multicollinearity in a statistical manner, variance inflation factor (VIF) or tolerance value is checked. In general, multicollinearity exists when the VIF value is over 10, or the value of the inverse number of VIF is less than 0.1 (Kutner et al. 2004). Remedies for multicollinearity are as follows: (1) doing nothing; (2) dropping one or more of the collinear variables; (3) transforming the variables; and (4) obtaining more observations with which the explanatory factors are not correlated. In this study, the multicollinearity needs to be checked, because the relevance between eWOM from each social media channel is expected to be higher.

Text Mining for Tweet Analysis

A tweet contains various kinds of writings, and does not offer the information of valence as numerical value. Thus, this study carries out the text mining of tweets. Text mining can extract key elements from large unstructured data sets (Laudon and Laudon 2012).

Hence, the irrelevant, intention, and review classifiers are largely divided, and based on this criterion, four classifications are further made, namely, intention tweet, positive tweet, neutral tweet, and negative tweet. Text mining primarily utilizes lexicons to manually extract features from tweets and secondarily a naïve Bayesian model. A classification that only uses a naïve Bayesian model in terms of a tweet composed of 140 letters is less accurate; thus, hybrid text mining is used.

Naïve Bayesian classifier refers to "a simple probabilistic classifier based on applying Bayes's theorem with strong (naïve) independence assumptions."[3] This methodology defines the class within a category, and calculates the probability that belongs to a particular category depending on the features that the document has.

$$P(C|F) = \frac{P(F) * P(F|C)}{P(C)}$$

In the formula, *F* represents the feature that the document has, and *C* represents the class that belongs to a category. *P(C|F)* represents the possibility of belonging to the *C* class when document has the *F* feature. Therefore, *P(C|F)* is the value to be found through a naïve Bayesian model, and the value is obtained through the formula presented.

In this study, the order of text mining to classify tweet is as follows. The lexicons for text mining are presented in the Appendix.

1. Filtering
   ① Unnecessary words are filtered utilizing lexicons for stop words.
   ② Movie title is replaced with a Query-Term.

2. Irrelevant classifier
   ① Relevant tweet is classified utilizing lexicons for relevant words.
   ② Irrelevant tweet is classified utilizing lexicons for irrelevant words.

[3] http://en.wikipedia.org/wiki/Naive_Bayes_classifier

③ Among the remaining sets to the exclusion of the threes fixed in 2-① and 2-②, relevant tweets and irrelevant tweets are classified utilizing a naïve Bayesian model.

3. Intention classifier

① The sets classified as relevant tweets are classified through 2.

② The non-intention tweet is classified utilizing lexicons for non-intention words.

③ The intention tweet is classified utilizing lexicons for intention words.

④ Among the remaining sets to the exclusion of the threes fixed in 3-② and 3-③, intention and non-intention tweets are classified utilizing a naïve Bayesian model.

4. Review classifier

① The sets classified as non-intention tweets are classified through 3.

② The neutral tweet is classified utilizing lexicons for neutral words.

③ The negative tweet is classified utilizing lexicons for negative words.

④ The positive tweet is classified utilizing lexicons for positive words.

⑤ Among the remaining sets to the exclusion of the threes fixed in 4-②, 4-③, and 4-④, positive, neutral, and negative tweets are classified utilizing a naïve Bayesian model.

Figure 4-6 represents the classifiers made for this study.

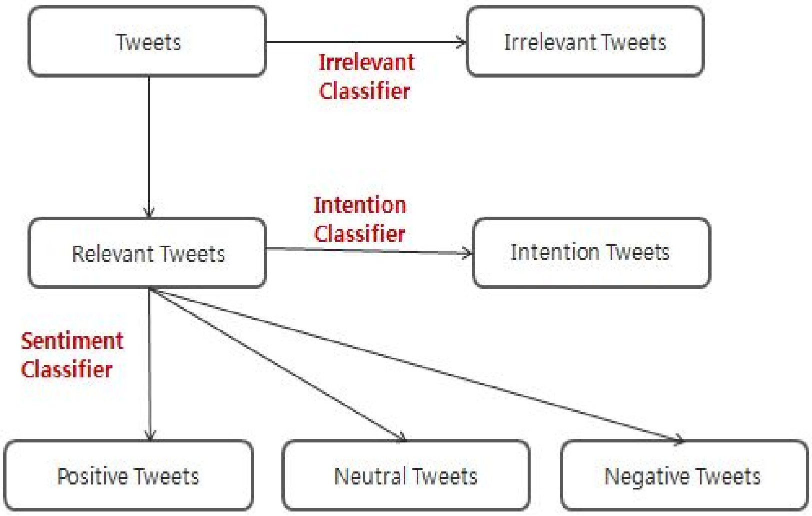

Figure 4 -6. Tweet Classifiers

To test the classifier accuracy, 2,000 movie tweets are manually classified into intention tweet, positive tweet, neutral tweet, and negative tweet. Amazon Mechanical Turk (AMT) is utilized as manual labeling. Cross checking is performed by two native speakers, and only the case in which identical classification occurs is utilized for manual labeling data. Among these data, 1,700 pieces of these data are used for training and 300 for accuracy test.

The results of accuracy measurement suggested that the irrelevant classifier showed 96% accuracy, intention classifier 86% accuracy, positive tweet 84% accuracy, neutral tweet 73% accuracy, and negative tweet 89% accuracy (Table 4-8).

Table 4 -8. The Result of Accuracy for Tweet Classifiers

Classifier		Accuracy
Irrelevant Classifier		0.96
Intention Classifier		0.86
Sentiment Classifier	Positive	0.84
	Neutral	0.73
	Negative	0.89

Figure 4-7 shows a snapshot to classify each tweet manually utilizing AMT.

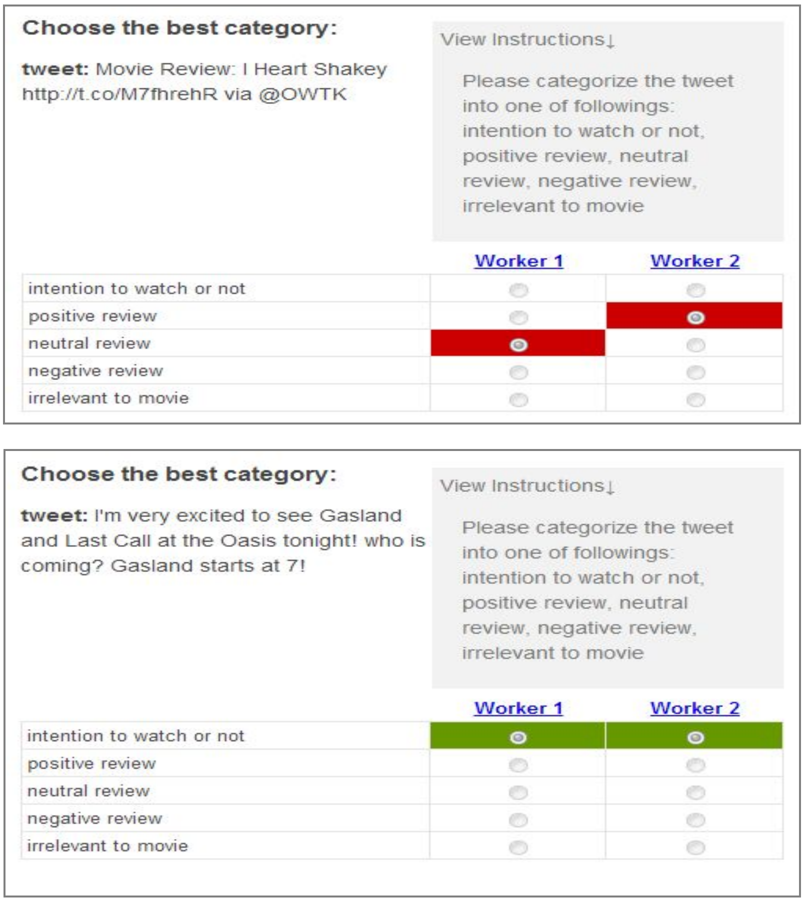

Figure 4 -7. Tweet Manual Classification using AMT

CHAPTER 5 ANALYSIS RESULTS

5.1 Descriptive Statistics

This study attempted to collect information on eWOM and revenue regarding 145 films; however, the eWOM information could not be obtained identically from all social media channels. In the case of Twitter, for example, collecting data on the film “Gone” from tweets was impossible to do because the movie itself as well as the film title “Gone” frequently appeared in tweets, which were unrelated to the film. Moreover, the information on movie revenue regarding 145 films could not be collected from BoxofficeMojo.com. Table 5-1 presents the descriptive statistics on the weekly eWOM volume from each social media channel and weekly movie revenue. The analysis implied that approximately 20 blog posts per film on average were written weekly, including 17.7 ratings, 16,236 tweets, and 21,971 views.

Table 5 -1. Descriptive Statistics on the Weekly eWOM Volume

Variable		Mean	Std. Dev.	Min	Max	N ($week_{i,t}$)	N ($movie_i$)
YouTube	weekly view	21971	99624.48	0	2493728	2202	138
	weekly comment	34.212	300.6974	-65	9698	2178	
Yahoo! Movies	weekly rating number	17.68	86.34247	-1	1737	1819	80
	weekly review number	5.97	33.649	-587	599	1845	
Blog	weekly blog	20.17	73.42	0	2692	4881	126
Twitter	weekly tweet	16236	61311.8	0	1267820	2486	122
Mojo	weekly gross	4.24e+06	1.61e+07	25	2.70e+08	1176	108

Note: Often, the number of comment from YouTube and that of rating and review from Yahoo!Movies has reduced, which is believed to be that eWOM has been deleted by a user or social media.

Table 5-2 shows the correlation matrix between each form of eWOM. The comment and view counts in YouTube appear to have a high correlation value at 0.926. In addition, the rating number and review number in Yahoo! Movies suggest a relatively higher correlation value at 0.750. The correlation between the forms of eWOM from the same social media is relatively higher. Moreover, most forms of eWOM from various social media channels suggest a high correlation value. The correlation value between the weekly rating number and other forms of eWOM indicates a relatively higher correlation than the correlation between other forms of eWOM.

Table 5 -2. Correlation Matrix for eWOMs

	weekly comment	weekly view	weekly rating	weekly review	weekly tweet	weekly blog
weekly comment	1.000					
weekly view	0.926**	1.000				
weekly rating	0.611**	0.553**	1.000			
weekly review	0.358**	0.338**	0.750**	1.000		
weekly tweet	0.566**	0.537**	0.817**	0.566**	1.000	
weekly blog	0.599**	0.548**	0.841**	0.573**	0.772**	1.000

*Note: *p<.01, **p<.001*

Figure 5-1 illustrates the weekly variance showing the weekly eWOM or movie revenue. To unify the dimensions, the graph is drawn on the basis of the standardized values. Week 1 means opening week, and one week before opening is marked "-1" and two weeks before opening "-2." Generally, most forms of eWOM are found to be moving in a trend similar to that of movie revenue. The weekly rating number is relatively higher in terms of the week difference, whereas the weekly view is not so.

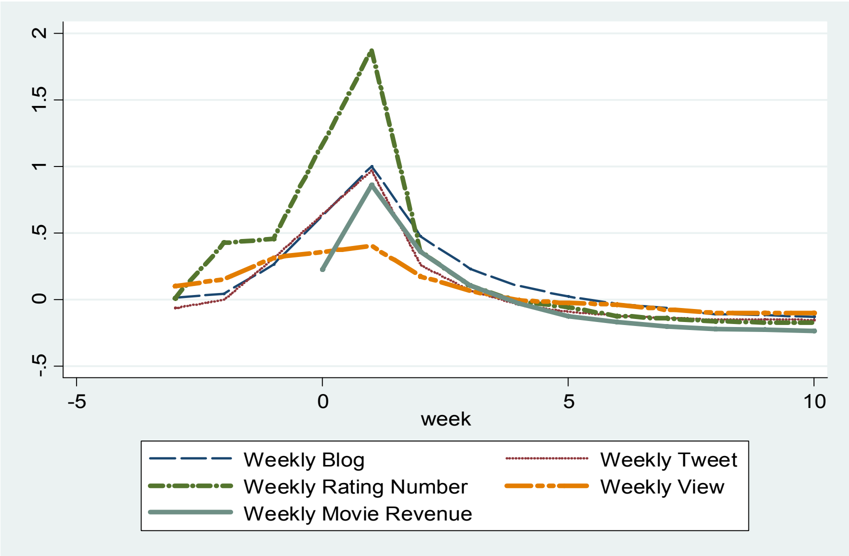

Figure 5 -1. Weekly Variance of eWOM and Movie Revenue

Table 5-3 presents the correlation values between the lagged weekly eWOM volume and the weekly movie revenue.

Table 5 -3. Correlation between Weekly eWOM and Weekly Revenue

Week		Weekly $View_{t-1}$	Weekly Rating $Number_{t-1}$	Weekly $Blog_{t-1}$	Weekly $Tweet_{t-1}$	N
1	Weekly $Gross_t$	0.8356	0.9559	0.8715	0.8738	26
2	Weekly $Gross_t$	0.7867	0.8580	0.7715	0.8268	59
3	Weekly $Gross_t$	0.7845	0.8385	0.7854	0.7818	67
4	Weekly $Gross_t$	0.8340	0.8266	0.7229	0.7059	67
5	Weekly $Gross_t$	0.7638	0.8477	0.7068	0.7069	70
6	Weekly $Gross_t$	0.6839	0.8680	0.7645	0.7199	70
7	Weekly $Gross_t$	0.7609	0.9425	0.6872	0.5606	70
8	Weekly $Gross_t$	0.7713	0.9045	0.7515	0.5957	63
9	Weekly $Gross_t$	0.7608	0.9634	0.7960	0.6125	52
10	Weekly $Gross_t$	0.5939	0.9613	0.7744	0.6291	40

Twitter

Figure 5-2 shows the average weekly tweet volume. On average, the first week of film release shows the largest number of tweets, and the number of tweets tends to decline after film release. Figure 5-2 also shows a graph that represents the changes in the tweet volume of each film.

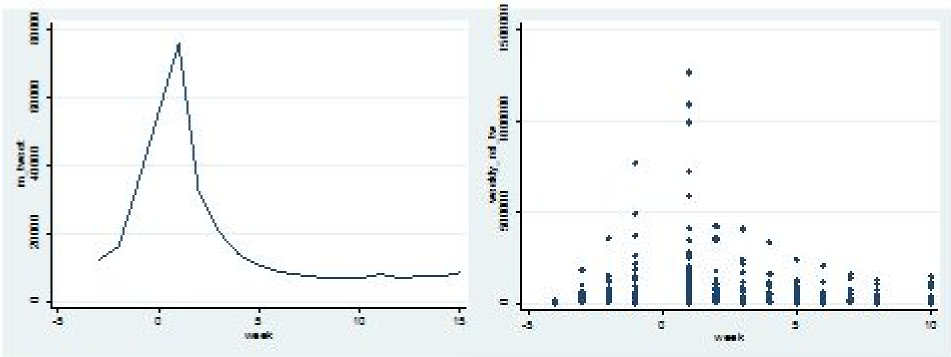

Figure 5-2. Weekly Tweet Volume Trend

Figure 5-3 shows the percentage of intention tweets, positive tweets, neutral tweets, or negative tweets of the entire film-related tweets. Positive tweets comprise 52% of the entire tweets, negative tweets 7%, and intention tweets 14%. Neutral tweets either include a URL, or contain objective opinions, comprising 27% of the entire tweets.

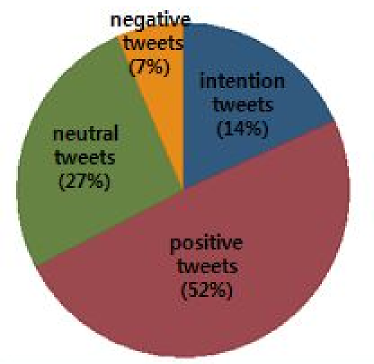

Figure 5-3. Percentage of Each Tweet

Figure 5-3 presents the average volume of daily intention tweets, positive tweets, neutral tweets, or negative tweets for one film. Each film has an average of 2,156 tweets written daily; among these tweets, 1,126 are positive, 146 are negative, and 308 are intention tweets.

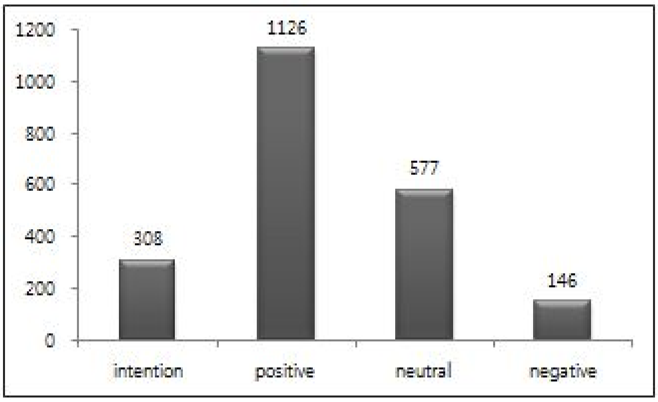

Figure 5 -4. Volume of Daily Tweet

Figure 5-5 presents the average size of the audience for daily intention tweets, positive tweets, neutral tweets, and negative tweets for one film. The size of the audience, if it is mentioned, represents the number of people who are mentioned; if it is not mentioned, the audience size represents the number of followers for a person who wrote each tweet. The size of the daily neutral tweet audience per a movie (1,899,100 individuals per movie on average) is found to be the highest. The size of the audience for neutral tweets (3,293 individuals per tweet on average) is found to be the highest (Figure 5-6).

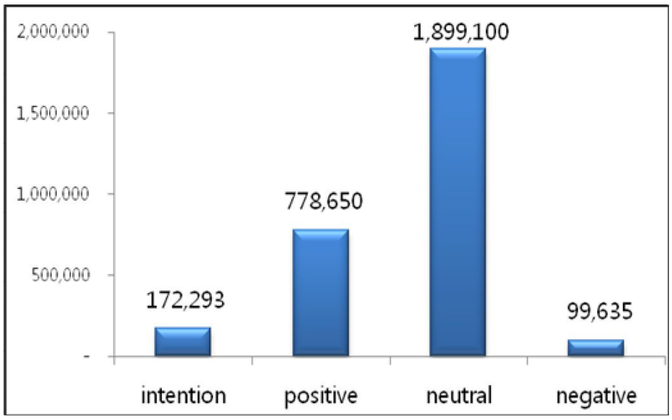

Figure 5 -5. Number of daily tweet audiences per Movie

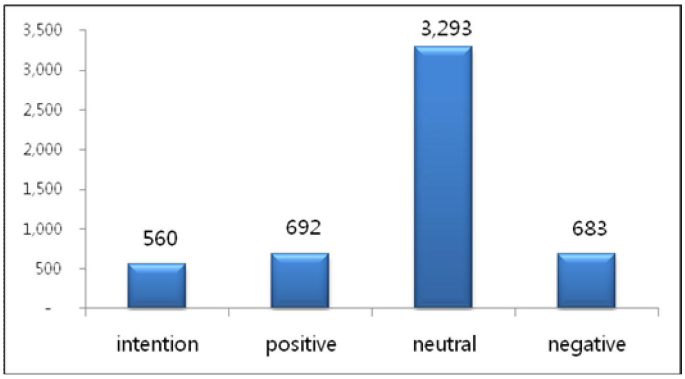

Figure 5 -6. Number of Audiences per Tweet

Figure 5-7 presents the film whose percentage of negative tweets of the entire tweets of the collected films belongs to the top five. On average, 4.3% were found to belong to negative tweets, whereas the film that belongs to the top five had negative tweets ranging from 13.8% to 21.4%. “Piranha 3DD” has negative tweets at 21.4%, and movie revenue was recorded three weeks after release, when it dropped sharply after the first week.

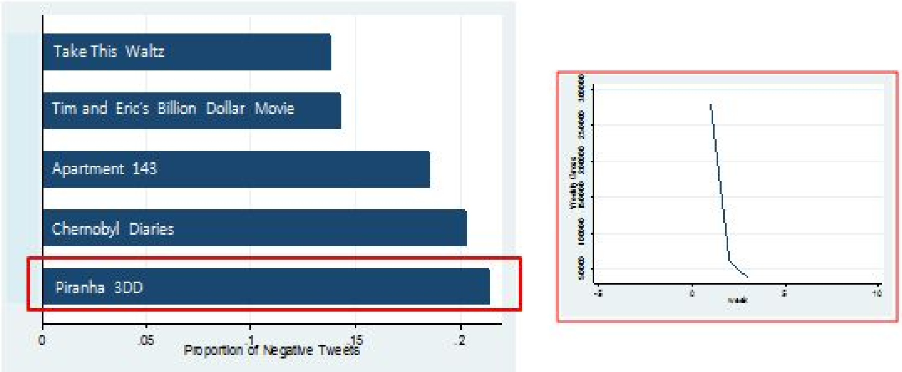

Figure 5-7. Top 5: Percentage of Negative Tweet

To determine the impact of negative tweets on movie revenue, LSDV analysis is conducted. Consequently, movie revenue decreased by $42.8 million when the percentage of negative tweets increased by 1% (Table 5-4).

Table 5-4. Impact of Percentage of Negative Tweet on Movie Revenue

	Estimates
Weekly proportion of negative tweets$_{t-1}$	-4.28e+07**
(constant)	6494042***
R^2	0.1669
N	1,067

*Note: *p<.05, **p<.01, ***p<.001*
Dependent Variable: weekly gross

Figure 5-8 presents the weekly volume of intention tweets, positive tweets, neutral tweets, or negative tweets, as well as the weekly percentage of each tweet. Before film release, intention tweets accounted for a significant proportion, but its percentage gradually decreased; meanwhile, subjective tweets (positive tweet + negative tweet) tended to increase gradually after film release.

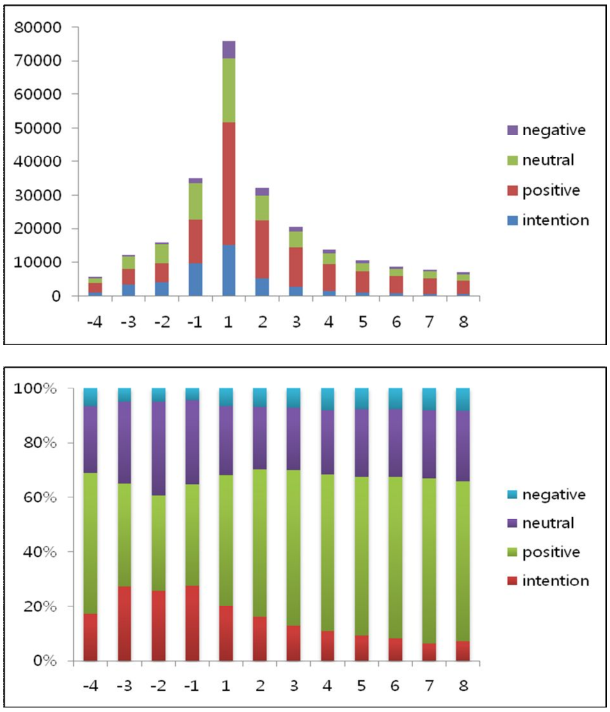

Figure 5 -8. Weekly Volume (Percentage) of Each Tweet

To determine the tweet that is more influential on movie revenue (i.e., intention tweet or subjective tweet), LSDV analysis is performed. Consequently, intention tweet is found to be statistically more influential on the weekly movie revenue than subjective tweet (Table 5-5).

Table 5 -5. Impact of Intention Tweet and Subjective Tweet

	Intention Tweet		Subjective Tweet		Chin's T-value
	Coefficient	Standard Error	Coefficient	Standard Error	
weekly $tweet_{t-1}$	589.83***	24.38	194.92***	10.23	14.95
(constant)	1819022***	396545.8	1259564***	443687.7	
R^2		0.4788		0.3911	
N		1067		1067	

*Note: *p<.05, **p<.01, ***p<.00, Dependent Variable: weekly gross*

YouTube

As mentioned previously, stating that only a particular trailer represents one film is difficult, because multiple trailers on the same film appear on YouTube. Therefore, this study selected 10 trailers with the most number of view counts for each film on the basis of two or three weeks before film release, and utilized the average value of the trailer as the view count of each film. Table 5-6 presents the number of trailers per movie used to calculate the view count in YouTube. Trailers are deleted during the collection data period due to copyright issues and other concerns; thus, this study analyzed only the trailers containing all information during the data collection period. In conclusion, this study analyzed the average value of 8.74 trailers per film.

Table 5 -6. Number of Trailers per Movie from YouTube

Movie	Trailer No	Movie	Trailer No
21 Jump Street	8	Hit and Run	8
30 Beats	9	Hope Springs	9
360	9	Ice Age Continental Drift	10
A Little Bit of Heaven	9	Jeff, Who Lives At Home	10
A Thousand Words	10	Jiro Dreams Sushi	8
Abraham Lincoln	10	John Carter	10
Ai Weiwei Never Sorry	10	Katy Perry Part Of Me	9
American Reunion	4	Killer Joe	9
Apartment 143	10	Klown	8
Battlefield America	8	Kumare	10
Beasts Of The Southern Wild	9	Last Call at the Oasis	7
Being Flynn	10	Last Days Here	7
Bel Ami	10	Lola Versus	8
Bully	9	Lovely Molly	9
Casa de Mi Padre	8	Madagascar 3	10
Celeste And Jesse Forever	9	Magic Mike	9
Chernobyl Diaries	9	Marvels The Avengers	10
Chicken With Plums	10	Meeting Evil	7
Cosmopolis	10	Men in Black 3	10
Damsels In Distress	6	Mirror Mirror	8
Dark Shadows	10	Moonrise Kingdom	9
Darling Companion	6	Neil Young Journeys	9

Decoy Bride	9	Nitro Circus The Movie 3D	10
Diary Of A Wimpy Kid Dog Days	9	ParaNorman	10
Easy Money	8	Peace Love and Misunderstanding	10
For A Good Time Call	8	People Like Us	10
For Greater Glory	10	Piranha 3DD	8
Friends With Kids	9	Polisse	10
Girls in Progress	8	Premium Rush	10
Goats	9	Project X	10
Goon	8	Prometheus	9
Hit and Run	8	Red Hook Summer	10
Your Sisters Sister	9	Wrath of the Titans	10
Red Lights	10	The Expendables 2	9
Reuniting the Rubins	10	The Five Year Engagement	8
Robot and Frank	10	The FP	7
Rock of ages	10	The Good Doctor	10
Ruby Sparks	10	The Hunger Games	8
Safety not guaranteed	10	The Hunter	7
Wild Horse Wild Ride	9	The Imposter	6
Salmon Fishing Yemen	10	The Island President	6
Searching For Sugar Man	8	The Kid with a Bike	10
Seeking A Friend For The End Of The World	8	Tyler Perrys Madeas Witness Protection	9
Seeking Justice	9	The Lucky One	10
Dr. Seuss's The Lorax	9	The Magic Of Belle Isle	7
Silent House	10	The Moth Diaries	7
Sleepwalk With Me	10	The Odd Life of Timothy Green	10
Snow White and the Huntsman	10	The Pirates Band of Misfits	10
Sound of My Voice	8	The Possession	10
Sparkle	9	The Raid Redemption	6
Step Up Revolution	9	The Raven	9
Take This Waltz	10	The Samaritan	7
Ted	7	The Snowtown Murders	8
Thats My Boy	8	The Three Stooges	8
The Amazing Spider-Man	10	The Trouble with Bliss	8
The Apparition	9	The Watch	10
The Babymakers	9	Tim Eric Billion Dollar	8
The Best Exotic Marigold Hotel	11	To Rome With Love	8
The Bourne Legacy	10	To the Arctic	7
The Cabin in the Woods	8	Total Recall	10
The Campaign	10	Trishna	9
The Cold Light of Day	8	The Last Lide	9
The Dark Knight Rises	10	Union Square	9
The Dictator	10	We Have A Pope	8
The Do-Deca Pentathlon	10	What to Expect When you're expecting	8
Woman Thou Art Loosed	6	**Average**	**8.74**

Figure 5-9 presents the average weekly view count. On average, the weekly view count of the first week after film release is the highest, and the view count after film release tends to decline. Unlike the other forms of eWOM, the view count of YouTube has a considerable volume before film release. Figure 5-9 also illustrates the changes in the view count of each film.

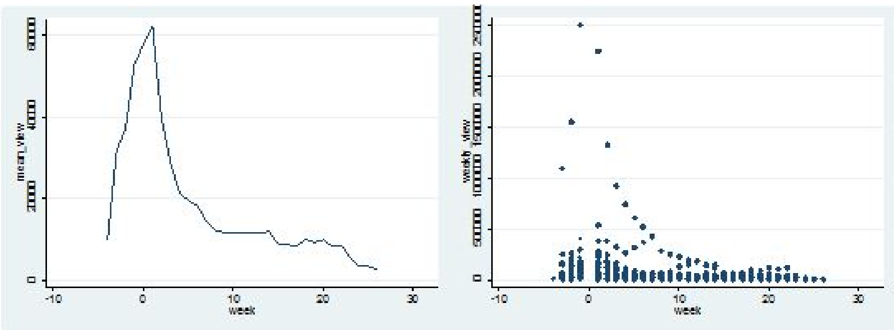

Figure 5 -9. Weekly View Count Trend

Yahoo! Movies

Figure 5-10 presents the average weekly rating number. On average, the weekly rating number of the first week after film release is the highest, and it tends to decline continuously after film release. Figure 5-10 also illustrates the changes in the rating number of each film.

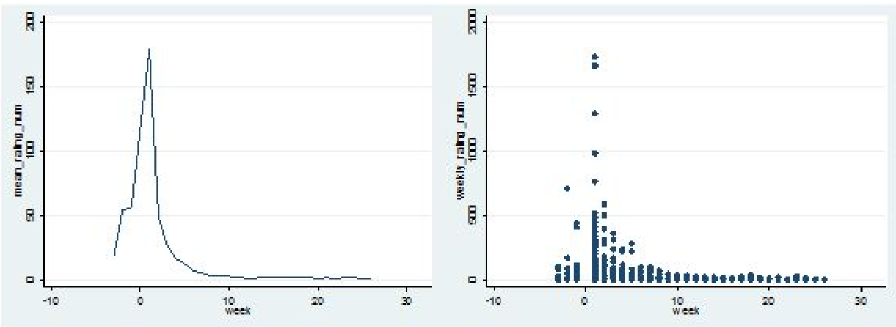

Figure 5 -10. Weekly Rating Number Trend

Blog

Figure 5-11 presents the average number of weekly blogs. On average, the number of blog posts is the highest in the first week of film release, and it continues to decline after film release. Figure 5-11 also illustrates the changes in the number of blogs of each film.

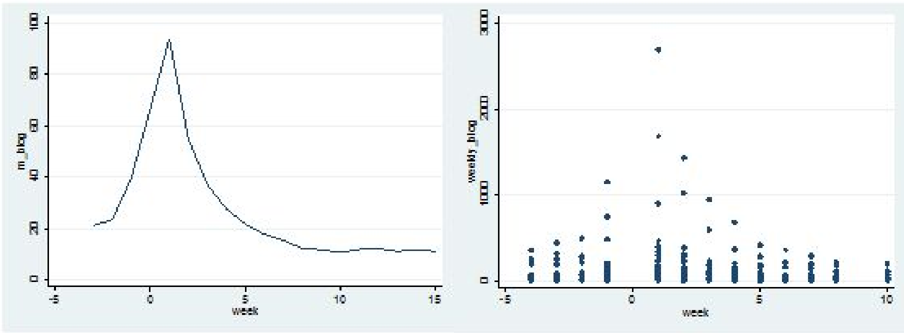

Figure 5 -11. Weekly Blog Post Number Trend

Movie Revenue

Figure 5-12 presents the weekly movie revenue. On average, movie revenue is the highest in the first week of film release, and it continues to decline after film release. The film that earns movie revenue in week 0 means the one that is released earlier than Friday when ordinary films are usually shown.

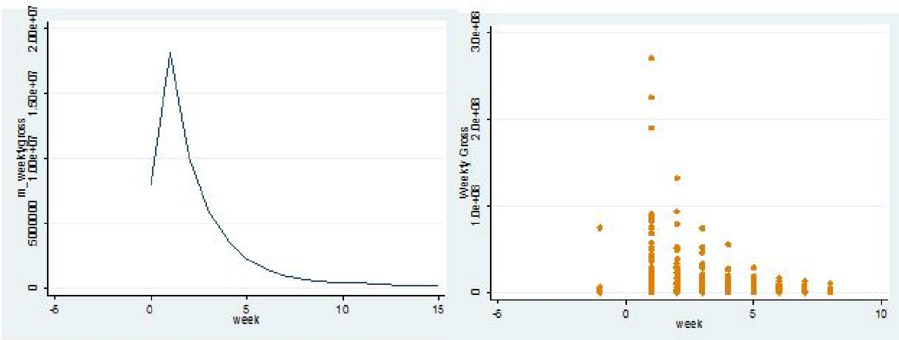

Figure 5 -12. Weekly Movie Revenue Trend

5.2 Study 1: Time of eWOM

Study 1 analyzes the impact of eWOM on movie revenue considering the period when eWOM is written. To this end, Hypotheses 1, 2, and 3 are verified. The impact of pre-consumption eWOM on the opening week movie revenue, the impact of post-consumption eWOM on movie revenue after the second week, and the impact of the volume disconfirmation of pre- and post-consumption eWOM on movie revenue are verified in this chapter.

5.2.1 Impact of Pre-consumption eWOM

To verify Hypothesis 1, the impact of pre-consumption eWOM on the opening week revenue is verified. As mentioned previously, when analyzed via the multiple regression model, multicollinearity problem occurs due to the high correlation between the eWOM forms of each social media channel. Therefore, this study performs the hierarchical regression analysis of eWOM from each social media channel, respectively. Tables 5-7, 5-8, 5-9, and 5-10 present the analysis results for verifying Hypothesis 1. Model 1 examines the presence of series, MPAA ratings, and impact of the opening week revenue when the movie genre was set as a control variable. Consequently, the presence of series and movie genres (i.e., action and adventure) appeared to have an impact on the opening week movie revenue. Additionally, Model 2 performs a regression analysis with the weekly eWOM volume one week before film release as an independent variable. To verify the impact of each form of eWOM on movie revenue, the lagged weekly eWOM volume was considered as an independent variable. As a result, weekly tweet volume, weekly view volume, weekly blog volume, and weekly rating number before film release have a significant positive impact on the opening week revenue (i.e., Hypothesis 1 is supported); moreover, even when the movie characteristics such as movie genre, MPAA ratings, and the presence of series are considered, the explanatory power is at the level ranging from 72% to 96%.

Table 5 -7. Impact of Pre-consumption Tweet Number on Revenue

Independent Variable	Model 1	Model 2
Series	4.63e+07***	3.18e+07***
R & NC_7	5579749	-1226424
PG_13	1.08e+07	3776571
Science Fiction	1.20e+07	9899739
Kid	2.87e+07	3.00e+07**
Thriller	1738099	1854565
Comedy	5633351	3163018
Drama	-786277.9	1984299
Action/Adventure	6.87e+07***	2.15e+0*
Weekly Tweet_{-1}		**293.1775*** **
R^2	484	.845
R^2 Increase	484***	.361***
N	120	108

*Note: *p<.05, **p<.01, ***p<.001, Dependent Variable: open week movie revenue*

Table 5 -8. Impact of Pre-consumption View Count on Revenue

Independent Variable	Model 1	Model 2
Series	4.63e+07***	2.50e+07 **
R & NC_7	5579749	2460572
PG_13	1.08e+07	9278733
Science Fiction	1.20e+07	1.07e+07
Kid	2.87e+07	3.62e+07**
Thriller	1738099	7147065
Comedy	5633351	6345802
Drama	-786277.9	1175872
Action/Adventure	6.87e+07***	5.11e+07***
Weekly View_{-1}		**90.71914*** **
R^2	484	.726
R^2 Increase	484***	.242***
N	120	106

*Note: *p<.05, **p<.01, ***p<.001, Dependent Variable: open week movie revenue*

Table 5 -9. Impact of Pre-consumption Blog Number on Revenue

Independent Variable	Model 1	Model 2
Series	4.63e+07***	3.96e+07***
R & NC_7	5579749	3051794
PG_13	1.08e+07	5897865
Science Fiction	1.20e+07	1.06e+07
Kid	2.87e+07	3.13e+07**
Thriller	1738099	1532004
Comedy	5633351	7402201
Drama	-786277.9	-100601.8
Action/Adventure	6.87e+07***	2.56e+07**
Weekly Blog_{-1}		**196685.7*** **
R^2	484	.795
R^2 Increase	484***	.311***
N	120	117

*Note: *p<.05, **p<.01, ***p<.001, Dependent Variable: open week movie revenue*

Table 5 -10. Impact of Pre-consumption Rating Number on Revenue

Independent Variable	Model 1	Model 2
Series	4.63e+07***	1.11e+07
R & NC_7	5579749	-2028041
PG_13	1.08e+07	-4622368
Science Fiction	1.20e+07	3.49e+07
Kid	2.87e+07	7.26e+07**
Thriller	1738099	6882209
Comedy	5633351	8636132
Drama	-786277.9	3989223
Action/Adventure	6.87e+07***	9850644
Weekly Rating Number_{-1}		**527768.7 *** **
R^2	484	.964
R^2 Increase	484***	.480***
N	120	31

*Note: *p<.05, **p<.01, ***p<.001, Dependent Variable: open week movie revenue*

5.2.2 Impact of Post-consumption eWOM

To verify Hypothesis 2, the impact of post-consumption eWOM on movie revenue after the second week is verified. To this end, the hierarchical regression model is utilized; for each model, LSDV analysis is performed for the fixed effect model. Table 5-11 shows the analysis results of the hierarchical regression model for verifying Hypothesis 2. Panel data are utilized; thus, idiosyncratic characteristics associated with each movie are not considered separately. To verify the impact of each form of eWOM on movie revenue, the lagged eWOM is considered as an independent variable. The eWOM information from each social media channel is added to each model for analysis. Consequently, all eWOM forms have a significant positive impact on movie revenue (i.e., Hypothesis 2 is supported), and the explanatory power is at the 88% level. Multicollinearity does not have to be considered because the VIF value is 3.46.

Table 5 -11. Impacts of Post-consumption eWOMs on Weekly Revenue

Independent Variable	Model 1	Model 2	Model 3	Model 4
Weekly Tweet_{t-1}	89.00 ***	53.71***	36.59***	28.19***
Weekly Blog_{t-1}		28461.8***	10869.8***	10793.4***
Weekly Rating Num_{t-1}			31500.8***	17587.0***
Weekly View_{t-1}				34.79***
R^2	.7244	.7940	.8199	.8787
R^2 Increase	.7244***	.0696***	.0259***	.0588***
N	959	930	821	729

*Note: *p<.05, **p<.01, ***p<.001*
Mean VIF=3.46 (pooled), Dependent Variable: movie revenue after 2nd week

The VIF value is relatively low; nevertheless, based on the correlation analysis between each form of eWOM presented previously, the multicollinearity problem is severe due to the high correlation. Therefore, the impact of each form of eWOM on movie revenue after the second week is analyzed as follows (Tables 5-12, 5-13, 5-14, and 5-15). According to these analyses, the impact of post-consumption eWOM on movie revenue after the second week is significantly positive.

Table 5 -12. Impact of Post-consumption Rating Number on Revenue

Independent Variable	Weekly $Gross_t$
Weekly Rating Num_{t-1}	100701.3***
R^2	.7119
N	818

*Note: *p<.05, **p<.01, ***p<.001, FE2SLS*

Table 5 -13. Impact of Post-consumption View Count on Revenue

Independent Variable	Weekly $Gross_t$
Weekly $View_{t-1}$	74.7701***
R^2	.5926
N	869

*Note: *p<.05, **p<.01, ***p<.001, FE2SLS*

Table 5 -14. Impact of Post-consumption Tweet Number on Revenue

Independent Variable	Weekly $Gross_t$
Weekly $Tweet_{t-1}$	120.5423 ***
R^2	.6056
N	959

*Note: *p<.05, **p<.01, ***p<.001, FE2SLS*

Table 5 -15. Impact of Post-consumption Blog Number on Revenue

Independent Variable	Weekly $Gross_t$
Weekly $Blog_{t-1}$	53031.17***
R^2	.5764
N	1005

*Note: *p<.05, **p<.01, ***p<.001, FE model (Within Transformation)*

5.2.3 Impact of Disconfirmation between Pre- and Post-consumption eWOM

To verify Hypothesis 3, hierarchical regression analysis is performed with the total gross as a dependent variable; the presence of a movie series, MPAA ratings, and genre as control variables; and pre-consumption eWOM, and the difference between pre- and post-consumption eWOM as independent variables. As eWOM, the volume of tweets is selected.

For the analysis in this study, the pre-consumption eWOM pertains to the number of weekly tweets one week before film release, whereas the post-consumption eWOM denotes the number of average weekly tweets for five weeks after film release. When these variables are considered as independent variables, standardization values are used for analysis. The reason is that the direct comparison between pre- and post-consumption eWOM is unreasonable.

Table 5-16 presents the analysis results of the hierarchical regression model for verifying Hypothesis 3. In Model 1, the movie characteristics-related variables are included as control variables. Consequently, a film that is a series and the genre is children or action/adventure is found to have a positive impact on the total gross. Model 2 adds the pre-consumption eWOM as an independent variable. Consequently, pre-consumption eWOM is found to have a positive impact on the total gross. In Model 3, the difference between pre- and post-consumption eWOM is considered as a supplement. The results show that the difference between the pre- and post-consumption eWOM is found to have a negative impact on the total gross, which supports Hypothesis 3. In other words, the higher the difference in eWOM before and after film release is, the lower the total gross becomes.

Table 5-16. Impact of Disconfirmation of eWOM on Total Gross

Independent Variable	Model 1	Model 2	Model 3
Series	1.079***	.770***	.716**
R & NC_7	.082	-.040	-.018
PG_13	.261	.104	.095
Science Fiction	.227	.174	.160
Kid	.964*	.881***	.872***
Thriller	.024	.004	-.008
Comedy	.101	.094	.110
Drama	.017	.074	.070
Action/Adventure	1.642***	.566*	.543*
Pre eWOM		.634***	.781***
Disconfirmation (Pre eWOM, Post eWOM)			**-.720*** **
R^2	.518	. 827	.840
R^2 Increase	.518***	.308***	.013***
N	109	108	108

*Note: *p<.05, **p<.01, ***p<.001*
Standardized Coefficients, Mean VIF=2.28

5.3 Study 2: Channel of eWOM

5.3.1 Impact of eWOM on Innovator and Imitator

To test Hypotheses 4 and 5, the Bass model is used to estimate the coefficient of innovation and the coefficient of imitation for each movie using the daily movie revenue in the first place. Bass (1969) describes *S(T)*, the number of purchases at *T*, in Equation (1) below.

$$S(T) = pm + (q - p)Y(T-1) - \frac{q}{m}Y(T-1)^2 \tag{1}$$

m : Total number of purchases during the entire period

p : Coefficient of innovation

q : Coefficient of imitation

$S(T)$: Number of purchases at *T*

$Y(T)$: Total number of purchases in the (*0, T*) interval

Equation (1) can be expressed as Equations (2) and (3).

$$S(T) = [m - Y(T-1)][p + \frac{q}{m}Y(T-1)] \tag{2}$$

$$S(T) = p[m - Y(T-1)] + \frac{q}{m}Y(T-1)[m - Y(T-1)] \tag{3}$$

As a result, the number of innovators and imitators can be calculated in Equations (4) and (5) (Chang 2008).

$$PY(T) = \sum_{t=0}^{t} p[m - Y(T)] \tag{4}$$

$$QY(T) = \sum_{t=0}^{t} \frac{q}{m} Y(T)[m - Y(T)] \tag{5}$$

Table 5 -17. Coefficient of Innovation and Imitation

Movie	Coefficient of innovation	Coefficient of imitation	Potential revenue
Project X	0.52617	0.105868	54731865
A Thousand Words	0.4555362	0.0309137	18450127
Friends With Kids	0.3800499	0.1310023	7251073
Jiro Dreams of Sushi	0.0648943	0.03369491	2552478
Salmon Fishing in the Yemen	0.0738425	0.5421415	9047981
Casa de Mi Padre	0.4844869	0.0800949	5909483
Jeff, Who Lives At Home	0.2608863	0.2363246	4269426
The Kid with a Bike	0.0745636	0.4623564	1389524
Goon	0.4507779	0.2013187	4168528
Damsels In Distress	0.1216895	0.3160306	1008455
The Hunter	0.1809136	0.6593159	176669
We Have A Pope	0.0913564	0.2196153	486902
The Cabin in the Woods	0.462055	0.0651729	42073277
Darling Companion	0.0872255	0.3793776	793815
Sound of My Voice	0.1418612	0.4298605	408015
The Dictator	0.2394992	0.6708579	59650222
What to Expect When You're Expecting	0.3676996	0.1772501	41152203
Chernobyl Diaries	0.6311629	0.1164686	18119640
Peace Love and Misunderstanding	0.3026539	0.7372261	542762
Rock of Ages	0.545238	0.1870945	38518613
That's My Boy	0.5559761	0.2988948	36859147
Your Sister's Sister	0.1471734	0.4735328	1586249
To Rome With Love	0.1156666	0.5647546	16473666
Beasts Of The Southern Wild	0.0373797	0.4403626	10779226
People Like Us	0.5685306	0.1031292	12434778
Katy Perry Part Of Me	0.2606855	0.9041004	25326071
The Magic Of Belle Isle	0.1538305	0.3945269	102388
Trishna	0.2060237	0.9050546	237173
Easy Money	0.0778248	0.4765542	189163
To the Arctic	0.02074	0.1015622	8573603
The Best Exotic Marigold Hotel	0.0888093	0.449194	46221676
Moonrise Kingdom	0.0482658	0.5590477	45033744
Madagascar 3	0.395773	0.0224709	215672792
Safety Not Guaranteed	0.0991423	0.3344087	3937915
Neil Young Journeys	0.0926726	0.2336173	202420
The Amazing Spider-Man	0.3177875	0.4468865	261224225
The Watch	0.5636816	0.2064292	34179638
Step Up Revolution	0.5154468	0.0988469	34819591
Ai Weiwei Never Sorry	0.1663379	0.3764162	481501

From the above formulas, the diffusion model parameters, such as coefficient of innovation (p), coefficient of imitation (q), and potential revenue (m) are estimated from the weekly movie revenue data. Thirty-nine films whose significance of diffusion model coefficients is less than p-value 0.1 are selected (Chang 2008; Wang et al. 2010) (Table 5-17).

Figure 5-13 presents the weekly variance of the revenue by innovator and imitator on an average of 39 films that can be significantly explained by the diffusion model. Figure 5-13 also illustrates the variance by revenue by the innovator and imitator in “Salmon Fishing in the Yemen” and “The Amazing Spider-Man.”

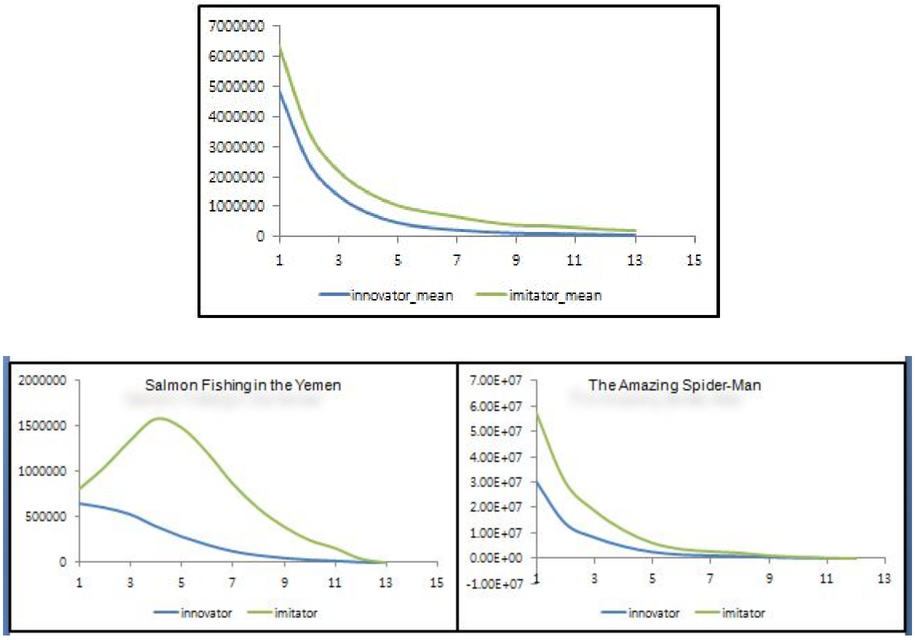

Figure 5-13. Weekly Innovator and Imitator

Table 5 -18. Correlation between eWOM and Innovator and Imitator

	weekly tweet	weekly blog	weekly rating	weekly view	innovator	imitator
weekly tweet	1.0000					
weekly blog	0.222**	1.0000				
weekly rating	0.540**	0.454**	1.0000			
weekly view	0.711**	0.222**	0.624**	1.0000		
innovator	0.392**	0.187**	0.552**	0.535**	1.0000	
imitator	0.328**	0.299**	0.688**	0.524**	0.461**	1.0000

Table 5-18 presents the correlation between the eWOM from each social media channel and the innovator and imitator. To the innovator and imitator, Yahoo! Movies and YouTube show a relatively higher correlation.

Tables 5-19 and 5-20 present the analysis results to test Hypotheses 4 and 5. Our analysis is conducted with the innovator and imitator as dependent variables, and the eWOM volume from Twitter and Yahoo! Movies as independent variables. As a result, all eWOM forms had a significant impact on the innovator and imitator; nevertheless, the impact has the characteristics as follows. The number of ratings appears to have a statistically stronger impact on the imitator than the innovator, which supports Hypothesis 5a. Although not statistically significant, the number of tweets appears to have a relatively stronger impact on the innovator than the imitator, which rejects Hypothesis 4a.

Table 5 -19. Impacts of Rating Number on Innovators and Imitators

	$Innovator_t$		$Imitator_t$		Fisher's Z
	Coefficient	Standard Error	Coefficient	Standard Error	
Weekly Rating Num_{t-1}	46049.7***	4577.69	40659.9***	3249.028	-3.020***
R^2	.2630		.3404		
N	343 (group=33)		343 (group=33)		

*Note: *p<.05, **p<.01, ***p<.001, Generalized 2SLS (RE Model+2SLS)*

Table 5 -20. Impacts of Tweet Number on Innovators and Imitators

	$Innovator_t$		$Imitator_t$		Fisher's Z
	Coefficient	Standard Error	Coefficient	Standard Error	
Weekly $Tweet_{t-1}$	30.15***	3.463	13.58***	1.749	1.113
R^2	.1534		.1073		
N	460(group=36)		460(group=36)		

*Note: *p<.05, **p<.01, ***p<.001, RE Model*

Tables 5-21 and 5-22 present the results of analysis with the innovator and imitator as dependent variables, and the eWOM volume from blogs and YouTube as independent variables. Although not statistically significant, blogs appear to have a relatively stronger impact on the imitator. Moreover, no significant difference is observed between the impacts of eWOM from YouTube on the innovator and imitator.

Table 5 -21. Impacts of Blog Number on Innovators and Imitators

	$Innovator_t$		$Imitator_t$		Fisher's Z
	Coefficient	Standard Error	Coefficient	Standard Error	
Weekly $Blog_{t-1}$	37873.8***	7045.201	28996.6***	3146.429	-1.827
R^2	.0349		.0895		
N	469 (group=39)		469 (group=39)		

*Note: *p<.05, **p<.01, ***p<.001, FE Model*

Table 5 -22. Impacts of View Count on Innovators and Imitators

	$Innovator_t$		$Imitator_t$		Fisher's Z
	Coefficient	Standard Error	Coefficient	Standard Error	
Weekly $View_{t-1}$	77.057 ***	6.234552	38.254***	2.90462	0.230
R^2	.2866		.2747		
N	440 (group=39)		440 (group=39)		

*Note: *p<.05, **p<.01, ***p<.001, FE Model*

The number of films that can be explained by the Bass model is limited to 39. Nevertheless, a stable result can be obtained through the panel data analysis. However, all films cannot be explained by the diffusion model. To compensate for this shortcoming, the impact of each form of eWOM on movie revenue by week is analyzed.

5.3.2 Impact of eWOM by Week

The impact of each form of eWOM by week on movie revenue is analyzed. Figure 5-14 shows the simple linear regression analysis by week and by social media channel to determine the impact of each form of eWOM on the weekly revenue. Given that the dimension of each form of eWOM is not identical, the standardized coefficients are used for interaction comparison. Figure 5-15 also illustrates the changes in the coefficients of determinants by week and by social media channel.

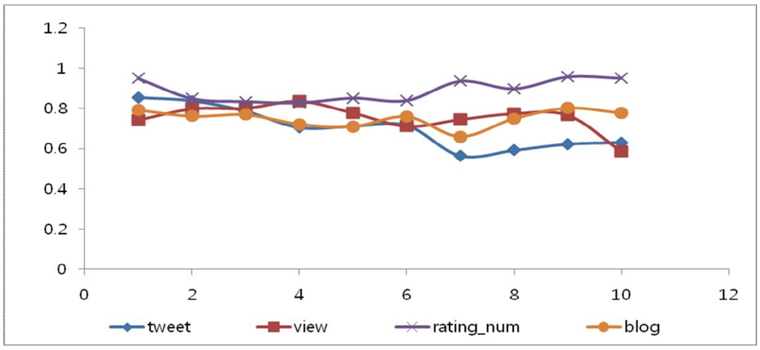

Figure 5 -14. Weekly Standardized Coefficients of Each eWOM

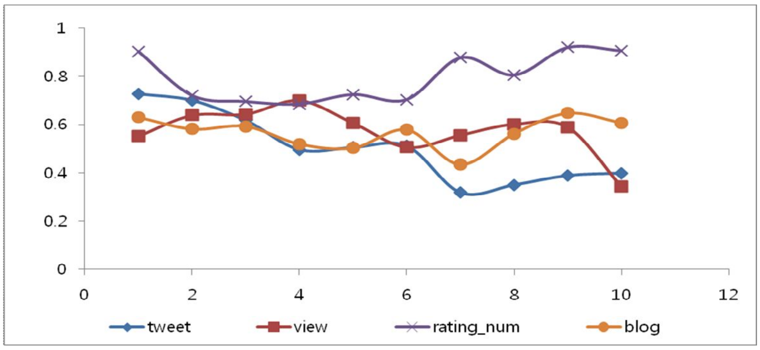

Figure 5 -15. Weekly Coefficient of Determinants of Each eWOM

From Table 5-23, the findings are summarized as follows. Twitter appears to have a significantly stronger impact on the initial time of opening than in later times, which supports Hypothesis 4b. Yahoo!Movies generally shows the largest impact throughout the opening, and its impact on movie revenue tends to be significantly stronger in the later stages than in the initial stages, which supports Hypothesis 5b. The result also shows that blog has the stronger impact on movie revenue in the later times of opening than the initial times of opening, and throughout the opening, the impact of YouTube appears to be relatively consistent. A similar result to the verification by the diffusion model is drawn. According to Cheon (2004) and Cho (2006), initial time of opening is from week 1 to week 3, whereas later time of opening is from week 4 in this analysis.

Table 5 -23. Comparison of the Impact of Each eWOM by Week

	Correlation		Transformed Correlation		N1	N2	Fisher's Z
	Week 1,2,3	Week 4~	Week 1,2,3	Week 4~			
Twitter	0.632	0.492	0.745	0.538	296	771	**3.005**
Blog	0.561	0.681	0.634	0.831	322	800	-2.977
Yahoo!Movies	0.552	0.842	0.622	1.231	179	741	**-7.254**
YouTube	0.710	0.704	0.887	0.876	293	728	0.164

Twitter

Table 5-24 presents the results of the simple linear regression analysis to determine the impact of weekly tweet volume on movie revenue. Tweets continue to have an impact on movie revenue for 10 weeks after opening; however, the impact tends to decrease over time.

Table 5 -24. Impact of Tweet Number on Movie Revenue

Week	Coefficient of weekly tweet$_{t-1}$	Standardized coefficient of weekly tweet$_{t-1}$	R^2
1	356.8754***	.853	.7272
2	78.91557***	.837	.7007
3	104.0529***	.786	.6171
4	92.8931***	.704	.4958
5	76.05651***	.711	.5054
6	67.53301***	.715	.5112
7	47.15095***	.564	.3186
8	44.52456***	.592	.3502
9	36.04096***	.623	.3885
10	19.59662***	.631	.3982

*Note: *p<.05, **p<.01, ***p<.001*

YouTube

Table 5-25 shows the results from the simple linear regression analysis to determine the impact of weekly view count on movie revenue. The view count of YouTube appears to have an impact on movie revenue consistently for 10 weeks after opening.

Table 5 -25. Impact of View Count on Movie Revenue

Week	Coefficient of weekly view$_{t-1}$	Standardized coefficient of weekly view$_{t-1}$	R^2
1	126.448***	.742	.5519
2	69.1453***	.798	.6380
3	65.54626***	.801	.6430
4	62.74369***	.836	.6993
5	40.72433***	.778	.6059
6	27.96593***	.711	.5060
7	20.97528**	.745	.5557
8	24.95245***	.775	.6008
9	23.00548***	.767	.5886
10	12.07967***	.587	.3450

*Note: *p<.05, **p<.01, ***p<.001*

Yahoo!Movies

Table 5-26 shows the results from the simple linear regression analysis to determine the impact of the weekly rating number on movie revenue. The rating number of Yahoo! Movies appears to have a constant impact on movie revenue for 10 weeks after opening. However, the impact of rating tends to increase after opening over time (as more reviews from consumers are accumulated). Compared to other social media channels, Yahoo! Movies appears to have the largest impact on movie revenue.

Table 5 -26. Impact of Rating Number on Movie Revenue

Week	Coefficient of weekly $rating_{t-1}$	Standardized coefficient of weekly $rating_{t-1}$	R^2
1	540463***	.950	.9026
2	57308.44***	.848	.7204
3	99689.39***	.833	.6954
4	110972.2***	.827	.6853
5	102277.0***	.851	.7246
6	64817.96***	.839	.7040
7	111528.3***	.936	.8772
8	87043.49***	.897	.8062
9	91341.04***	.958	.9190
10	75859.6***	.951	.9055

*Note: *p<.05, **p<.01, ***p<.001*

Blog

Table 5-27 shows the result from the simple linear regression analysis to determine the impact of weekly number of blogs on the movie revenue. Blogs appear to have an impact on movie revenue constantly for 10 weeks after opening.

Table 5 -27. Impact of Blog Number on Movie Revenue

Week	Coefficient of weekly $blog_{t-1}$	Standardized coefficient of weekly $blog_{t-1}$	R^2
1	241464.4 ***	.794	.6301
2	47903.69***	.762	.5812
3	49117.37***	.770	.5924
4	48274.78 ***	.721	.5196
5	38777.06***	.709	.5032
6	40301.58***	.760	.5782
7	27911.88***	.659	.4345
8	27545.8***	.750	.5622
9	24024.51***	.804	.6471
10	16033.65 ***	.779	.6072

*Note: *p<.05, **p<.01, ***p<.001*

5.4 Study 3: Value of eWOM

5.4.1 Impact of Helpful Review on Movie Sales

This study attempts to verify whether the impact of helpful reviews on product sales is stronger than that of non-helpful reviews using review data from Yahoo!Movies. Review helpfulness (Helpfulness) refers to the percentage of people who found the review helpful. For each review in Yahoo! Movies, consumers are asked, "Was this review helpful?" and the consumers can answer either "yes" or "no." The study collects the responses and calculates the proportion of helpful votes to the total votes as helpfulness. The reviews are excluded if the total number of answers to a question asking whether the review is helpful is less than or equal to three answers because the helpfulness is not meaningful (Kim et al. 2006; Wu et al. 2011). The reviews are divided into the high-helpfulness group and the low-helpfulness group on the basis of the group whose helpfulness is more than 50% and that whose helpfulness is less than 50%. Whether the impact of the review rating between groups on movie revenue is significantly different is verified using Chin's T-test.

$$t_{12} = \frac{p_1 - p_2}{\sqrt{\frac{(n_1-1)^2}{(n_1+n_2-2)} * SE_1^2 + \frac{(n_2-1)^2}{(n_1+n_2-2)} * SE_2^2} * \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \quad ;$$

p_i: Coefficient of path *i*
n_i: Sample size of path *i*
SE_i: Standard error of path *i*

Using the aforementioned formula proposed by Chin (2012), the moderating effect of review helpfulness on the relationship between review ratings and movie sales was found to be significant (Table 5-28).

Table 5 -28. Moderating Effect of Review Helpfulness

	Non-helpful Review		Helpful Review		Chin's T-statistics
	Coefficient	Standard Error	Coefficient	Standard Error	
weekly review rating$_{t-1}$	3582464*	1492316	1.81e+07***	2110692	-5.75***
(constant)	-6813466	5006074	-6.05e+07***	7765867	
R^2	0.1747		.2406		
N	934		771		

*Note: *p<.05, **p<.01, ***p<.001, LSDV*

5.4.2 What is a Helpful Review?

To test Hypothesis 7, this study collects actual online review data from Amazon.com in October 2010 using web data mining. A crawler developed by Python is used to download web pages containing consumer reviews, reviewers, and product information from Amazon.com. Another Python-based system is developed to parse the HTML web pages into a database. To collect random review data, 23 different kinds of products are selected by considering various product categories in Amazon.com, and the reviewers who had written the reviews for these products are chosen. Eventually, information related to all the reviews written by these reviewers is collected. A total of 75,226 online consumer reviews written by 4,613 reviewers on different kinds of products are obtained. The reviews are excluded if the total number of answers to a question asking whether the review is helpful is less than or equal to five answers because the helpfulness is not meaningful (Kim et al. 2006; Wu et al. 2011). After elimination, an analysis of 15,059 reviews written by 1,796 reviewers is conducted. Table 5-29 presents the data collected for analysis.

Table 5 -29. Data from Amazon.com

Data Collected		Definition	Instrumentation
Product level	Average Rating	Average star rating on the product	Numerical Value (Scale)
Review level	Review Rating	A star rating value on a review	Numerical Value (1, 2, 3, 4, 5)
	Word Count	Number of words in a review message	Numerical Value (Scale)
	Contents	Contents of a review message	Textual Description
	Date	Date when a review is written	Numerical Value (Scale)
	Total Vote	Total number of answers to question asking if the review is helpful	Numerical Value (Scale)
	Helpful Vote	Number of positive answers to question asking if the review is helpful	Numerical Value (Scale)
	Helpfulness	Proportion of positive answers to total answers to question asking if the review is helpful	Numerical Value (Scale)

The average review rating of the data collected is 3.83, and the mean value of the product average rating is 4.03. The average helpfulness is also found to be 76.98% (Table 5-30).

Table 5 -30. Descriptive Statistics of Amazon Review

Variable	Mean	Std. Dev.	Min	Max	N
Review Rating	3.83	1.37	1	5	15059
Average Rating	4.03	.62	1	5	15059
Helpfulness	76.98	25.63	0	100	15059

To verify Hypothesis 7, the impact of the difference between review rating and product average rating on the review helpfulness is verified.

First, to verify whether the first-order linear equation or the second-order quadratic equation is appropriate, the explanatory power by each analysis is compared. Before the analysis, the outlier is screened with Cook's D; however, the outliers following this standard are not found. To reduce the multicollinearity between variables, all variables are centered on the basis of the mid-point of criterion before analysis (Edwards and Parry 1993). The results of the analysis suggest that the explanatory power of the second-order quadratic equation is significantly increased by 4.4% compared to the first-order linear equation (Table 5-31). Therefore, this study uses the response surface methodology for the second-order quadratic equation.

Table 5 -31. Predicting Review Helpfulness Using Star Rating

	First-Order Linear Equation		**Second-Order Quadratic Equation**	
Dependent Variable	Independent Variable	B	Independent Variable	B
Review Helpfulness	(Constant)	41.018 ***	(Constant)	25.845***
	R_{dif}	-14.185***	R_{ind}	3.071***
			R_{ave}	-2.124***
			R_{ind}^2	-1.897***
			$R_{ind}R_{ave}$	6.975***
			R_{ave}^2	-1.808***
R^2	.200		.244	
R^2 Increase	.200***		.044***	
N	15059		15059	

*Note: *p<.05, **p<.01, ***p<.001*

The response surface methodology is the visual and statistical test to understand the polynomial model (Venkatesh and Goyal 2010). The response surface methodology to solve the difficulty in interpreting the coefficients drawn by the equation of polynomial model plays a role in understanding the meaning of these coefficients (Edwards and Parry 1993; Venkatesh and Goyal 2010).

The response surface methodology can draw three key features.

The first feature is the stationary point, which means that the slope of the surface is 0 in all directions (Edwards and Parry 1993). The second feature is the principal axes (first principal axis and second principal axis), which are perpendicular to each other and intersect at the stationary point (Edwards and Parry 1993). The first principal axis is the line along which the slope of a concave surface is minimum, and the second principal axis is the line along which the slope of a concave surface is maximum (Venkatesh and Goyal 2010). The third feature is the shape of the surface along the lines in the X or Y plane (Edwards 2002).

To test the hypothesis, the conversion to the statistical tests using the features of the response surface model is necessary. Based on the quadratic equation obtained earlier, the tests to verify the hypothesis of this study are presented.

The quadratic polynomial equation for this study is as follows:

$$H = b_0 + b_1 R_{ave} + b_2 R_{ind} + b_3 R_{ave}^{\ 2} + b_4 R_{ave} R_{ind} + b_5 R_{ind}^{\ 2} + e$$

H: review helpfulness

R_{ave}: *product average rating*

R_{ind}: *individual review rating*

Based on the work of Edwards (2002), the stationary points are defined as:

$$(X_0, Y_0) = \left(\frac{b_2 b_4 - 2b_1 b_5}{4b_3 b_5 - b_4^{\ 2}}, \frac{b_1 b_4 - 2b_2 b_3}{4b_3 b_5 - b_4^{\ 2}}\right)$$

Edwards (2002) showed that the equation for the first principal axis is:

$$Y = p_{10} + p_{11}X$$

$$p_{11} = \frac{b_5 - b_3 + \sqrt{(b_3 - b_5)^2 + b_4^{\ 2}}}{b_4}$$

$$p_{10} = Y_0 - p_{11}X_0$$

Edwards (2002) also showed that the equation for the second principal axis is:

$$Y = p_{20} + p_{21}X$$

$$p_{21} = \frac{b_5 - b_3 - \sqrt{(b_3 - b_5)^2 + b_4^{\ 2}}}{b_4}$$

$$p_{20} = Y_0 - p_{21}X_0$$

To verify the study based on the methodology presented in Venkatesh and Goyal (2010), the specific test methods are presented as follows through the features provided by the response surface methodology. When the individual review rating differs from the product average rating in any direction, the slope of the response surface is deviated (Hypothesis 7). In other words, when the individual review rating is higher than the product average rating, the slope of the surface is positive, and in the opposite case, the slope of the surface is negative. The second principal axis is also parallel to the disconfirmation axis (X=-Y). Accordingly, if I test whether the value of P_{21} is significant and prove that this value is not significantly different from -1, then Hypothesis 7 is supported.

To verify the hypothesis, the standard errors and significance levels on the stationary points and slopes are estimated with a jackknife procedure. Jackknife is a general nonparametric procedure for calculating the standard error of an expression (Efron and

Gong 1983). If the number of samples is large as in the current study, jackknifing is preferred to bootstrapping in terms of efficiency (Efron and Gong 1983).

The three-dimensional graph is schematized via MATLAB, and the significance test through jackknife is analyzed through SAS 9.3. Figure 5-16 schematizes the relationship between two independent variables (the individual review rating and the product average rating) and the dependent variable of review helpfulness, three-dimensionally. The response surface for review helpfulness is concave, and the stationary point is (0.106, -0.382).

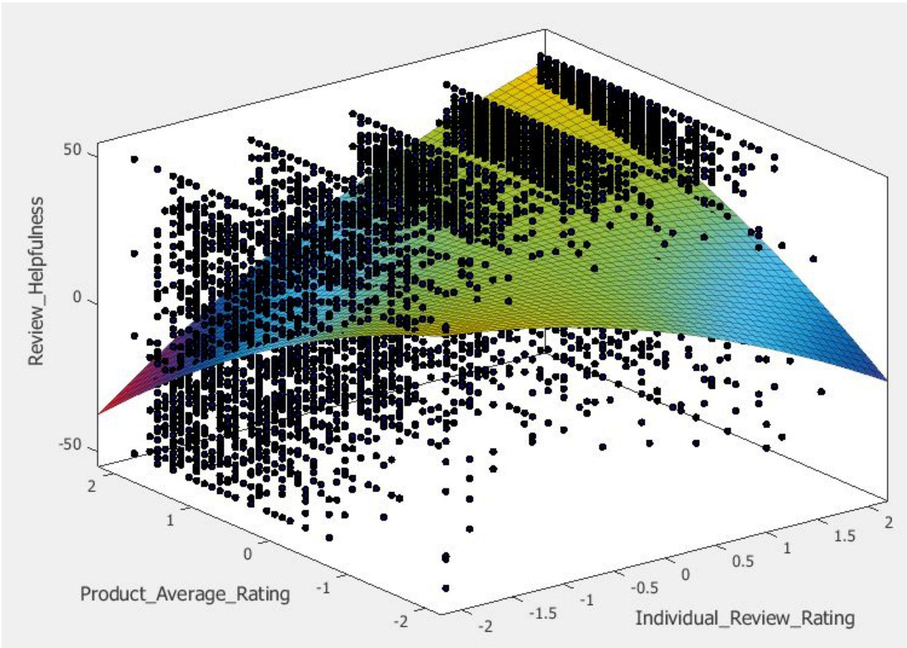

Figure 5 -16. Response Surface for Star Rating Predicting Helpfulness

The stationary points and principal axes are shown in Table 5-32.

Table 5 -32. Stationary Points and Principal Axes

		Estimates (t-value)
Stationary point	X_0	0.106*** (0.186)
	Y_0	-0.382***(0.095)
First principal axis	P_{10}	-0.490***(0.131)
	P_{11}	1.012***(0.069)
Second principal axis	P_{20}	-0.277***(0.260)
	P_{21}	-0.987***(0.067)

*Note: ***p>.05, **p>.01, *p>.001*
Jackknife method

Our conclusion that P_{21}= -0.987 is drawn, which is not significantly different from -1. In other words, the secondary principal axis is parallel to the disconfirmation axis. Thus, Hypothesis 7 is supported (Table 5-33).

Table 5 -33. Testing Hypothesis 7

		Estimates (t-value)
H7	P_{21}	-0.987***(0.067)
	$P_{21} = -1$	-0.987***(0.192)

*Note: ***p>.05, **p>.01, *p>.001*
Jackknife method

Additionally, this study aims to compare the review helpfulness when the individual review rating is higher than the product average rating with the review helpfulness when the individual review rating is lower than product average rating. The linear slope (b_1-b_2) at disconfirmation axis (Y = -X) is significant and positive at 5.195. From the results of the analysis, we can conclude that the review helpfulness is reduced more strongly when the individual review rating is lower than the product average rating (Table 5-34).

Table 5 -34. Slope at Disconfirmation Axis

		Estimates (t-value)
Y= -X	b_1-b_2	5.195[a]***(0.9029)
	b_1-b_2 > 0	5.195[b]***(5.753)

*Note: a: ***p>.05, **p>.01, *p>.001, b:*p<.05, **p<.01, ***p<.001*
Jackknife method

Robustness Check using Text Mining

This study aims to investigate whether the helpfulness of the negative review or the positive review is significantly different depending on the product average rating. The study attempts to perform sentiment analysis for mining review text, also called opinion mining, which quantifies subjective opinions in consumer feedback (Lee et al. 2008). The purpose of the analysis in the current study is to quantify the degree of subjective words (positive, negative). Thus, emotional words using SentiWordNet are detected (Esuli and Sebastiani 2006). SentiWordNet is a library that summarizes the degree of subjectiveness and objectiveness of words and is based on WordNet. The degree is devised from negative to positive, 1.0 being the maximum degree, enabling the comparison of relativity between words. This study analyzes the number of subjective adjectives that appear in review contents, based on SentiWordNet.[4]

The analysis is limited to the case when the review contents have more than five subjective (positive or negative) words, and moderate reviews (the positive words are

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[4] When the review content mining is conducted, negatives are dealt with as follows. In c ases where the negatives are in the form of “be not” (are not, is not, am not, were not, was not, not be, and so on) that negates adjectives within the three words before the a djective, the positive adjective is changed to a negative one, and the negative adjective t o a positive one.

not significantly different from the negative words) are also excluded from our analysis.[5] Consequently, 8,116 reviews remain for the analysis (Table 5-35).

Table 5 -35. Number of Positive, Moderate, and Negative Reviews

Moderate Review	Positive Review	Negative Review	Total Review
5,874	7,138	978	13,990

Table 5-36 shows that in the collected review contents, the average positive words in a review are used 17.97 times, and the negative words 12.4 times. Consumers are found to use positive words relatively more than negative words when writing their reviews.

Table 5 -36. Descriptive Statistics of Positive and Negative Words

Variable	Mean	Std. Dev.	Min	Max	N
Positive Word	17.97	15.480	0	258	13990
Negative Word	12.40	11.557	0	223	13990

Table 5-37 presents the descriptive statistics on the positive words and negative words used for each review depending on the product average rating. As the ratio of the positive words appears to be higher even when the product average rating is only 1, consumers are again found to use relatively more positive words when they write their reviews.

5 $\left|\frac{(Num\_positiveword - Num\_negativeword)}{(Num\_positiveword + Num\_negativeword)}\right| < 0.2$

Table 5-37. Descriptive Statistics of Positive and Negative Words depending on the Product Average Rating

Product Average Rating	Variable	Mean	Std. Dev.	Min	Max	N
1 (1~1.5)	Positive Word	10.73	19.28	0	117	41
	Negative Word	10.41	13.18	1	80	41
2 (1.5~2.5)	Positive Word	15.60	15.21	2	135	222
	Negative Word	12.35	12.35	1	91	222
3 (2.5~3.5)	Positive Word	16.88	14.48	0	136	1905
	Negative Word	12.53	11.30	0	101	1905
4 (3.5~4.5)	Positive Word	18.35	15.85	0	258	7959
	Negative Word	12.75	11.84	0	223	7959
5 (4.5~5)	Positive Word	17.94	15.09	0	167	3863
	Negative Word	11.65	10.96	0	152	3863

Those reviews are divided into positive and negative reviews, and which of these reviews is more helpful depending on the product average rating is determined via a t-test. Consequently, when the product average rating is at the level of 1, the helpfulness of the negative review is significantly higher than that of the positive review; however, when the product average rating is at the level of 5, the helpfulness of the positive review is found to be significantly higher than that of the negative review (Table 5-38).

Table 5 -38. Results of T-test for Review Helpfulness

Product Average Rating	Positive vs. Negative	Review Helpfulness (Mean)	Standard Error	N	P-value
1 (1~1.5)	Negative Review	90.62	2.091	15	0.0254
	Positive Review	63.73	.8749	11	
2 (1.5~2.5)	Negative Review	75.00	4.984	25	0.2949
	Positive Review	80.68	2.476	91	
3 (2.5~3.5)	Negative Review	64.50	2.091	178	0.0001
	Positive Review	73.02	.8749	836	
4 (3.5~4.5)	Negative Review	70.91	1.172	545	0.0000
	Positive Review	77.62	.3863	3975	
5 (4.5~5)	Negative Review	77.03	2.020	215	0.0000
	Positive Review	85.79	.4481	2225	

Figure 5-17 illustrates a graph representing how the review helpfulness of the positive review versus the negative review changes depending on the product average rating. The existing research has argued that for positivity bias or negativity bias, the positive review or the negative review is more credible; nevertheless, the result may differ depending on the product average rating, which confirms Hypothesis 7.

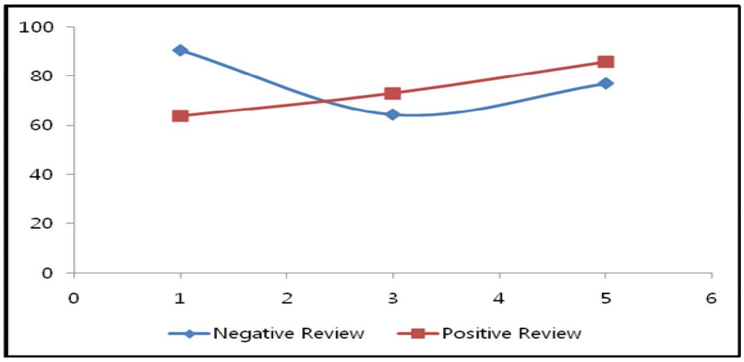

Figure 5 -17. Review Helpfulness by Product Average Rating

CHAPTER 6 CONCLUSION

6.1 Summary and Discussion

This study overcomes the limitations of the existing research that could not provide a unified interpretation of eWOM despite the interest of every sector of society in eWOM. Therefore, the impact of eWOM on movie revenue was analyzed from three aspects of eWOM: the time when eWOM is written, the social media channel on which eWOM is written, and the value of eWOM. From the findings of the analysis, the following research questions can be addressed:

- Does the difference between pre- and post-consumption eWOM (disconfirmation) have an impact on movie revenue?

Hierarchical regression analysis was performed with the total gross as a dependent variable; the presence of a movie series, MPAA ratings, and genre as control variables; and the pre-consumption eWOM (the number of weekly tweets one week before film release), post-consumption eWOM (the number of weekly tweets for five weeks after film release), and the difference between pre- and post-consumption eWOM as independent variables. This study indicated that the impact of the disconfirmation of pre- and post-consumption eWOM is negatively related to movie revenue. The findings are expected to provide recommendations on the time-periodic management of eWOM from the company perspective with the hope of maximizing product sales.

■ How does the impact of eWOM on movie revenue change depending on the difference among social media channels on which eWOM is written?

With the emergence of various social media channels, various kinds of eWOM are exerting their influences on the customer purchase decision. The existing research has conducted an empirical analysis of the impact of eWOM from various social media channels on consumer decision making. However, whether the influence of eWOM from various social media channels shows what differences with what characteristics was not analyzed at all. The present study investigates the time-periodic impact of four social media channels, such as Twitter, blog, Yahoo!Movies, and YouTube, on movie sales.

Twitter was found to be strongly influential in the initial stage of opening and Yahoo!Movies in the later stage. This outcome is explainable by the diffusion of innovation theory that the influence of mass media is stronger in the initial stage of innovation spread, and that of interpersonal communication in the late stage.

Twitter is the mass media channel that was the most influential in the initial stage of movie opening. The reason is that Twitter has a strong "awareness effect" in real time through the push mode and a rapid spread via the retweet function. Twitter configures social networks and conveys opinions in relatively short words, but has relatively weak persuasive effects as the opinions on the same theme are not condensed but scattered compared to those in other social media channels. According to the data from Twitter used in this study, the average number of followers per user is 2,142,[6] and the ratio of retweets among the total number of tweets is 26%, which suggests that Twitter has the characteristic of mass media.

[6] In general, this numerical value differs significantly from the average number of follow ers per user. The neutral tweet has 3,298 followers on average, because it is used mainl y for publicity.

Meanwhile, Yahoo!Movies' online review is characteristic of interpersonal communication that its persuasive effects are stronger based on the pull mode. The existing research involved an in-depth study of the awareness and persuasive effects of online reviews. However, the consensus on which is more strongly influential—the awareness effect (Duan et al. 2008a) or the persuasive effect—has not been reached yet. The online review is considered to have relatively stronger persuasive effects (Rui et al. 2011) because it provides the condensed and quantified information made by the public (collective intelligence). In addition, the influence of the online review is considered to be relatively lower in the initial stage of opening because it has to secure volume to some extent until the value as collective intelligence can be exerted. Based on this study, the online review was found to be a form of collective intelligence with strong persuasive effects, which suggests that Yahoo!Movies has the characteristic of interpersonal communication.

Additionally, the impact of YouTube on movie revenue is consistent from the initial stage of opening until the late stage. YouTube is the structure on which a buying decision is made by watching trailers rather than by listening to opinions, and thus has a similar structure to TV commercials, one of the existing traditional media platforms. In addition to this characteristic of mass media, YouTube is considered to have the additional characteristic of interpersonal communication because it is shared with other channels through the link to Twitter or the blog. On the other hands, the impact of blog on movie revenue is stronger in the late stage of opening than the initial stage of opening as like Yahoo!Movies. This result can be interpreted that as a kind of social network service, the blog has the characteristic of interpersonal communication.

- Is the impact of a valuable eWOM stronger than other forms of eWOM? If so, what is a valuable eWOM?

The research on the impact of message sidedness on the message credibility has been conducted consistently, and the study on the impact of the rating extremity of the online review on the review helpfulness has recently been carried out. However, the research findings on the relationship between the existing rating extremity and the review helpfulness are inconclusive. This study attempted to analyze why this inconclusive result had been drawn from the perspective of collective intelligence.

This research attempted to find the relationship between review extremity and review credibility by analyzing online consumer review data from Amazon.com. Consequently, consumers appear to have confidence in the review with relatively similar ratings with product average rating. The review that consumers think helpful is the one that is close to the collective intelligence. According to Malone et al. (2010), the average rating of the reviews for a specific product by the public can be seen as a form of collective intelligence. Moreover, using online review data from Yahoo!Movies, the current study finds that the moderating effect of review helpfulness on the relationship between review ratings and movie sales is significant.

6.2 Discussion and Contribution

6.2.1 Academic Contribution

Theoretically, this study makes several contributions.

First, this study tried to classify social media channels by performing an empirical analysis. From my viewpoint, this is the first study to classify the social media channels based on the actual data from the perspective of social media impact. The existing research has attempted to classify the social media channels, but mainly consisted of intuitive rather than empirical analysis. Kaplan and Haenlein (2010) attempted to classify social media channels based on characteristics such as self-presentation and media richness.

Second, this study is also significant in that social media is explained by the characteristics of mass media and interpersonal communication from Rogers's perspective of the innovation diffusion model. Social media tends to be regarded as an evolved form of the existing mass media, but also has characteristics of interpersonal communication. The findings indicate that the eWOM from each social media channel shows a different degree of convergence between mass media and interpersonal communication. Accordingly, eWOM by platform is expected to have a different influence by period.

Third, the result of the third study indicates that previous research on the relationship between the review extremity and review helpfulness has failed to consider the consumer perception toward product quality, resulting in inconsistent findings. This study analyzed why these mixed findings are drawn from the collective intelligence perspective. This study is intended to serve as a starting point in developing new perspectives on the effect of consumer attitudes toward product quality on the relationship between review rating and review helpfulness.

6.2.2 Practical Contribution

In practice, the results of this study have several implications, and provide useful insights to eWOM management and social media providers.

First, the results of the first study suggest that disconfirmation between pre- and post-consumption eWOM is negatively related to total revenue. The findings are expected to provide some suggestions on the time-periodic management of eWOM from the company perspective, hoping to maximize product sales. For example, implications that the management of eWOM is not always the best way to increase the expectations of a specific movie have emerged. Conversely, the strategy of maximizing the revenue by lowering the expectations of a movie is also inappropriate. This approach may lead to the loss of opportunity to increase the revenue by creating difficulty in mobilizing the audience in the initial stages. In other words, it is significant in forming the expectations appropriate for the actual movie values.

Second, the finding that disconfirmation between pre- and post-consumption eWOM has a negative impact on total revenue, can be utilized to increase the accuracy of revenue forecasting. Revenue forecasting has a significance in that it provides key baseline data on the major strategic variables in the business activities, such as the timing of new product introduction, determination of price levels, product design, productive planning, and marketing. Therefore, the findings of this study are expected to help a company's strategic decision making by increasing the accuracy of revenue forecasting.

Third, the results of the second study suggest that Twitter has mass media characteristics that are more influential among innovators than imitators, and that Yahoo!Movies has interpersonal communication characteristics that are more influential among imitators than innovators. The findings of this study are expected to present some strategic directions for corporate eWOM management. The findings are also expected to provide suggestions for determining the social media channel that is appropriate to use according to the purpose of eWOM management in the current situations when various social media channels exist. For example, increasing the utilization of social media channels that have the characteristic of mass media such as Twitter seems necessary to increase the awareness of new products and manage the social media with high persuasive effects such as online reviews for the products that have already gained public awareness.

Fourth, the findings of the third study are expected to be helpful in drawing a strategy to reduce the information overload for consumers as online market owners begin to understand the characteristics of helpful online reviews. For example, Amazon.com hoped to reduce the information overload by placing the most helpful favorable reviews and the most helpful critical reviews at the top of the web page. However, based on this analysis, placing the reviews with high helpfulness among those that have similar ratings to the product average ratings on top is also helpful in consumer purchase decisions.

6.3 Limitations and Future Research

First, this study selects the movie domain to investigate the impact of eWOM on product sales. However, extremely diverse types of products in practice are available. Limitations in generalizing the findings of this study, which are limited to the movie domain, exist. To generalize, verifying the impact of eWOM on the other products sales is necessary. Investigating the impact of eWOM on the election, which has recently been the subject of attention, is interesting as well.

Second, this study investigates how the impacts of eWOM from four kinds of social media channels differ. However, numerous kinds of social media channels are available, such as social network services, collaborative projects, online review sites, discussion forums, and virtual social worlds. To overcome this limitation, future research should conduct a comparative analysis of the impact of eWOM on the other social media channels, such as Facebook, Second Life, and Wikipedia, as well as Twitter, Yahoo!Movies, YouTube, and the blog used in this study.

Third, limitations also exist in that the study was carried out mainly in terms of the impact of the eWOM volume. However, eWOM has various dimensions, such as valence and dispersion. Thus, determining the impact of eWOM from the perspective of valence or dispersion in future research will be necessary.

6.4 Conclusion

Although numerous changes are evident in every corner of society due to the impact of social media, existing studies cannot present a unified interpretation of eWOM. Therefore, this study aims to analyze the impact of eWOM from three aspects: time, channel, and value.

Expectation confirmation theory, innovation diffusion model, and collective intelligence are employed as theoretical bases. This study collected weekly movie revenue and daily eWOM information on 145 movies from Twitter, Yahoo!Movies, blog, and YouTube.

On the basis of empirical tests, the results provide support for most of the hypothesized relationships. First, from the first study, disconfirmation in the number of tweets before and after the movie opening is revealed to have a negative impact on movie sales. This result suggests that forming a higher value than the substantial value does not always bring about positive results. Second, the second study performs a comparative analysis of how the impact differs depending on the social media channel where eWOM is written. Based on Rogers's innovation diffusion model, this study finds that Twitter is more influential among innovators than imitators, whereas the online review site is more influential among imitators than innovators. This study is academically significant in that this is the first to attempt to classify social media channels from the perspective of the "impact of social media" using the actual eWOM data. This study is also expected to be utilized as basic data to present strategic directions for which social media will be utilized from the corporate perspective by period or by purpose. Third, the third study reveals that all eWOM forms do not have the same influence. Based on collective intelligence, this study finds that when the individual review ratings are more consistent with the product average ratings, the helpfulness of the reviews increases. The findings of this study can be utilized to draw a strategy to reduce the information overload in the online market.

This study makes three contributions. First, from the research methodology perspective, in this analysis, eWOM is collected as panel data from Twitter, Yahoo! Movies, YouTube, and the blog. The information on the contents of eWOM is quantified and secured as data via text mining. Based on these data, eWOM information is utilized from various social media channels, and a more extensive range of analyses is performed. Second, from the theoretical perspective, this study finds that social media is divided into that which is characteristic of mass media and interpersonal communication based on the innovation diffusion model. The third contribution is from the practical perspective. This study is expected to present strategic directions for corporate eWOM management. Based on the findings from this study, a company is expected to identify the characteristics of eWOM by period and by social media channel, and consider the differentiation of valuable eWOM that can be utilized to uncover more efficient eWOM management methods. This study is also expected to be utilized to suggest the future direction of social media.

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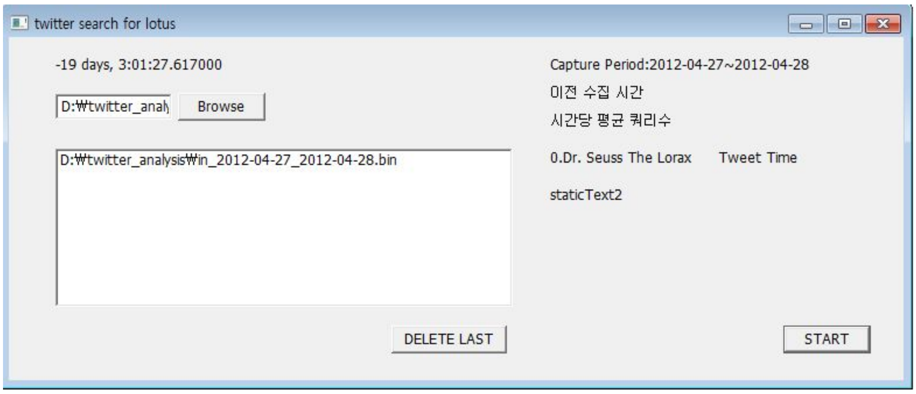
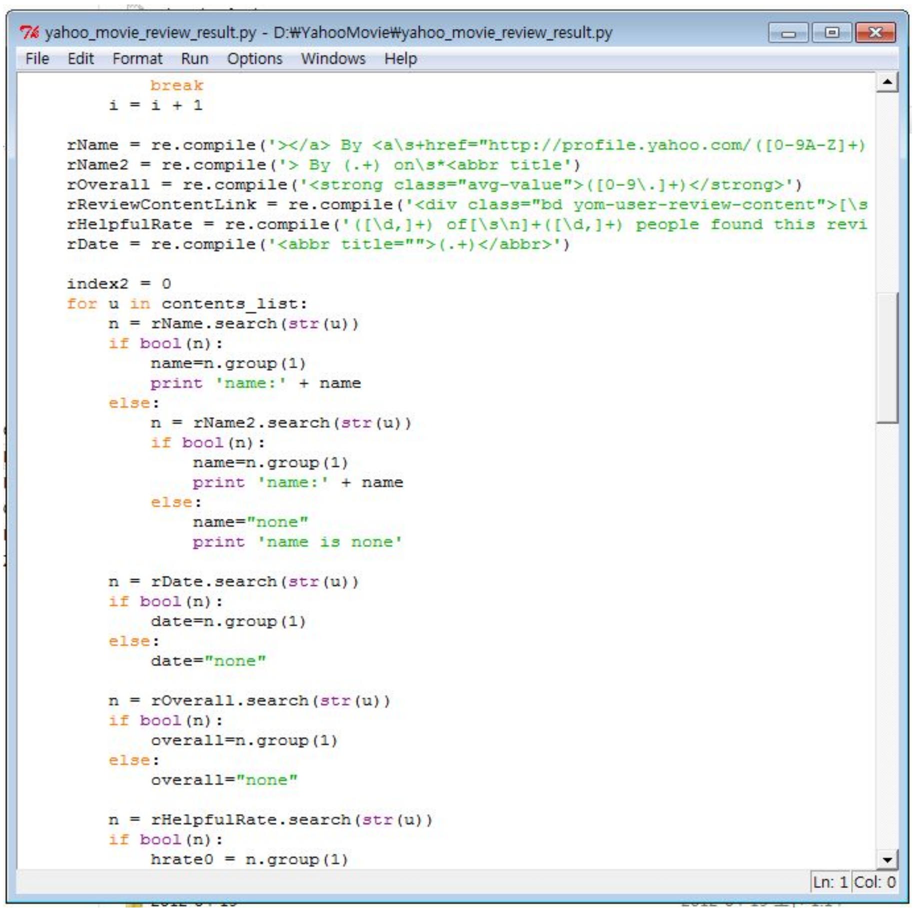
Appendix A: Movie List

Movie List	
Dr. Seuss The Lorax	*That's My Boy*
Project X	*Your Sister's Sister*
Being Flynn	*Kumaré*
Last Days Here	*Abraham Lincoln: Vampire Hunter*
The Snowtown Murders	*Seeking A Friend For The End Of The World*
Tim and Eric's Billion Dollar	*The Last Ride*
Movie	*To Rome With Love*
Silent House	*Beasts Of The Southern Wild*
A Thousand Words	*Magic Mike*
The Decoy Bride	*People Like Us*
John Carter	*Ted*
Friends With Kids	*Tyler Perry's Madea's Witness Protection*
Jiro Dreams of Sushi	*Neil Young Journeys*
Salmon Fishing in the Yemen	*Take This Waltz*
Seeking Justice	*The Amazing Spider-Man*
21 Jump Street	*Katy Perry Part Of Me*
Casa de Mi Padre	*The Do-Deca Pentathlon*
Jeff, Who Lives At Home	*The Magic Of Belle Isle*
The Kid with a Bike	*Ice Age Continental Drift*
Reuniting the Rubins	*The Imposter*
The Hunger Games	*Red Lights*
The Raid: Redemption	*Trishna*
The Trouble with Bliss	*Union Square*
The Island President	*Easy Money*
Mirror Mirror	*The Dark Knight Rises*
Wrath of the Titans	*30 Beats*
Bully	*Ruby Sparks*
Goon	*The Watch*
American Reunion	*Step Up Revolution*
The Cold Light of Day	*Ai Weiwei Never Sorry*
Damsels In Distress	*Killer Joe*
The Hunter	*Klown*
We Have A Pope	*Searching For Sugar Man*
The Cabin in the Woods	*Diary Of A Wimpy Kid Dog Days*
The Three Stooges	*Total Recall*
Woman Thou Art Loosed_on the	*360*
Seventh Day	*The Babymakers*
The Lucky One	*Celeste And Jesse Forever*
Darling Companion	*The Bourne Legacy*
The Moth Diaries	*The Campaign*
To the Arctic	*Hope Springs*
The Five Year Engagement	*Nitro Circus The Movie 3D*
The Pirates Band of Misfits	*Goats*
The Raven	*Red Hook Summer*
Sound of My Voice	*The Odd Life of Timothy Green*
Marvel's The Avengers	*The Expendables 2*
The Best Exotic Marigold Hotel	*ParaNorman*
Last Call at the Oasis	*Sparkle*
A Little Bit of Heaven	*Chicken With Plums*
Meeting Evil	*Cosmopolis*

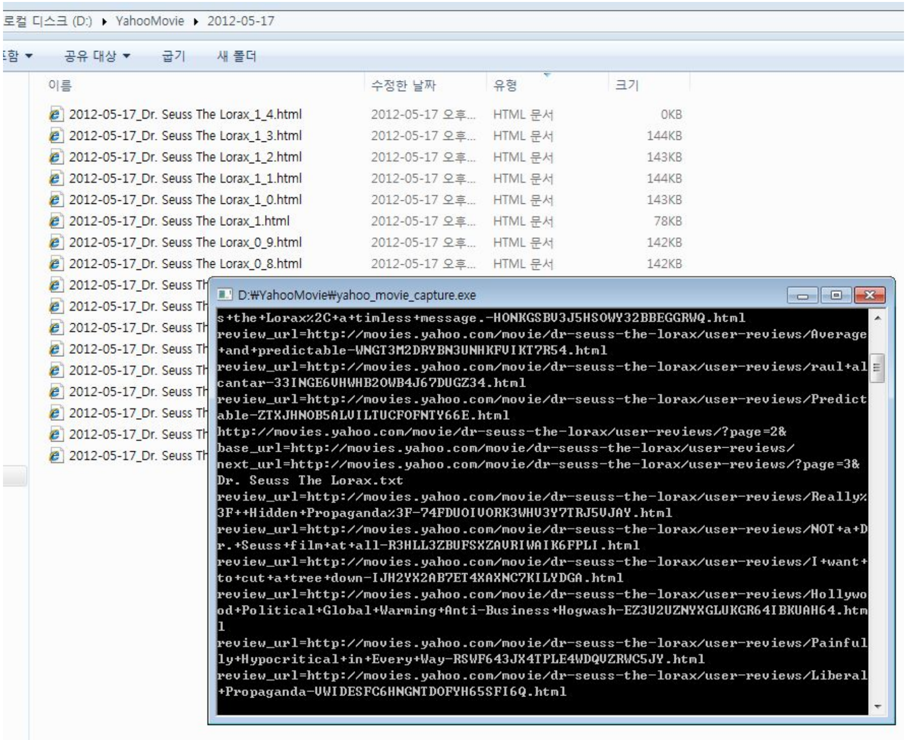
Dark Shadows *Girls in Progress* *The Dictator* *The Samaritan* *What to Expect When youre expecting* *Lovely Molly* *Polisse* *Men in Black 3* *Chernobyl Diaries* *Moonrise Kingdom* *Battlefield America* *Piranha 3DD* *Snow White and the Huntsman* *Apartment 143* *For Greater Glory* *Madagascar 3* *Prometheus* *Bel Ami* *Lola Versus* *Peace Love and Misunderstanding* *Safety not guaranteed*	*Why Stop Now* *The Apparition* *Premium Rush* *General Education* *Hit and Run* *Robot and Frank* *Sleepwalk With Me* *Thunderstruck* *Wild Horse Wild Ride* *Lawless* *The Day* *The Possession* *For A Good Time Call* *The Good Doctor* *The Tall Man* *The Words* *Bachelorette* *Branded* *Rock of Ages*

Appendix B: Web Crawler






```python
            break
        i = i + 1

    rName = re.compile('></a> By <a\s+href="http://profile.yahoo.com/([0-9A-Z]+)
    rName2 = re.compile('> By (.+) on\s*<abbr title')
    rOverall = re.compile('<strong class="avg-value">([0-9\.]+)</strong>')
    rReviewContentLink = re.compile('<div class="bd yom-user-review-content">[\s
    rHelpfulRate = re.compile('([\d,]+) of[\s\n]+([\d,]+) people found this revi
    rDate = re.compile('<abbr title="">(.+)</abbr>')

    index2 = 0
    for u in contents_list:
        n = rName.search(str(u))
        if bool(n):
            name=n.group(1)
            print 'name:' + name
        else:
            n = rName2.search(str(u))
            if bool(n):
                name=n.group(1)
                print 'name:' + name
            else:
                name="none"
                print 'name is none'

        n = rDate.search(str(u))
        if bool(n):
            date=n.group(1)
        else:
            date="none"

        n = rOverall.search(str(u))
        if bool(n):
            overall=n.group(1)
        else:
            overall="none"

        n = rHelpfulRate.search(str(u))
        if bool(n):
            hrate0 = n.group(1)
```



로컬 디스크 (D:) ▸ YahooMovie ▸ 2012-05-17
공유 대상 ▾
굽기
새 폴더
이름
수정한 날짜
유형
크기
2012-05-17_Dr. Seuss The Lorax_1_4.html 2012-05-17 오후... HTML 문서 0KB
2012-05-17_Dr. Seuss The Lorax_1_3.html 2012-05-17 오후... HTML 문서 144KB
2012-05-17_Dr. Seuss The Lorax_1_2.html 2012-05-17 오후... HTML 문서 143KB
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2012-05-17_Dr. Seuss The Lorax_1_0.html 2012-05-17 오후... HTML 문서 143KB
2012-05-17_Dr. Seuss The Lorax_1.html 2012-05-17 오후... HTML 문서 78KB
2012-05-17_Dr. Seuss The Lorax_0_9.html 2012-05-17 오후... HTML 문서 142KB
2012-05-17_Dr. Seuss The Lorax_0_8.html 2012-05-17 오후... HTML 문서 142KB
D:₩YahooMovie₩yahoo_movie_capture.exe
s+the+Lorax%2C+a+timless+message.-HONKGSBV3J5HSOWY32BBEGGRWQ.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/Average+and+predictable-WNGT3M2DRYBN3UNHKFVIKT7R54.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/raul+alcantar-33INGE6VHWHB2OWB4J67DUGZ34.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/Predictable-ZTXJHNOB5ALVILTUCFOFNTY66E.html
http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/?page=2&
base_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/
next_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/?page=3&
Dr. Seuss The Lorax.txt
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/Really%3F++Hidden+Propaganda%3F-74FDUOIVORK3WHV3Y7TRJ5VJAY.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/NOT+a+Dr.+Seuss+film+at+all-R3HLL3ZBUFSXZAVRIWAIK6FPLI.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/I+want+to+cut+a+tree+down-IJH2YX2AB7ET4XAXNC7KILYDGA.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/Hollywood+Political+Global+Warming+Anti-Business+Hogwash-EZ3U2UZNYXGLUKGR64IBKUAH64.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/Painfully+Hypocritical+in+Every+Way-RSWF643JX4TPLE4WDQVZRWC5JY.html
review_url=http://movies.yahoo.com/movie/dr-seuss-the-lorax/user-reviews/Liberal+Propaganda-VWIDESFC6HNGNTDOFYH65SFI6Q.html

Appendix C: Lexicons for Movie Tweet

Lexicons for Relevant Tweet and Irrelevant Tweet

Relevant	***Irrelevant***
movie	*book*
movies	*books*
trailer	*read*
trailers	*game*
theater	*games*
theaters	*recording*
theatre	*recordings*
theatres	*club*
film	*party*
films	*monkey*
clip	*music*
clips	*reads*
video	*picture*
videos	
dvd	
digital copy	
netflix	
torrent	
youtube	
AT_GETGLUE	
getglue	
motion picture	
blu-ray	
bluray	
want to see	
want to watch	
wanna go see	
wanna watch	
wana see	
wanna c	
wana watch	
want to go	
wanna see	
wanna watch	
want see	
want watch	
going to see	
need to watch	
need to see	
need to go	
cannot wait	
can not wait	

cant wait *caint wait* *can't wait* *wait to see* *about to watch* *about to see* *about to go* *going to watch* *gonna see* *gonna watch* *will go see* *will go watch* *would go see* *would go watch* *got to see* *gotta go see* *gotta see* *got to go see* *wants to see* *wants to watch* *gonna go see* *have to see* *have to go see* *have to watch* *must go see* *must see* *trying to see* *trying to go see* *tryna go see* *trynna go see* *tryna see* *tryna watch* *excited to see* *excited to watch* *QUERY_TERM looks* *QUERY_TERM look* *until QUERY_TERM* *i aint seen* *i havent seen* *i have not seen* *i still aint seen* *i still havent seen* *i havnt seen* *i still havnt seen* *i still have not seen* *i aint watched* *i havent watched* *i have not watched*	

i still aint watched *i still havent watched* *i havnt watched* *i still havnt watched* *i still have not watched* *just saw* *just finished watching* *just finish* *just watched* *just watching* *saw* *watched* *i saw* *i watched* *went to see* *went to watch*	

Lexicons for Intention Tweet and Non-intention Tweet

Non-intention	***Intention***
saw	*will see*
just saw	*will watch*
i saw	*want to see*
i watched	*want 2 c*
just watched	*want 2 watch*
just finished watching	*want to watch*
just finish	*wanna go see*
went to see	*wana go see*
went to watch	*wanna se*
watching	*want to go*
netflix	*wants to go*
torrent	*wanna see*
again	*wanna c*
one more	*wana c*
URL	*wana see*
after watching	*wants see*
after seeing	*wants watch*
	wana watch
	wanna watch
	want see
	want watch
	going to see
	needs to see
	needs to watch
	need to watch
	need to see
	need 2 c
	need 2 see

	need to go *cannot wait* *can not wait* *cant wait* *caint wait* *can't wait* *cnt wait* *wait to see* *about to watch* *about to check* *about to enter* *about to see* *about to go* *abt to go* *abt to see* *abt 2 go* *abt 2 see* *abt to watch* *abt 2 watch* *might go see* *going to watch* *gonna see* *gonna watch* *will go see* *will go watch* *would go see* *would go watch* *got to see* *gotta go see* *gotta see* *got to go see* *going to* *going see* *wants to see* *wants to watch* *gonna go see* *i have to see* *i have to go see* *i have to watch* *i must go see* *i must see* *i must watch* *until QUERY_TERM* *till QUERY_TERM* *until i see QUERY_TERM* *trying to see* *trying to go see* *tryna go see*

	trynna go see *tryna see* *tryna watch* *ready to see* *ready to watch* *excited to see* *excited to watch* *QUERY_TERM looks* *QUERY_TERM look* *i aint seen* *i havent seen* *i have not seen* *i still aint seen* *i still havent seen* *i havnt seen* *i still havnt seen* *i still have not seen* *i aint watched* *i havent watched* *i have not watched* *i still aint watched* *i still havent watched* *i havnt watched* *i still havnt watched* *i still have not watched* *going see*

Lexicons for Positive Tweet, Neutral Tweet, and Negative Tweet

Positive	*Neutral*	*Negative*
good	*URL*	*boring*
excellent	*AT_GETGLUE*	*shit*
best	*torrent*	*waste*
brilliant	*online*	*wasted*
excited	*download*	*weird*
incredible	*youtube*	*bad*
must see	*come out*	*annoyed*
love	*comes out*	*annoy*
loved	*coming out*	*mess*
awesome		*awful*
like		*worst*
liked		*worse*
happy		*overrated*
enjoy		*dumb*
enjoyed		*dumbest*
worth		*bland*
interesting		*disgusting*
goood		*disgusted*

okay		*disgust*
entertained		*terrible*
adorable		*suck*
great		*sucked*
funny		*messed*
favorite		*ridiculous*
fantastic		*hate*
loveit		*crap*
beautiful		*kidding*
hilarious		*bitch*
amazing		*stupid*
gd		*stupidest*
better		*creepy*
nice		*fail*
cute		*ruin*
loving		*unreal*
lovesit		*insane*
perfect		*moron*
greatest		*hated*
wonderful		*overated*
funniest		*creepiest*
cool		*crack*
success		*shittt*
recommend		*disappointed*
recommending		*disappoint*
must see		*disappointing*
mustsee		*bored*
must watch		*pointless*
addicted to		*annoying*
cutie		*weirdest*
		failure
		don't watch
		fake
		fucked
		drag
		shittiest
		not good
		not great
		badly
		unrealistic

Appendix D: Impact of eWOM on Movie Revenue

This study examines the impact of eWOM on each social media channel on movie revenue, and conducts the Chow test on the eWOM of each social media channel to determine whether the impact of eWOM on the opening week revenue and the impact of eWOM on movie revenue after the second week are structurally different. The Chow test is widely used as a test of the structural stability of two regression models (Chow 1960). The structural change of two regression equations demonstrates the combination of changes in section, in slope, in both section and slope, and the parameter changes in both section and slope. The present study also investigates the extent of the impact of previous eWOM forms on movie revenue through the Ad Hoc Estimation (Alt 1942; Tinbergen 1949) that lag variables are consecutively added until the coefficients of the lag variable are statistically insignificant, or until the sign of the coefficient of at least one variable changes.

YouTube

The impact of weekly_view$_{t-1}$ on the opening week movie revenue and movie revenue after the second week is significantly different [Chow Test statistics = 361.035 (p = 0.00)].

Table D-1. Impact of View Count on Open Week Revenue

Independent Variable	Estimate	R^2
weekly_view$_{t-1}$	313.1886***(49.51611)	.7886
weekly_view$_{t-2}$	472.936 ***(45.16351)	

*Note: *p<.05, **p<.01, ***p<.001*

Table D-2. Impact of View Count on Movie Revenue after the Second Week

Independent Variable	Estimate	R^2
weekly_view$_{t-1}$	.447935(.2381348)	.0048

*Note: *p<.05, **p<.01, ***p<.001, Fixed effect model*

Yahoo! Movies

The impact of weekly_rating_number$_{t-1}$ on the opening week movie revenue and movie revenue after the second week is significantly different [Chow Test statistics = 300.664 (p = 0.00)].

Table D-3. Impact of Rating Number on Open Week Revenue

Independent Variable	Estimate	R^2
weekly_rating_num$_{t-1}$	304385.6***(71733.26)	.4616

*Note: *p<.05, **p<.01, ***p<.001*

Table D-4. Impact of Rating Number on Movie Revenue after the Second Week

Independent Variable	Estimate	R^2
weekly_rating_num$_{t-1}$	34261.23 ***(2270.391)	.4635
weekly_rating_num$_{t-2}$	12291.02 ***(2039.943)	

*Note: *p<.05, **p<.01, ***p<.001, Fixed effect model*

Blog

The impact of weekly_blog$_{t-1}$ on the opening week movie revenue and movie revenue after the second week is significantly different [Chow Test statistics = 514.892 (p = 0.00)].

Table D-5. Impact of Blog Number on Open Week Revenue

Independent Variable	Estimate	R^2
weekly_blog$_{t-1}$	241464.4 ***(17252.49)	.6301

*Note: *p<.05, **p<.01, ***p<.001*

Table D-6. Impact of Blog Number on Movie Revenue after the Second Week

Independent Variable	Estimate	R^2
weekly_blog$_{t-1}$	53031.17***(1423.427)	.5764

*Note: *p<.05, **p<.01, ***p<.001, Fixed effect model*

Twitter

The impact of weekly_tweet$_{t-1}$ on the opening week movie revenue and movie revenue after the second week is significantly different [Chow Test statistics = 421.364 (p = 0.00)].

Table D-7. Impact of Tweet Number on Open Week Revenue

Independent Variable	Estimate	R^2
weekly_tweet$_{t-1}$	356.8754 ***(21.22811)	.7272

*Note: *p<.05, **p<.01, ***p<.001*

Table D-8. Impact of Tweet Number on Movie Revenue after the Second Week

Independent Variable	Estimate	R^2
weekly_tweet$_{t-1}$	81.07754**(2.393387)	.658
weekly_tweet$_{t-2}$	16.06142***(2.557303)	
weekly_tweet$_{t-3}$	10.91611***(2.161543)	

*Note: *p<.05, **p<.01, ***p<.001, Fixed effect model*

초 록

온라인 口傳이 映畫 賣出 에 미치는 影響에 관한 研究: 時期, 媒體, 價値를 中心으로

白賢美

서울大學校 大學院

經營學科 經營學 專攻

최근 소셜미디어의 등장은 과거에는 상상할 수 없었던 많은 것들을 변화시키고 있다. 한류 스타들의 유튜브를 통한 홍보 전략, 트위터를 통한 선전포고, 선거 운동을 위한 소셜미디어의 활용 등 사회 곳곳에서 소셜미디어로 인한 변화가 관찰된다.

이처럼 소셜미디어의 영향력에 대한 관심이 급증하고 있는 실태와는 달리 소셜미디어의 온라인 구전에 관한 기존 연구는 통합적인 해석을 제시하지 못한다는 한계를 지니고 있다. 이러한 기존 연구의 한계점을 극복하기 위해 본 연구에서는 온라인 구전의 세가지 측면 – 온라인 구전이 쓰여진 시기, 온라인 구전이 쓰여진 소셜미디어 채널, 온라인 구전의 가치 – 에서 그 영향력을 분석하고자 하였다. 세부적인 연구문제는 크게 다음의 세가지로 구분된다.

- ■ 개봉전 온라인 구전과 개봉후 온라인 구전의 차이가 영화 매출에 어떻게 영향을 미치는가?
- ■ 소셜미디어에 따라 온라인 구전의 영향력이 시기별로 차이를 보이는가?
- ■ 가치있다고 판단되는 온라인 구전은 그렇지 않은 온라인 구전에 비해 그 영향력이 더욱 강할 것인가? 그렇다면, 가치있는 온라인 구전은 무엇인가?

기존 연구는 온라인 구전의 영향력을 다소 단편적으로 보았다면, 본 연구에서는 온라인 구전을 다양한 측면에서 살펴봄으로써 기업의 온라인 구전 활동에 대한 전략적 방향을 제시하고자 하였다.

이를 위해 2012년 2월부터 8월까지 개봉되는 영화 145편을 대상으로 개봉 2주 혹은 3주전부터 개봉 종영되는 시기까지 트위터, 야후!무비즈(온라인 리뷰 싸이트), 블로그, 유튜브의 온라인 구전 정보를 일별 수집하였다. 또한 영화에 대한 매출 정보도 주별 집계하였다. 또한 트위터의 경우 텍스트 마이닝을 실시함으로써 각 트윗을 의도 트윗, 긍정 트윗, 중도 트윗, 부정 트윗의 네 가지로 분류하였다. 추가적으로 세번째 연구문제를 위해 아마존닷컴에서 다양한 물품에 대해 무작위로 온라인 리뷰 15,059개를 수집하였다.

첫번째 연구에서는 개봉전 구전과 개봉후 구전의 매출에 대한 영향력을 기대 일치 이론을 통해 살펴보고자 하였다. 분석 결과, 트위터의 개봉전 트윗수와 개봉후 트윗수의 불일치 정도가 클수록 영화 매출에 부정적인 영향을 미치는 것으로 나타났다. 이를 통해 영화의 실질적 가치에 대한 구전이 빠르게 확산되는 현상황에서 실질적 가치 보다 높은 기대치를

형성하는 것이 항상 긍정적 결과를 가져오지 않는다는 시사점을 도출하였다.

두번째 연구에서는 온라인 구전이 쓰여진 소셜미디어 매체에 따라 그 영향력이 어떻게 다를 것인지를 비교 분석하였다. 이를 위해 본 연구에서는 Rogers의 혁신 확산 모델을 바탕으로 각 소셜미디어가 혁신수용자와 모방수용자에게 미치는 영향력이 유의미하게 차이가 있는지를 분석하였다. 또한 이를 보완하기 위해 개봉 초기와 개봉 후기에 미치는 영향력이 유의미하게 차이가 있는지도 분석하였다. 분석 결과, 트위터는 정보의 빠른 확산성과 실시간성 등을 특징으로 하는 매스미디어의 특성을 가지는 매체로 혁신수용자 및 개봉 초기에 비교적 영향력이 강한 것으로 나타났다. 반면 온라인 리뷰 사이트인 야후!무비즈는 집단지성의 형태로서 강한 설득력을 가지는 대인커뮤니케이션의 특성을 가지는 매체로 모방수용자 및 개봉 후기에 비교적 영향력이 강한 것으로 나타났다. 본 연구는 실제 온라인 구전 데이터를 통해 소셜미디어의 영향력 관점에서 소셜미디어를 분류한 최초의 연구라는 점에서 학술적 의의를 찾을 수 있다. 또한 본 연구는 기업이 시기별 혹은 목적에 따라 어떤 소셜미디어 매체를 활용하여야 할 것인지에 대한 전략적 방향을 제시할 수 있을 것으로 기대된다. 여기에 더해 본 연구 결과는 향후 소셜미디어의 진화 방향에 대한 방향성을 제시해줄 수 있을 것으로 기대된다.

세번째 연구에서는 모든 온라인 구전이 동일한 영향력을 가지지 않음을 밝히고, 어떤 온라인 구전이 가치있는 구전인지를 살펴보고자 하였다. 기존 연구에서는 리뷰 평점의 극단성과 리뷰의 유용성간에 있어서 일관적인 결론을 도출하지 못하였다. 본 연구에서는 이러한 이유를 집단지성 관점에서

살펴보고자 하였다. 이를 위해, 아마존닷컴의 온라인 리뷰 정보를 활용하여 반응표면분석방법을 통해 리뷰 평점이 제품 평균 평점과 일치될수록 리뷰 유용성이 증가됨을 밝혀냈다. 즉, 집단지성의 한 형태인 제품 평균 평점에 가까운 평점을 지니는 리뷰를 소비자들은 신뢰하는 경향을 보임을 확인하였다. 본 연구 결과를 통해 기존 연구는 소비자들의 제품 질에 대한 태도를 고려하지 않은 상황에서 리뷰 평점의 극단성과 리뷰의 유용성간의 관계를 분석하였기 때문에 일관되지 않은 결론이 도출되었음을 확인할 수 있었다. 또한 온라인 마케터들이 유용한 리뷰가 가지는 특성을 이해함으로써, 소비자들의 구매 결정에 있어서의 정보 과잉 현상을 줄일 수 있는 전략을 도출하는데 도움을 줄 것으로 기대된다.

본 연구의 기여점은 다음과 같다. 첫째, 연구방법론 측면에서의 기여점이다. 본 분석을 위해 트위터, 야후!무비즈, 유튜브, 블로그의 온라인 구전을 패널 데이터로 수집하였고, 수집된 온라인 구전의 텍스트 마이닝을 실시하여 온라인 구전 내용에 대한 정보도 수량화하여 데이터로 확보하였다. 이를 통해 다양한 소셜미디어로부터의 온라인 구전 정보를 활용하여 기존 연구보다 확대된 범위의 분석을 시도할 수 있었다. 둘째, 이론적 측면에서의 기여점이다. 기대 일치 이론을 통해 영화에 대한 개봉전 구전과 개봉후 구전의 불일치 정도가 영화 매출에 부정적 영향을 미침을 밝혀냈으며, 혁신 확산 모델을 기반으로 소셜미디어를 매스미디어 성격을 띄는 매체와 대인커뮤니케이션 성격을 띄는 매체로 구분하였다는 데 본 연구의 의의가 있다. 셋째, 실무적 측면에서의 기여점이다. 본 연구는 기업의 온라인 구전 활동에 있어서 전략적 방향을 제시할 수 있을 것으로 기대된다. 기업은 본

연구 결과를 토대로 온라인 구전의 시기별, 매체별 특성을 파악하고, 가치있는 온라인 구전에 대한 차별화를 고려함으로써 좀 더 효율적인 온라인 구전 활동을 펼칠 수 있을 것으로 기대된다.

주요어: 온라인 구전, 소셜미디어, 온라인 리뷰, 트위터, 기대 일치 이론, 혁신 확산 이론, 집단지성
학 번: 2008-30155