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Research on the Movie Reviews Regarded as Unsuccessful in Box Office Outcomes in Korea: Based on Big Data Posted on Naver Movie Portal*

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Abstract

Purpose - Based on literature studies of movie reviews and movie ratings, this study raised two research questions on the contents of online word of mouth and the number of movie screens as mediator variables. Research question 1 wanted to figure out which topics of word groups had a positive or negative impact on movie ratings. Research question 2 tried to identify the role of the number of movie screens between movie ratings and box office outcomes.

Design/methodology/approach - Through R program, this study collected about 82,000 movie reviews and movie ratings posted on Naver's movie website to examine the role of online word of mouths and movie screen counts in 10 movies that were considered commercially unsuccessful with fewer than 2 million viewers despite securing about 1,000 movie screens. To confirm research question 1, topic modeling, a text mining technique, was conducted on movie reviews. In addition, this study linked the movie ratings posted on Naver with information of KOBIS by date, to identify the research question 2.

Findings - Through topic modeling, 5 topics were identified. Topics found in this study were largely organized into two groups, the content of the movie (topic 1, 2, 3) and the evaluation of the movie (topics 4, 5). When analyzing the relationship between movie reviews and movie ratings with 5 mediators identified in topic modeling to probe research question 1, the topic word groups related to topic 2, 3 and 5 appeared having a negative effect on the netizen's movie ratings. In addition, by connecting two secondary data by date, analysis for research question 2 was implemented. The outcomes showed that the causal relationship between movie ratings and audience numbers was mediated by the number of movie screens.

Research implications or Originality - The results suggested that the information presented in text format was harder to quantify than the information provided in scores, but if content information could be digitalized through text mining techniques, it could become variable and be analyzed to identify causality with other variables. The outcomes in research question 2 showed that movie ratings had a direct impact on the number of viewers, but also had indirect effects through changes in the number of movie screens. An interesting point is that the direct effect of movie ratings on the number of viewers is found in most American films released in Korea.

Keywords: Box Office Outcomes, Movie Ratings, Movie Reviews, Number of Movie Screens, Topic Modeling,
JEL Classifications: C3, L82, M3

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Ⅰ. Introduction

Since many films are released every year, achieving box office performance becomes inescapable task to anyone involved in the movie industry. About 10 years ago, Kim (2010) and Lee and Jang (2006) said that if film got more than a million viewers after the movie was released, it could be considered as box office hits. Kim and Hong (2011) analyzed 316 films released in one year in 2010, with an average audience was 470,000 and only 3.2 percent of the films attracted more than 3 million people. Recently, the movie's break-even point is centered on evaluating the movie's success. When the average movie production cost is around 5 billion in Korea, it is likely that the movie's break-even point will not be reached if film doesn't get 3 million viewers. For example, Gunchukhak Gaeron (i.e., an introduction to architecture), which was released in 2012, had a break-even point of around 1.5 million viewers with 2.3 billion won in production costs, but the actual audience was over 4 million. This film was classified as a movie that succeeded even with a small budget (Kim, 2021). Nevertheless, the burden of uncertain investment in movie industry has led to an increased interest in marketing activities to attract more audiences. As part of the film company's marketing efforts, the movie magazine Cine 21 reported that movie companies were likely to manipulate movie ratings and sympathy numbers to improve the movie's box office performance before and after its release (Kim and Kim, 2018). This article suggests that movie officials are responding sensitively to movie ratings, a representative online word of mouth, in the early stages of release.

Research on movie ratings and movie box office success is a field where a lot of research has already been done, so it is hard to see that this area deserves to get new attention. However, the reason for conducting this study was that if some of the limitations seen in prior researches could be supplemented, it could provide new implications for film marketing. At previous studies, when exploring the relationship between movie ratings and movie box office, individual films were mainly used as a unit of analysis to explore the relationship between the two variables (Chon and Yi, 2019; Kim and Hong, 2011). Although this method is advantageous for ease of data collection and analysis, it is believed that the number of movie ratings and screens counts used are representative values, such as average, and that if the data's variance is relatively high, there may be a problem of poor explanation to reflecting the actual parameter. Considering that movie ratings can be generated after the movie is over, and that the number of screens continues to change depending on the box office performance or online word of mouth, it is thought that there may be a limit in previous studies to explain the various causal relationships between movie ratings and box office outcomes.

The value chain of the film industry can be largely divided into production, distribution and screening stages and it suggests that factors affecting the success of the film may vary. In general, movie genres, scenarios and audience rating of films are considered important factors in the production phase of the film, the number of screens secured by film companies is regarded as important factors in the distribution phase, and online word of mouth, which this study is interested in, is described as influential factors in the screening phase (Eliashberg et al., 2006). In particular, the number of movie screens, an important variable in the distribution phase, is described as one of the substantial variables determining the success of the film in a study of American films (Kim and Hong, 2011). With the spread of multiplexes in Korea, nationwide release of films has become common and securing a proper number of screens before releasing a film is bound to be an important factor in influencing the success of the movie. Also, movie ratings posted on the internet's major movie portals have drawn attention as a powerful online word of mouth that occurs at the screening stage, exerting impact on potential consumers. However, previous studies that probed the effectiveness of movie ratings mainly focused on outcome variables such as movie box office performance (Chon and Yi, 2019). It is thought that there was a limitation in not dealing with various influencing factors across the film industry. Given that the number of screens can change depending on the box office performance after the release of the film, it can be inferred that screen counts also may have a significant relationship with movie ratings of internet movie portal. However, this point of view was not confirmed at prior studies.

Therefore, this study linked statistical information of KOBIS (i.e., www.kobis.or.kr), an integrated network of Korean Film Council, to movie ratings and movie reviews posted on Naver (i.e., https://movie.naver.com) for 10 films that were regarded as unsuccessful to make box office hits with less than 2 million viewers. Based on the data obtained from the opening to the end of the movie, we wanted to comprehensively check the impact of the contents of the movie reviews on movie ratings and the effect of such movie ratings on box office outcomes through the number of movie screens. The reason why this study chooses films that failed to make box office hits despite having a significant number of screens in the early stages of release is because it can exclude coverage issues in the distribution stage, and it can give us the chance to learn the effect of customer's online activity on the box office performance and the changes of movie screen.

This study extracted more than 82,000 movie reviews and movie ratings from the Naver, Korea's leading portal, and used topic modeling, one of the text mining techniques, to analyze them. Through topic modeling, the frequency of the appearance of word groups related to each topic was determined and the relationship between movie reviews and movie ratings was identified. Topics derived from topic modeling were thought to be an appropriate means for measuring consumers' opinions in terms of being less affected by the outliers and having qualitative information linked movie ratings (Chen and Zimbra, 2010; Liu et al., 2010). In addition, by connecting the movie ratings, the number of screens and box office outcomes together from release date, we also wanted to identify the comprehensive causal relationship between the movie ratings and the movie's box office outcomes.

II. Literature Reviews

1. Topic Modeling

Topic modeling is one of the data mining techniques using probability model algorithms that extract meaningful topics from large amounts of textual material. Topic modeling uses LDA (Latent Dirichlet Allocation) algorithms, with only the topic numbers and textual data being used in the analysis. The derivative method of the topic is relatively clear and results are regarded as highly replicable even if other researchers perform similar studies. It is also a useful technique for analyzing vast amounts of textual data, given that researchers are required to determine the only number of topics, even if they do not have much prior knowledge of the subject. In addition, it is common to determine the number of topics afterwards based on the interpretability of the topics produced and the similarity of the word groups that compose each topic (DiMaggio et al., 2013; Oh, 2020).

Topic modeling codes textual materials to extract meaningful topics through LDA algorithms and it calculates the probability that the extracted word groups belong to each topic, while showing the composition and distribution of the topics. Due to these characteristics of algorithms, it is believed that topic modeling has a strong inductive aspect. Topic modeling was mainly used to classify various opinions posted on corporate websites, but has recently expanded to the field of literature research and game industry due to its advantages of finding meaningful topics from large scale text materials (Kim and Park, 2010; Nahm, 2016). Determining the number of topics in topic modeling may vary depending on the researcher's purpose, but verification of this can be seen by whether the word groups derived from topic modeling have similar meanings within the topic and move in the direction predicted when analyzed with other variables. From this perspective, we tried to derive various topics from movie reviews through topic modeling and to check the relationship between frequency of each word groups extracted and movie ratings.

2. Movie Review and Rating

Since movie reviews are textual information, relatively few studies have identified the impact of movie reviews on movie’s box office compared to movie ratings posted in scores. Nevertheless, the reason why this study is interested in movie reviews is that movie reviews play an important role in online word of mouth communication. Kim and Seo (2017) used emotion analysis, one of the text mining techniques, to analyze the effect of emotions in movie reviews on box office outcomes. They found that if the audience's emotions in movie reviews were positive, it had a positive relationship with the movie's box office success. Kim and Kim (2019), who analyzed movie reviews using text mining technique, said that regardless of genre or audience rating, movie reviews consisted of the content elements of movies such as story, actor and director, and the evaluative aspects of movie such as fun and criticism. Grönroos (1984) argued that quality of service products can be largely divided into process quality and outcome quality, and this study thought that the content elements of the film might represent the process quality and the evaluative aspects of the film were related to the outcome quality. In addition, if the movie reviews mean the quality assessment of service product, we can understand why these topics affect consumer’s satisfaction expressed as movie ratings. Nevertheless, there are not many studies that have identified the role of movie reviews as a source of information in movies evaluation, which can be thought to reflect the difficulties of research in quantifying the contents of reviews written in text. This study aims to quantify the contents of movie reviews presented as text materials and to verify their role as mediator on the relationship between movie reviews and movie ratings.

Movie ratings, one of the most powerful online word of mouth in recent years, are not clear in origin, but it is a common view that they started with Leonard Maltin's rating on 5 star scale (Koo, 2011). Currently, movie ratings have been recognized as one of the important information that can predict the film's performance in advance (Chon and Yi, 2019; Kim and Seo, 2017; Kim et al., 2010). Movie ratings are regarded as information of subjectivity produced by film experts or general audiences depending on their consumption experiences (Oh and Chae, 2015). Eliashberg and Shugan (1997) also argued that movie ratings were meaningful as information about the movies. If it was a highly rated movie, potential consumers would value the movie's quality based on this information before watching it, and if it was a low rated movie, they would think about whether it was worth the time and money. In particular, movie ratings is expected to exert greater influence on commercial films targeting ordinary consumers rather than art oriented films having fixed core customers. Ordinary consumers tend to value consumption of time when they choose commercial films. This was why commercial films were highly dependent on recommendations or evaluations by other audiences (Chon, 2002; Sung et al., 2014). Since movie was essentially a service product, consumers explored information about the film through various channels in advance and the ratings provided by film experts or pre-viewers had become important information that allowed them to estimate the quality of the film and determined the consumption (DeVany and Walls, 1996). These findings from previous studies provide the basis for marketing activities that many film makers perform to improve movie ratings in time for release.

The movie rating is a comprehensive evaluation of the various factors the movie has, including scenarios, actors and directors, so it is bound to be closely related to the movie's box office performance (Choi et al., 2013; Chon and Yi, 2019). In recent years, the influence of movie reviews provided by online movie portals has begun to draw attention as a determinant of box office success. Kim (2007) and Oh (2005) confirmed a significant correlation between the number of reviews posted on the internet movie portal and the number of movie audiences, and found that movie ratings provided by the movie portal could be a precedent factor to estimate the success of the movie (Jung, 2009; Kim M.H. et al., 2010; Kim S.Y. et al., 2010). These results might be related to the fact that movie portals began to be activated in online as netizen started posting their thoughts, experiences and views, and sharing them with each other. The sources of rating information included studies that collected and analyzed rating scores from several portal sites and studies that used rating information derived from only one movie portal (Chon and Yi, 2019; Kim and Kim, 2019).

The activation of movie ratings in the Korean film industry can be said to have started with the publication of many film magazines since the 1990s (Koo, 2011). Initially, some groups of experts, including film directors, were critical of movie ratings due to the film's artistry oriented features, but now most experts recognized movie ratings as information product in movie industry. Currently, most portals that provide movie ratings present a 10 point scale and viewers who watched the movie grade their own evaluative scores within that scale. Most movie portals do not reward consumers for providing movie ratings and allow netizen to input their scores freely. This free management policy has been criticized in terms of reliability of information since it provides room for film makers and distributors to exert their effort on movie ratings (Chon and Yi, 2019; Kim and Nam, 2018). If movie ratings are influenced by marketing or promotional purposes, the variance of the scores can be increased, and if the rating structure is polarized by marketing activities, the rating information based on the average is likely to provide distorted information to potential consumers (Choi and Yeu, 2018).

The entities that provide movie ratings can be divided into experts and ordinary consumers. The experts belong to print media such as magazines and newspapers, and provide ratings in the form of movie reviews before the release of the film. Dong-A Ilbo and Cine 21 are examples that provide movie reviews information (Koo, 2011). On the other hand, most portal sites, such as Naver and Daum, provide spaces for movie reviews and movie ratings to netizens who have watched the movie. They can only participate in movie ratings after the movie is released. Compared to the expert ratings provided by a small number of specialists, tens of thousands of netizen can participate in movie ratings, which may lead to greater variance of ratings depending on individuals' tastes in movies.

3. Major Factors Influencing Box Office Outcomes

The value chain of the film industry can be largely categorized into production, distribution and screening stages, which mean there are wide variety of factors for the box office success (Eliashberg et al., 2006). From the marketing perspective, the number of movie screens determined in the distribution phase is bound to be a major factor that can affect the film's box office performance. Small film makers, investors and distributors try to anticipate the number of viewers before the release of the movie and make efforts to secure the right number of screens in advance to maximize profits (Jeon, 2016). Since the release period of the film is relatively short, with an average of about four weeks in Korea, it is common for film companies to respond quickly to consumer responses in the market to maximize the return on investment in the film production. If the audience's response is positive after the release, it is desirable to increase the number of screens quickly, but if not, the number of screens will be subject to reduction.

Studies probing the influence of online word of mouth on the movie success also claim that variables related on movie genres, actors, directors and audience ratings can be major factors in affecting movie success before release, but distributor's power, screen counts and online word of mouth become the factors determining movie success after release (Kim and Hong, 2011; Kim and Seo, 2017). These results suggest that movie ratings play a important role as online word of mouth in the screening phase, but at the same time they may affect the number of screens after the movie is released. However, it seems that prior researches did not reflect the changing natures of movie screens by applying representative values such as average in their analysis.

Studies that analyzed the effect of movie ratings on box office outcome can be divided into those that choose sales and that use number of viewers (Kim and Hong, 2011; Lim and Jun, 2018). Regardless of the type of dependent variables, movie ratings have a significant impact on movie box office success. In particular, Kim and Hong (2011) argued that the influence of movie ratings on box office performance was very significant when they chose the number of viewers as dependent variable. According to their argument, movie ratings seem to play a role as information product that impacts potential consumer's choice of movies. Kim and Nam (2018) claimed that the movie ratings provided by experts were not very influencing, but the movie ratings given by netizen were closely related to the movie's success. In the similar vein, Chon and Yi (2019) and Kwon (2014) also argued that the movie ratings provided by experts had no statistical significance in predicting the success of the film.

In addition, a comparative analysis of the impact of movie ratings on the U.S. and Korean markets showed that movie ratings had more close relationship with box office outcomes in the U.S. market (Kim and Lee, 2009). This result suggests that the impact of movie ratings on box office success may vary depending on the market's characteristics. Other studies, which assessed the influence of movie ratings by movie portals, asserted that the movie ratings posted on Naver and Watcha were more closely related to the movie's box office performance compared to other movie portals (Chon and Yi, 2019). Considering the claims of prior studies and the representativeness of Naver among the movie portals in Korea, this study extracted movie reviews and movie ratings from Naver's movie website.

Ⅲ. Research Question and Method

1. Research Question

This study tried to identify which topics of movie reviews are highly related to movie ratings and how movie ratings collected by date affect box office performance through the number of screens. For this purpose, 10 films that were considered as unsuccessful in Korea were selected. In previous studies, movie reviews can be largely divided into content elements such as story, actor and director and evaluative factors such as fun and criticism (Kim and Kim, 2019). We further inferred that all the topics found in topic modeling of movie reviews could have a causal relationship with movie ratings of commercial films which was unsuccessful in box office outcomes.

〈Research Question 1〉 When analyzing movie reviews regarded as unsuccessful in box office performance, all the topics found in movie reviews may be related to movie ratings.

Number of screens are found to be related to the movie's box office performance in previous studies. However, it was thought that their implication was limited in that they did not reflect the feature of movie screens that was sensitive to customer responses and box office outcomes. Therefore, this study measured movie ratings, the number of screens and box office outcomes on a daily basis after the film was released. By linking and analyzing these variables based on the date, we wanted to explore the causal relationship between these variables in more depth. In particular, movie ratings posted on the movie portals might directly affect the box office performance of the next day by becoming online word of mouth to potential consumers. At the same time, given that movie officials monitored both movie ratings and box office outcome on a daily basis, we thought movie ratings could affect the number of screens of the next day as well. In addition, we inferred that films analyzed in this study might have a greater direct effect on box office outcomes than an indirect effect through the number of movie screens, since these films were started with a considerable number of screens when they were released and it was expected that they tried to maintain their screen counts.

〈Research Question 2〉 Movie ratings identified by date may have both a direct and an indirect effect on box office performances. In unsuccessful commercial films analyzed in this study, the direct effect will be greater than indirect effect through screen counts when movie ratings affect box office outcomes measured in number of film audiences.

2. Research Method

2.1. Selection and Measurement

This study selected 10 films that their cumulative audience did not reach 2 million even though they secured around 1,000 screens in Korea. The reason why this study chose films that did not make box office hits despite securing a considerable number of screens at the beginning of its release was that it was possible to focus on the audience's response to identify the causes for the unsuccessful box office regardless of screen coverage issues. In particular, if the audience's response factors that affected the unsuccessful box office outcomes could be confirmed through post-verification, it was thought that research findings could provide meaningful implications for film marketing.

Data on movie reviews and movie ratings were collected from Naver's movie website, which had a majority share in the Korean portal market (FT Times, 2019). At first, 11 films were identified to have failed to make the box office hits by mobilizing less than 2 million viewers by the end of release, even though they secured nearly 1,000 movie screens at the beginning since 2015. However, a total of 10 films were selected for final analysis except for one film which was regarded as lacking sufficient movie ratings to perform topic modeling analysis. Movie review and rating data were obtained through scraping techniques using R program. Especially, research questions 2 was probed in conjunction with data from Naver and KOBIS. ⟨Table 1⟩ describes the films that have been analyzed in this study. Depending on the purpose of the analysis, the movie was marked with an alphabet, not a real name.

Table 1. Major Features of Selected Films

Movie	Genre	Nationality	Audience Rating	Release Date	End Date	Cumulative audiences (thousand people)	Maximum Number of screens
U1	Action	U.S.A.	15	2015. 11	2015. 12	1,820	1,105
K1	Drama	Korea	12	2015. 12	2016. 01	1,584	892
E1	Crime/Drama	U.K.	12	2016. 01	2016. 02	1,278	891
U2	Action	U.S.A.	12	2016. 06	2016. 08	1,500	926
K2	Drama	Korea	15	2017. 04	2017. 06	1,362	1,154
U3	Action	U.S.A.	12	2017. 11	2018. 01	1,786	1,308
U4	Action	U.S.A.	12	2018. 12	2019. 01	1,561	1,016
K3	Action	Korea	15	2018. 12	2019. 02	1,671	1,081
U5	Fantasy	U.S.A.	12	2019. 10	2019. 11	1,444	1,108
U6	Action/Drama	U.S.A.	12	2019. 12	2020. 02	1,371	986

Note: The end date is based on when the screen share is actually 0% and therefore the cumulative number of audiences is also decided based on this date (visit www.kobis.or.kr to get more information).

According to the release date, two films were in 2015, two were in 2016, two were in 2017, two were in 2018, and two were 2019. The nationality of the film is found that six were in American, one was in British and three were in Korean. In addition, it was regarded that the impact of the audience rating could be controlled because all the films in ⟨Table 1⟩ were rated for 12 or 15 years of age or older. Nevertheless, there may be a limitation in that we selected only commercial films that were unsuccessful in making box office hits with a significant number of movie screens.

2.2. Procedures of Research

This study obtained movie reviews and movie ratings posted on Naver through scraping method. Scraping brought movie reviews and movie ratings registered on Naver movie portal from release date to ending date of each films. More than 82,000 movie reviews and movie ratings were recruited for 10 films. 〈Table 2〉 describes the number of movie reviews scraped by R program.

Table 2. The Number of Movie Reviews Scraped from Naver Movie Portal (Unit: Number)

Movie	U1	K1	E1	U2	K2	U3	U4	K3	U5	U6
Reviews	6,158	10,371	7,751	10,542	7,318	11,295	5,800	10,837	4,270	8,177

To confirm research question 1, this study conducted topic modeling to cluster similar words by topics and to identify what was the main topics that made up the movie reviews. At the same time, the frequency of appearance of topic words by date was calculated and the sum of individual movie ratings identified by that day was determined. Topic modeling for probing research question 1 also used R program. The extraction of the key words used the Korean Natural Language Processing (KoNLP), a Korean morpheme analysis library, which sorted the words that appeared in the movie reviews in order of appearance and processed them into an analyzable state. In addition, prior to conducting topic modeling, the preprocessing of data applied the following criteria: first, we deleted meaningless words such as articles of Korean, second, words of the same meaning were incorporated, and third, unnecessary words other than nouns and adjectives were deleted (e.g., exclamations, adverbs, etc.). Through this process, topic modeling was carried out and related words listed for each topic was derived. And the frequency of appearance of each topic words was calculated on a daily basis. By connecting topic modeling outcomes and the sum of individual movie ratings by date, the relationship between each topic and movie ratings was analyzed.

Research question 2 also used the sum of the individual movie ratings posted on Naver's movie website by date and linked them to the number of movie viewers and screen counts registered on the same date on KOBIS to confirm the relationship between movie ratings and result variables. The collection of data to identify the research question 2 also used R program. 〈Table 3〉 describes the number of movie reviews and movie ratings posted on the Naver's movie website for a week after each movie was released.

Table 3. Number of Movie Reviews Posted on Naver for a Week after Release of Film (Unit: Number)

Movie	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
U1	508	646	521	1,190	523	269	153
K1	584	733	475	530	700	459	326
E1	1,580	1,611	988	710	420	198	193
U2	1,313	1,287	1,108	1,209	1,400	656	511
K2	824	907	454	564	675	929	362
U3	1,254	1,386	1,048	1,289	1,048	682	530

U4	1,036	656	301	219	295	349	253
K3	1,675	1,412	795	974	953	582	636
U5	317	368	396	437	233	197	218
U6	274	454	353	440	568	372	258

Source: Naver's movie website (https://movie.naver.com).

IV. Results

1. Research Question 1

1.1. Outcomes of Topic Modeling

For the decision of number of topics, this study first identified the major topics through literature reviews and later examined the relevance between topics found and key word groups derived from topic modeling to determine the appropriate number of topics. We first set up multiple topic numbers, then compared the each results from topic modeling with those found in the literature reviews to examine whether the categorization of the topic was reasonable for explaining each results, and subsequently verified the optimal number of topics with statistical algorithms. The algorithm applied in this study used the value of the perplexity, probability distribution proposed by Lee and Sohn (2015). The probability distribution model results in a small value when the number of topics is optimal. Perplexity has a feature that the higher the number of topics, the smaller the value (Oh 2020), however, more topics could make it difficult to interpret topics. This study determined if the portion of the decrease in perplexity occurred significantly, it could be the optimal number of topics. The analysis started with the two topics and then increased the number of topics to 10, and the analysis found that the decrease in performance was large in the four and five topics. The extent of the reduction was relatively large in the four topics, but the consistency between the key word groups derived by topic modeling and the major topics found in the literature studies determined that the five topics were the most appropriate in the movie reviews.

The key words and proportion of each topic extracted through topic modeling are described in 〈Table 4〉. Each five topics extracted were named into story/background, actor, director, touching/fun and criticism. And the five topics showed similar proportions. It could be regarded as the result of a convergence of the word frequencies since this study used the large amounts of data in the analysis. According to study by Park and Song (2010), the major words found in film reviews were divided into cinematic quality, director's directing, actor's performance, story composition and image style but the outcomes of topic modeling showed that film's image style and criticism were tied into single topic and topic related to the cinematic quality was not found. As confirmed in previous studies, the major topics found in literature reviews could be divided mainly into two categories which were the topics for movie's content and evaluation (Kim and Kim 2019). This study could classify the story/background, actors and directors as having movie's content elements and categorize touching/fun and criticism as having movie's evaluative aspects.

Table 4. Topic Modeling Results for Movie Reviews

	Key Words						Proportion
Topic 1	Story	Content	Scale	Development	Politics	Action	19.98%
Topic 2	Actor	Dialogue	Performance	Understand	Last	Charm	19.96%
Topic 3	Director	People	Character	Reality	Director	Prequel	19.94%
Topic 4	Touching/Fun	Thinking	Appreciation	Commitment	Tension	Top	20.07%
Topic 5	Criticism	Boring	plausible	Expect	Visual	Regret	20.03%

1.2. The Relationship between Word Frequencies of Each Topic and Movie Ratings

This study analyzed the movie reviews of commercial films and estimated that all topics related the film's process quality and outcome quality affected netizen's movie ratings. To check this research question, topic modeling conducted based on the movie reviews and the outcomes showed that the movie reviews could be largely divided into five topics. And after extracting the top 20 words mentioned most frequently from movie reviews by date, these words were grouped into five topics to calculate the frequency of words of each topic by date. At the same time, additional data were obtained by calculating the sum of the individual movie ratings identified on Naver by date. Considering that more than 90% of the movie reviews were posted for a month after film's release, analysis data for each movie was set for a month period.

To identify the issues raised by research question 1, we first set up the number of movie reviews as independent variable and movie ratings as dependent variable. The reason for setting this analytical model was that the count of movie reviews was identified as independent variables that significantly affected movie ratings in the previous studies (Kim and Seo, 2017). In this study, we went one step further by dividing the text-composed film reviews into multiple exclusive topics and quantifying appearance of similar words within the each topic, which enabled us to meet the assumption of the independence required for parallel mediation analysis. Thus, we considered the five topics as parallel mediator variables and analyzed the impact of these mediator variables on movie ratings. To perform this parallel mediation analysis, we conducted a bootstrapping method called PROCESS Macro proposed by Hayes (2013). This study selected 'Model 4' to perform parallel mediation analysis and repeatedly extracted the same-sized samples 5,000 times to establish confidence intervals to confirm statistical significance at a level of 0.05. 〈Figure 1〉 illustrates the concept of parallel mediation analysis used in this study.

Figure 1. Parallel Mediation Analysis to Identify Research Question 1

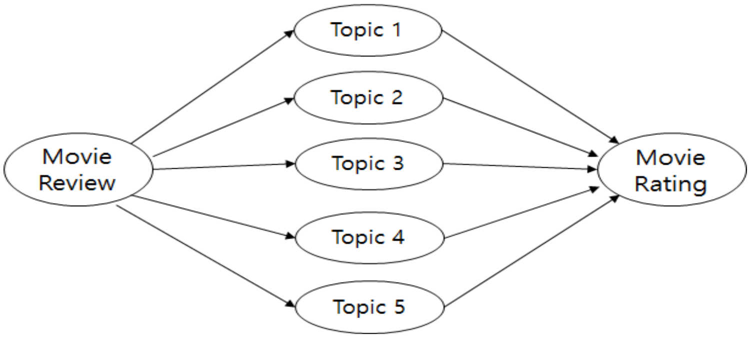

Table 5. Results of Parallel Mediation Analysis

Movie		Topic 1 (Story)		Topic 2 (Actor)		Topic 3 (Director)		Topic 4 (Touching/Fun)		Topic 5 (Criticism)	
		Coefficient	t value	Coefficient	t value	Coefficient	t value	Coefficient	t value	Coefficient	t value
U1	U.S.A.	-0.042	-1.011	0.142	2.388	-0.082	-3.257	-0.135	-2.517	-0.127	-5.836
K1	Korea	0.065	2.888	0.270	4.523	-0.033	-0.712	0.062	1.895	-0.060	-3.207
E1	U.K.	0.367	2.718	-1.122	-1.592	-0.813	-0.940	-0.058	-1.255	-0.555	-7.796
U2	U.S.A.	-0.018	-0.172	-0.089	-2.932	-0.121	-2.537	-0.153	-0.702	-0.157	-2.812
K2	Korea	0.218	2.967	-0.052	-0.927	0.115	3.328	0.040	0.480	-0.002	-0.088
U3	U.S.A.	**0.116**	**3.407**	**-0.690**	**-2.582**	**0.044**	**1.890**	**-0.016**	**-0.648**	**0.031**	**3.220**
U4	U.S.A.	-0.065	-0.993	-0.048	-2.324	0.001	1.798	-0.119	-3.112	-0.042	-3.636
K3	Korea	-0.091	-0.519	0.399	2.997	-0.119	-0.526	-0.021	-0.149	-0.151	-2.591
U5	U.S.A.	-0.055	-0.946	0.103	1.476	-0.098	-3.104	-0.064	-0.755	-0.105	-3.253
U6	U.S.A.	**0.007**	**0.706**	**0.013**	**0.659**	**0.017**	**3.131**	**0.001**	**0.115**	**-0.038**	**-4.145**

Notes: 1. Shading represents statistically significant coefficients.
2. Whether the coefficients are statistically significant or not is 95% confidence in t values.

As the research question 1 claimed, the topics both related to the movie's content and evaluation seem to have negatively influenced netizens when they rate the movie. 〈Table 5〉 illustrates the results of parallel mediation analysis. What is shown in 〈Table 5〉 is that the more topics related to film criticism appear, the more negative the movie's ratings. And the more references to actor and director, the more likely negative the movie's ratings. However, when the audience mentioned the background of the movie in the movie review, it did not seem to have a significant negative impact on movie rating. It was also interesting to note that the more frequently words related to touching/fun appeared in films, the more negative the evaluation score. This is not to say that there were no audiences who felt touching or fun in movies. However, these reviews seemed to have failed to form a rapport with other viewers, which was believed to have resulted in low scores in the movie ratings. Considering the outcomes shown in 〈Table 5〉, it could be said that the overall results were supporting this study's argument.

2. Research Question 2

In order to check the indirect effect of the number of screens when movie ratings affected the box office success, a bootstrapping method called PROCESS Macro was also used. This study repeatedly extracted 5,000 samples of the same size and confirmed statistical significance at a level of 0.05 to verify the mediation effect of the number of movie screens. Since the unit of analysis was date, the sum of individual movie ratings posted for a day on the Naver was calculated as an independent variable, the number of screens registered on the same day in KOBIS was set as a mediator variable, and box office outcomes measured by the number of viewers in KOBIS was selected as a dependent variable. The analysis model is defined such that the movie rating of a specific date impacts the number of screens and audiences on the next day in consideration of the time difference it affects. 〈Figure 2〉 describes the concept of analysis to identify the research question 2, while 〈Table 6〉 describes the number of movie screens that change during the week after release of the film.

Figure 2. Mediation Analysis to Identify Research Question 2

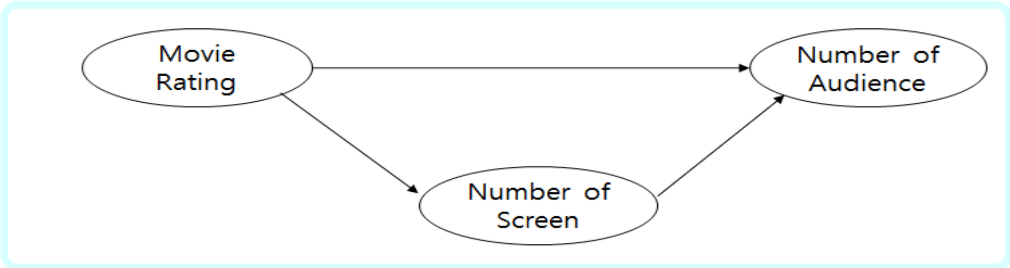

Table 6. Changes in the Number of Screens in a Week after Release (Unit: Number)

Movie	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
U1	991	1,065	1,085	1,105	1,076	1,025	1,039
K1	892	863	832	719	706	736	730
E1	831	891	736	747	712	563	575
U2	844	873	889	926	912	828	831
K2	1,154	1,132	1,150	1,148	1,113	1,087	1,134
U3	1,192	1,261	1,308	1,260	1,237	1,168	1,174
U4	1,016	898	879	843	841	815	799
K3	1,047	1,027	1,081	1,027	995	957	893
U5	987	1,043	1,103	1,108	1,020	1,034	762
U6	986	930	935	917	934	947	954

Source: KOBIS (www.kobis.or.kr).

〈Table 7〉 shows the mediation effects of the number of movie screens in the process of affecting the number of audience. First, bootstrapping method was used to verify the statistical significance of the mediation effects for each films. The bootstrapping approach estimates that there is a statistically significant mediation effect if t value is relative high and zero is not included between the lower and upper 95% confidence intervals. In nine out of ten films, the mediation effect of the screen counts was identified, supporting this study's argument. When checking the t values of each paths in 〈Table 7〉, five of the nine films showed partial mediation effects and four appeared having full mediation effect.

Table 7. Verifying the Mediation Effect of the Number of Screens with Boot Scrapping

Movie		Rating → Screen		Screen → Audience		Rating → Audience		Sample	Mediation Effect
		Coefficient	t value	Coefficient	t value	Coefficient	t value		
U1	U.S.A.	0.756	7.137	0.395	3.492	0.556	4.915	40	Partial
K1	Korea	0.916	15.238	0.621	3.090	0.243	1.208	46	Full
E1	U.K.	0.798	8.173	0.311	2.325	0.602	4.498	40	Partial
U2	U.S.A.	0.869	13.639	0.395	3.008	0.499	3.797	62	Partial
K2	Korea	0.927	16.642	1.152	6.749	-0.272	-1.594	47	Full
U3	U.S.A.	0.899	13.768	0.113	0.669	0.767	4.531	47	No
U4	U.S.A.	0.667	5.147	0.701	5.024	0.149	1.069	35	Full
K3	Korea	0.745	7.656	0.651	5.669	0.244	2.129	50	Partial
U5	U.S.A.	0.837	9.438	0.429	2.458	0.419	2.396	40	Full
U6	U.S.A.	0.939	25.623	0.812	5.225	0.058	0.374	90	Partial

In previous studies, movie ratings and number of screens were described as the independent variables that affected box office performance, but this study confirmed that movie ratings and number of screens were connected to each other and influenced the number of audiences together. The number of samples used in this analysis was set based on the time frame of movie release. Most of the films analyzed in this study were found to have ended their release within two months.

Table 8. Direct and Indirect Effect of Movie Rating

Movie		Movie Rating --> Number of Audience		
		Direct Effect	Indirect Effect	Total Effect
U1	U.S.A	23.124	12.432	35.557
K1	Korea	8.051	18.877	26.928
E1	U.K.	11.138	4.600	15.738
U2	U.S.A	9.995	6.885	16.880
K2	Korea	-7.901	31.024	23.122
U3	U.S.A	18.768	2.493	21.262
U4	U.S.A	4.018	12.596	16.614
K3	Korea	7.113	21.698	46.965
U5	U.S.A.	25.266	21.698	46.965
U6	U.S.A	1.400	18.340	19.740

〈Table 8〉 describes direct effects and indirect effects when movie ratings affect number of audiences through screen counts. Looking at the direct effect of movie ratings on the box office success, five out of 10 movies had a greater direct effect on the number of audiences and five films had a greater indirect effect. Thus, the argument that the direct effect of movie ratings could be greater in the case of commercial films with unsuccessful box office outcomes, seemed to be partially supported. The movies that had a greater direct effect on the number of audiences in 〈table 8〉 were mainly American films. It could be inferred that even if the U.S. film distributor maintained the number of screens regardless of the audience's response to the movie, the impact of screen counts on the movie's box office was not significant. According to the analysis of approximately 82,000 movie reviews for 10 films, the movie ratings evaluated by netizen after watching the movie were regarded as having had a direct impact on potential audiences'choice and having had an indirect influence on film distributor's decision to the number of movie screens.

Ⅴ. Conclusion and Implication

1. Summary

The relationship between movie ratings and box office performance is not interesting research topic to draw reader's attention as many studies already have done, but it is thought that the study supplementing some of the limitations seen in previous researches gives new implication to research related to movie ratings. From this point of view, this study began with two research questions. First, the date was selected as a unit of analysis based on the release day of the movie, and the content analysis of the movie reviews was conducted to figure out how the topics mentioned in the movie reviews affected the movie ratings. To this end, the topic modeling for categorizing the words in the movie reviews into several topics was implemented and the frequency of the key words that appeared in each topic was calculated to determine the effect of the each topic on movie ratings. Second, the film industry consisted of a value chain called production, distribution, and screening stage, but there were not many studies that identified the inter relationships between variables of each stages. Considering that the number of movie screens, one of the variables determined in the distribution stage, continued to change even after the movie was released, it was thought that distribution and screening stages could be research areas in which various interactions were expected.

If a movie was considered as one of service products, the movie reviews might be regarded as a quality assessment of this product. When confirming the research question 1, the comments on movie's contents such as actor and director, and especially, evaluative element like criticism found at movie reviews were seemed to have negative impact on movie ratings for the films that did not make box office hits. These findings can be interpreted that assessments of both process and outcome quality on the movie could be linked to movie ratings in terms of customer dissatisfaction.

To probe the research question 2, a mediation analysis of number of screen on box office success was conducted. The outcomes found that nine of the ten films had shown the mediation effect. And five out of nine films were found to have partial mediation effects and four films had full mediation effects. Also, if we looked at the direct effects of movie ratings on box office outcomes, the direct effect of movie ratings was greater in five out of ten movies, which were mainly American films. This could be inferred that most of companies distributing the U.S. films showed more tendency to maintain the movie screens regardless of the consumer's responses on their films.

2. Implications

The research outcomes for identifying the relationship between movie reviews and movie ratings are as follows. Movie reviews are regarded as the personal opinions of those who watched the movie and generally are presented in a format of text. Thus, relatively few studies have identified the impact of movie reviews compared to movie ratings. Kim and Seo (2017) used emotion analysis to confirm that if the polarity of emotions is in a positive direction, it has a positive relationship with the success of the film. Their research outcome suggests that the positive content of movie reviews may have a positive impact on other consumers' decisions to watch movie. Thus, this study goes one step further to classify the various comments found in the movie reviews into several topics and quantify each topic's appearance in the movie reviews to identify the relationship between each topic words and movie ratings. And we found that the more topic words related to criticism appeared, the more negatively affecting the movie's ratings.

These results suggest that the information presented in text format is harder to quantify than the information given in scores, but if content information can be digitalized through text mining techniques, it can become variable and be analyzed with other variables. Given that netizens who have not watched the movie are more familiar with textual information, it could be thought that comment in text format is more likely to affect consumers'decision-making than figures. If movie marketers can classify various consumer comments found in movie reviews into several topics and analyze frequency of topic related criticism, it would give them a chance to get warning signs from customer in advance. And they can modify or strengthen existing marketing strategies according to market situation. In particular, it seems necessary to focus on marketing activities that can help potential customers to understand the story or background of the movie at a level that is not a spoiler.

This study also identified the mediation effect of screen counts in the relationship between movie ratings and box office performance. The value chain of the film industry can be largely divided into productions, distribution and screening stages (Eliashberg et al., 2006). This view means that the factors influencing the film's box office performance can vary widely. Previous studies that explored the leading factors of film success claimed that information on actors, directors, genres and audience ratings were the main factors before the film's release, but after it was released, the number of screens, distributor's power and online word of mouth became the main elements behind it (Kim and Hong, 2011; Kim and Seo, 2017). Movie ratings can be interpreted as online word of mouth in the movie industry's value chain. In this study, it is found that movie ratings have a direct impact on the number of viewers after the movie is released, but they also indirectly affect the movie's box office success by influencing the number of movie screens.

Rather than collecting primary data through experiments, this study linked two secondary data based on the release date to determine the causality of the related variables. Thus, this study proposed these relationships in the form of research questions rather than hypotheses because we could not control other variables that could affect the dependent variables. The results showed that the movie ratings affected both directly and indirectly the box office performance when we set movie ratings as an independent variable and the number of screens as mediator variable. In particular, five out of 10 movies have a greater direct effect on number of audience. If movie distributor might try to maintain the number of screens secured at the beginning even if consumers' responses were not positive, it could be one of the reasons for research findings. This feature was mainly seen in American films.

Although rigorous verification such as hypothesis has not been performed, we believe that the research outcomes have provided meaningful directions for future studies by showing inter-relationship between movie ratings, the number of screens and box office outcomes. The mediation effect found in this study implies that many movie officials are trying to secure the right number of screens at the beginning and they are adjusting these screen counts in response to film's market performance to optimize return on investment. This study collected data only from the Naver movie portal and conducted various analyses in connection with data from KOBIS. The analysis showed various meaningful results. However, this allows us to infer the influence of Naver movie portal in film industry since movie reviews and ratings posted on Naver are believed to have a significant impact not only on potential customers who have not seen the movie but also on film officials.

3. Recommendations for Future Study

The limitations of this study and directions for future research are shown below. First of all, this study was conducted on 10 commercial films that were regarded as unsuccessful in making box office hits since 2015. This selection was decided to identify the relationship between movie reviews and box office performance for commercial films. This sampling may be limited in that it didn't include various genres of movies such as independent films. In addition, this study has limitation of collecting movie reviews and ratings only from Naver. Although Naver's movie website is considered as popular movie portal having a significant customer base in Korea, the fact that it could not incorporate various movie ratings and reviews posted on other movie portals could be limitation.

This study also has a limitation of not being able to control other variables that may affect the dependent variable by performing the analysis based on secondary data. In future study, it may be necessary to control the effects of other variables in experimental settings for objectification of this study and then conduct research for identifying the relationship between movie ratings and the box office outcomes. In addition, we think it would be an interesting attempt to expand the meaning of this study if new study administered to examine the effect of move reviews which were successful in making box office hits in Korea.

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