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JungWon Lee
Post-Doc Researcher, Basic Science Research Institution, Chungbuk National University, Cheongju, South Korea, d2ljw510@naver.com

Cheol Park
Professor, College of Global Business, Korea University, Sejong, South Korea, cpark@korea.ac.kr

The Effect of eWOM on Movie Sales Considering Competition and Culture☆

JungWon Lee [a], Cheol Park [b,*]

[a] Post-Doc Researcher, Basic Science Research Institution, Chungbuk National University, Cheongju, South Korea
[b] Professor, College of Global Business, Korea University, Sejong, South Korea

Abstract

This paper aims to empirically analyze how competitive and cultural factors moderate the relationship between electronic word-of-mouth (eWOM) characteristics and sales in the US and Korean film industries. A conceptual model was developed based on the cue utilization theory (CUT) to analyze the role of cultural and competitive factors that moderate the relationship between three characteristics of eWOM (volume, valence, and variance) and movie sales. Data of 45 days of 163 films released in Korea and the US were collected and a total of 7,335 samples were analyzed by panel regression. As results, competitive factors enhanced the influence of the eWOM of a focal film and this moderating effect depended on the eWOM characteristics. It also revealed that the effect of eWOM had a greater effect on movie sales in Korea than in the US.

Keywords: eWOM, Competition, Culture, Cue utilization theory, Movie, Korea, US

1. Introduction

The film industry continues to be large and has risen to $4.22 billion worldwide by 2019 in the service industry. Yet it is difficult to predict the movie sales (c.f. Lee and Park 2023; Lee, Lee, and Park 2022) as movies represent experiential products (i.e., service) whose value and quality remain uncertain until experienced (Eliashberg and Sawhney 1994). In this respect, electronic word-of-mouth (eWOM) is an important source of information that enables consumers to predict product quality, and it has been reported to have a greater impact on consumer decision-making than marketing communications provided by companies (Sridhar and Srinivasan 2012). For this reason, as evidenced by the number of meta-analyses that have been published to date, eWOM has received a lot of attention from marketing researchers (Babić Rosario et al. 2016; King, Racherla, and Bush 2014; You, Vadakkepatt, and Joshi 2015) and, across a range of products and platforms, eWOM has been found to have a positive effect on marketing performance. However, according to a recent meta-analysis by Babić Rosario et al. (2016), further research is needed regarding the factors that moderate the relationship between eWOM and sales (See Table 1).

Competition has been pointed out by many recent studies as a potential moderator of the effects of eWOM (Babić Rosario et al. 2016; You, Vadakkepatt, and Joshi 2015). For example, Babić Rosario et al. (2016) suggested that more empirical research was required on the impact of the eWOM for competitors on the eWOM effect of a focal company. This would be of particular importance in the entertainment industry, in which a few competing films are regularly released at the same time. For example, the recent Dreamworks animated film "How To Train Your Dragon 3" was scheduled to be released in 2018, but was postponed to March 2019 to avoid competition with "Captain Marvel" and "Godzilla: King of the Monsters"[1].

However, research is limited as to how the eWOM effect differs depending on these competitive factors. Previous studies have analyzed the direct effects of competitive factors on the performance of a focal product (Jabr and Zheng 2014) or the relationship

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* Corresponding author.
E-mail addresses: d2ljw510@naver.com (J. Lee), cpark@korea.ac.kr (C. Park).

[1] See https://www.cinemablend.com/news/1596860/how-to-train-your-dragon-3-has-been-delayed-heres-when-its-hitting-theater

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Table 1. *Summary of selected eWOM researches in the film industry.*

Research	eWOM Metrics			Competitive factor	Cultural factor	Key finding
	Volume	Valence	Variance			
Liu (2006)	✓	✓	✗	–	–	WOM activities are the most active during a movie's prerelease and opening week and that movie audiences tend to hold relatively high expectations before release but become more critical in the opening week.
Duan, Gu, and Whinston (2008)	✓	✓	✗	–	–	Both a movie's box office revenue and WOM valence significantly influence WOM volume.
Moon, Bergey, and Iacobucci (2010)	✗	✓	✗	–	–	High early movie revenues enhance subsequent movie ratings. They also find that high advertising spending on movies supported by high ratings maximizes the movie's revenues.
Yang et al. (2012)	✓	✓	✗	–	–	The authors find a significant effect of WOM valence on box office revenue only in the case of non-mainstream movies.
Koschat (2012)	✗	✓	✗	–	–	Viewers who prefer literary genre motion pictures have distinct media portfolios that make them more responsive to professional reviews.
Rui, Liu, and Whinston (2013)	✓	✓	✗	–	–	Positive Twitter WOM increases movie sales, whereas negative WOM decreases them.
Hennig-Thurau, Wiertz, and Feldhaus (2014)	✓	✓	✗	–	–	Mcroblogging word of mouth shared through Twitter and similar services affects early product adoption behaviors by immediately disseminating consumers' post-purchase quality evaluations.
Keh et al. (2015)	✓	✓	✗	–	Hofstede's Theory	When the volume of online ratings is smaller and the valence (average rating) is lower, the moviegoers express higher risk perception and lower purchase intention.
Wang, Liu, and Fang (2015)	✓	✓	✓	–	–	High user reviews variance, in combination with high critic reviews variance, can elicit a sense of uniqueness and thus enhance purchase intentions of some consumers.
Song et al. (2017)	✗	✗	✗	–	Hofstede's Theory	The cultural congruence between the product and the market improves consumer reviews.
Chiu et al. (2019)	✓	✓	✓	–	Hofstede's Theory	eWOM variance has a positive impact on box office in China, but eWOM variance has no impact on the US box office.

between the eWOM characteristics of a competing product and a focal product (Ilhan, Kübler, and Pauwels 2018), but they have not sufficiently explained how competitive factors moderate the relationship between the eWOM characteristics of a focal product and movie sales. Although the influence of competitive movies is very strong (Vogel 2020), studies that consider competition factors are limited.

Another potential moderating factor of eWOM that has not been sufficiently investigated to date is cultural dimensions (Carrillat, Legoux, and Hadida 2017; King, Racherla, and Bush 2014). Since the film industry targets the global market, movie sales are significantly affected by consumer cultures in various countries around the world (Chiu et al. 2019; Lee and Park 2022). King, Racherla, and Bush (2014) argued that even these studies have not analyzed the structural differences between cultural factors in sufficient detail. Carrillat, Legoux, and Hadida (2017, p. 293), a meta-analysis of online reviews in the film industry, requested a study as follows: "Thus, whether the relationships we identify hold in the cultural milieu of China or other fast-growing film markets worldwide is a key empirical question that further research should address."

An analysis of cultural differences in eWOM variance ("a natural measure to capture the heterogeneity in consumer opinions [such that] upon seeing a high variance, consumers infer that the product is a niche one that some people love, and others hate"; Sun 2012, p. 697) has been particularly lacking (Babić Rosario et al. 2016). According to Wang, Liu, and Fang (2015), eWOM variance may be perceived by consumers as a risk of mismatch, but variance is likely to have a positive effect depending on the information processing method employed (i.e., with or without review text information processing). eWOM variance is salient across online review platforms and affects important financial performance such as consumers' willingness to pay and firms' abnormal returns (Wang, Liu, and Fang 2015). Therefore, analyzing the moderating effect of a consumer's information processing characteristics due to cultural differences could expand the understanding of eWOM variance. Cultural differences in information processing are very closely related to the differences in cultural information processing suggested by Hall's (1989) high- and low-context culture theory. Surprisingly, however, no previous study has used Hall's theory to explore the differences in the influence of eWOM variance. Therefore, the present study proposes the following important research questions:

- How is the influence of eWOM characteristics on consumer decision-making affected by competitive factors?
- How is the influence of eWOM characteristics on consumer decision-making affected by cultural factors?

To answer these research questions, a conceptual model was developed based on the cue utilization theory (CUT; Purohit and Srivastava 2001) to analyze the role of cultural and competitive factors in moderating the relationship between eWOM characteristics and sales. According to the CUT, a product provides a series of signals to the consumer, and the consumer judges the quality of the product based on these signals. Based on this theory, we analyzed differences in how consumers use eWOM signals depending on competitive and cultural factors.

In our empirical analysis, we collected audience reviews and sales data for the US and Korean film industries. Because eWOM plays a key role in the financial success of the film industry (Elberse and Eliashberg 2003), this industry especially appropriate for eWOM research (e.g., Duan, Gu, and Whinston 2008; Liu 2006). The US and Korea film industries were selected as the subjects for cultural comparison in this study because they represent the largest and fourth-largest film industries in the world, respectively[2], and because the two countries exhibit culturally opposite characteristics (Kim, Yang, and Kim 2013). Americans are generally individualistic and have a low tendency to avoid uncertainty, whereas Koreans are typically collaborative and have a strong desire to do so (Hall 1989). Korea is also a typical high-context culture, while the US is a low-context culture.

This study contributes to the eWOM research by revealing that competitive factors enhance the effect of eWOM for a focal film and that this moderating effect differs depending on the eWOM characteristics. It also contributes to eWOM research and international marketing by revealing that eWOM has a greater effect on movie sales in Korea than in the US. From a practical perspective, our study also presents evidence that companies in the film industry can maximize the effectiveness of eWOM by accounting for the cultural and competition characteristics of the target market.

2. Theoretical framework

2.1. Film industry and eWOM

Services are natural candidates for eWOM communication among consumers because they are generally difficult to evaluate prior to purchase and therefore are perceived as high-risk (Murray 1991). The inherent challenge in evaluating the quality of experiential goods, such as films, prior to consumption leads consumers to seek various cues as a means to reduce their uncertainty (Chiu et al. 2019; Duan, Gu, and Whinston 2008; Eliashberg and Sawhney 1994; Hennig-Thurau, Wiertz, and Feldhaus 2014; Keh et al. 2015; Koschat 2012; Liu 2006; Moon, Bergey, and Iacobucci 2010; Wang, Liu, and Fang 2015). Product reviews from fellow moviegoers offer non-expert or amateur perspectives, mostly shared through online posts or social media platforms (e.g., Facebook) (Duan, Gu, and Whinston 2008; Liu 2006; Wang, Liu, and Fang 2015; Zimmermann et al. 2018).

In this study, we classified and analyzed eWOM characteristics by volume, valence, and variance. Volume is defined as "the total amount of eWOM interaction" (Liu 2006, p. 75), which increases the awareness of a product, while valence is "the idea that eWOM can be either positive, negative, or neutral" (Liu 2006, p. 75). The latter is mainly measured by the average rating of reviews (Duan, Gu, and Whinston 2008) and refers to the expected product quality or reputation (Liu 2006). Research on eWOM variance has been limited compared to other characteristics (Babić Rosario et al. 2016), with the effect of eWOM variance on marketing performance generally reported as a comparison between positive and

[2] See https://www.technology.ihs.com/603117/cinema-admissions-box-office-database

negative eWOM (Clemons, Gao, and Hitt 2006; Wang, Liu, and Fang 2015).

Prior research has demonstrated that the eWOM volume positively influences the box office revenues of films (Duan, Gu, and Whinston 2008; Liu 2006; Rui, Liu, and Whinston 2013; Yang et al. 2012). However, scholars who have studied the effects of eWOM in the film industry are reporting mixed results for eWOM valence. Chintagunta, Gopinath, and Venkataraman (2010) argued that eWOM valence may affect product sales while Duan, Gu, and Whinston (2008) found that eWOM valence did not significantly affect the movie's box office revenue.

Moreover, in the case of eWOM variance, there are not enough studies on the film industry. Clemons, Gao, and Hitt (2006) argue that the higher the degree of differentiation, the more favorable it is to meet the needs of the target consumers and therefore the more positive the sales will be. On the contrary, Wang, Liu, and Fang (2015) argue that variance in online reviews negatively impacts film sales by negatively affecting consumers' final choices by signaling an increased risk of mismatch to consumers.

Although many eWOM studies have been conducted in the film industry, additional studies are needed for the following reasons. First, because the results of previous studies on eWOM valence and variance are mixed, it is necessary to search for boundary conditions that can explain these results. Although competitive factors are very important in the entertainment industry (Vogel 2020), discussions on these factors have been almost ignored in the film industry. Second, most of the existing research used samples focused on the US market, but few samples focused on other areas. Moreover, since the film industry operates in markets around the world, it is necessary to study the cultural differences of countries above all else.

Therefore, this study attempts to analyze competition and cultural factors that moderate eWOM effects through CUT theory. Through this, we intend to integrate the existing mixed knowledge about the eWOM effect of the film industry.

2.2. *Cue utilization theory*

We used the Cue utilization theory (CUT) to analyze the role of culture and competition in moderating the relationship between eWOM characteristics and sales. This theory posits that products provide an array of cues that act as surrogate indicators of quality for consumers (Purohit and Srivastava 2001). These cues consist of a predictive and a confidence value (Richardson, Dick, and Jain 1994). The predictive value (PV) of a cue represents the degree to which a consumer associates a particular signal with product quality. This PV is similar to the diagnostics of the signal and reflects the possibility of successfully solving the problem using this signal (Dick, Chakravarti, and Biehal 1990). In particular, the degree to which a particular signal is used for quality evaluation depends on its diagnostic level and the level of availability of other signals (Slovic and Lichtenstein 1970). The confidence value (CV) of a cue refers to the degree of confidence in the consumer's ability to judge and utilize a particular signal (Purohit and Srivastava 2001).

In the eWOM context, the PV and CV of eWOM characteristics are likely to differ depending on the cultural background of the consumer. According to Hall's high- and low-context culture theory, consumers in high-context cultures such as Korea are more likely to process information in online reviews in a way that considers the subtle and multiple contexts of their counterparts than are consumers in low-context cultures. This will, in turn, positively influence the CV of eWOM variance by facilitating the interpretation of information about taste (i.e., reviews). In addition, the higher the uncertainty avoidance tendency of a consumer (Hofstede, Hofstede, and Minkov 2010), the more likely they will focus on reducing perceived risk and actively utilize signals (i.e., the PV of eWOM) that reduce perceived risk in purchasing decisions.

In addition, there may be a difference in the PV of eWOM characteristics that a consumer perceives during their decision-making process depending on competition. Consumers are more likely to modify their decision-making process and the information that they use when the number of alternatives is higher (Inman 2001). Therefore, differences in a competitive environment will lead to differences in the PV of individual eWOM characteristics (i.e., volume, valence, and variance). Using this CUT-based framework, we develop a hypothesis that can be empirically analyzed in which competition and culture moderate the relationship between eWOM indicators and sales. This conceptual framework is presented in Fig. 1.

3. Hypotheses development

3.1. *eWOM and competition*

The competitive factors analyzed in the present study were the number and eWOM valence of competing products. The number of competing products is defined as the number of movies that were released at the same time as the target product, while the eWOM valence of competing products was defined as their average audience rating (Jabr and Zheng 2014).

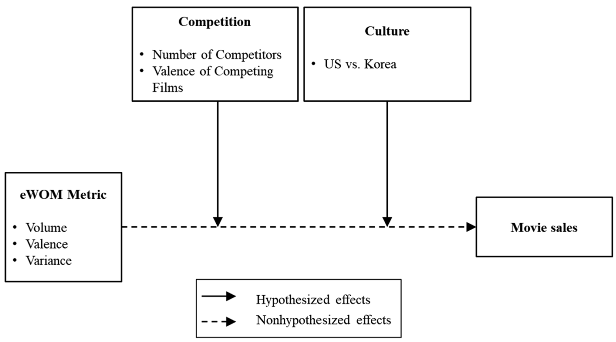

Fig. 1. Research model.

According to previous studies on competition, a higher number of competitors is likely to increase the sales of a focal company. Agglomeration is defined as "the concentration of specialized industries in particular localities" (Marshall 2012, p. 174), and many researchers agree that increasing agglomeration increases consumer demand because it minimizes exploration costs (Ellison, Glaeser, and Kerr 2007). In addition, according to the external effect theory, the external effect of major stores (e.g., department stores and brand stores) in a region increases the number of customers in other stores located nearby (Gould, Pashigian, and Prendergast 2005). According to a study by Stephen and Toubia (2009), these external effects occur not only in offline stores, but also in virtual environments such as social media (Liu, Steenkamp, and Zhang 2018).

On the other hand, there is also the possibility of negative effects, such as when the focal product is eliminated from the decision-making process by the competition. Consumers will evaluate the best alternative from among the movies in their consideration set based on eWOM valence (Liu 2006). In this case, it is more likely that the focal film's negative eWOM valence will lower sales the more positively a rival film's eWOM valence is. Furthermore, because the number of movies included in a consumer's consideration set is limited, there is a possibility that this negative effect will be stronger as the number of competitive films increases.

However, we believe that the positive effect will be stronger than the negative effect as competition increases in the movie industry. For hedonic industries such as movies, consumers may frequently look for different kinds of films to maintain an ideal level of stimulation (Raju 1980); as a result, they stand to gain from a wider selection of films available on the market (Inman 2001). In addition, the film industry is likely to generate stronger positive external effects for a focal film than are other industries because situational factors (e.g., screening times and sell outs) are important in the decision-making process. Therefore, in the film industry, it can be expected that the positive effects will be stronger than the negative effects.

CUT suggests that consumers' reliance on and use of a specific cue in a decision depends on its PV. Hence, changes in competitive conditions are likely to change the PV of each eWOM characteristic. The concrete logic is as follows.

First, an increase in competition is likely to enhance the PV of eWOM volume and valence. As "cognitive misers," consumers tend to set aside a limited amount of time and resources for decision making (Fiske 2017). In this case, moviegoers may limit their consideration set to movies that they are already aware of or that can be easily justified by their popularity (Tan, Netessine, and Hitt 2017, p. 645). According to Liu (2006), in the movie industry, eWOM volume increases consumers' awareness of movies and eWOM valence influences their attitudes toward movies. Therefore, as the number of competing films and their eWOM valence increases, the PV of eWOM volume and valence, which are key to evaluating films, will increase.

Second, as competition increases, consumers are more likely to consider the PV of variance because the relative heterogeneity of the alternatives that consumers can choose from decreases as the number of competing products increases (e.g., Liu, Steenkamp, and Zhang 2018). If the difference in quality between the films under consideration is wide, quality signals such as eWOM volume and valence play an important role in purchasing decisions; however, if it is higher than a certain level, it is highly likely that this importance will decrease (e.g., Clemons, Gao, and Hitt 2006; Mitra, Anusree, and Lynch 1995). As the importance of product quality signals decreases, it is more likely that specific tastes and uniqueness (i.e., variance) will act as important criteria. This is because consumers are more likely to find a movie that fully reflects their taste when the number of alternatives increases (Clemons, Gao, and Hitt 2006).

This study thus proposes the following hypotheses:

H1. *The positive moderating effect of competitive factors on eWOM will be strongest for eWOM variance.*

H1-1. *The positive moderating effect of the number of competing movies on on eWOM will be strongest for eWOM variance.*

H1-2. *The positive moderating effect of the eWOM valence of competing movies on eWOM will be strongest for eWOM variance.*

3.2. eWOM and culture

Culture is defined as a complex whole that includes the knowledge, beliefs, art, law, morals, custom, and any other capabilities and habits acquired as a member of society (Tylor 2010). According to earlier research, people from different cultural backgrounds are frequently expected to use different messages or communication techniques, and these cultural differences have a significant influence on how consumers behave when it comes to eWOM (Buzova, Sanz-Blas, and Cervera-Taulet 2018; Chiu et al. 2019; Keh et al. 2015; Park and Lee 2009).

The moderating mechanisms of culture can be explained based on our CUT-based framework. First, according to the CUT, the tendency to avoid uncertainty is likely to increase the PV of eWOM characteristics (i.e., volume and valence) with which consumers can predict quality. The tendency to avoid uncertainty can be defined as tolerating ambiguous situations that are difficult to predict or that are unstructured (Hofstede, Hofstede, and Minkov 2010). Korea and the US are classified as cultures with a high and low level of uncertainty avoidance, respectively (Hofstede, Hofstede, and Minkov 2010). The higher a consumer's tendency to avoid uncertainty, the higher the PV of eWOM volume and variance (Tang 2017). Cultures with high uncertainty avoidance prioritize minimizing risk and ambiguity more than low uncertainty avoidance cultures (Kale and Barnes 1992) and often leverage eWOM to mitigate uncertainty (Goldsmith and Horowitz 2006). Moreover, cultures with high uncertainty avoidance tend to have a positive correlation with information sharing and information retrieval activities (Dawar, Parker, and Price 1996).

Second, Chen and Xie (2008) suggested that online reviews created by users can work as "sales assistants" to help novice consumers identify the products that best match their idiosyncratic preferences. Consumers from high-context cultures will more highly evaluate the CV of eWOM variance (Hall 1989). CV represents the reliability of a consumer's ability to judge and utilize a particular signal. According to Hall (1989), the low-context culture of the US prefers accurate, simple, and direct conversation, whereas high-context cultures are characterized by subtle, multidimensional, and indirect conversation. Applying these information-processing characteristics to eWOM, consumers in high-context cultures such as Korea tend to process not only ratings but also written reviews in order to parse the subtle and multidimensional context of the reviewer.

eWOM variance represents the degree to which a product suits the taste of a specific consumer, while also indicating the potential for significant mismatch costs (Sun 2012). If a consumer only checks the average rating of a movie and does not read specific reviews, they will not have the opportunity to determine whether the movie actually represents high quality according to their taste (Wang, Liu, and Fang 2015). In other words, high-context consumers who attempt to understand a reviewer's context can reduce the mismatch effect of variance and enhance its positive effects. Therefore, the difference in consumption characteristics of eWOM in Korea (i.e., the higher reliance on reading reviews) is likely to have a positive effect on the CV of eWOM variance.

In contrast, uncertainty avoidance may be more negatively affected by the mismatch risk represented by eWOM variance in Korea. However, Zimmermann et al. (2018) found that risk-averse consumers prefer high-priced products with high eWOM variance, while Wu et al. (2013) showed that consumers with risk aversion to product uncertainty have a high willingness to pay for products with high eWOM variance when eWOM valence is low. Therefore, if we assume the same situation for the movie industry, we can expect the effect of uncertainty avoidance on eWOM variance to be nonsignificant. As a result, this study proposes the following hypotheses:

H2. *The positive effects of eWOM on movies sales will be stronger in Korea than in the US*

H2-1. *The positive effect of eWOM volume on movies sales will be stronger in Korea than in the US*

H2-2. *The positive effect of eWOM valence on movies sales will be stronger in Korea than in the US*

H2-3. *The positive effect of eWOM variance on movies sales will be stronger in Korea than in the US.*

4. Methodology

4.1. Data

Data for this analysis were gathered on films released in the US and Korea during 2017. Korean movie sales and screen count were sourced from the Korean Film Council (KOFICS), while eWOM metrics were derived from online movie reviews on Naver (http://movie.naver.com) via Python. Naver is recognized as Korea's leading movie review website (Yang et al. 2012). For the US market, revenue and the number of screens were obtained from Boxofficemojo.com, with consumer reviews sourced from Fandango.com, also utilizing Python for data extraction.

Because research comparing countries and cultures needs to control for factors other than those being

Table 2. The dataset used in the present study.

	US	KOR
Selected movies	142	108
Total revenue of the selected movies	$11,019,929,871	₩ 1,707,190,006,283
Total market size for 2017	$10,802,612,415	₩ 1,756,577,851,113
Market share of the selected movies	98.02%	97.18%

Table 3. Propensity score matching results.

	US	KOR
Selected movies	142	108
Matched movies	131	105
Removed movies	11	3

analyzed, the following methods were used in the present study. First, for the purpose of gathering samples that accurately represent the film industries of the US and Korea, 142 films from the US and 108 films from Korea were chosen based on their box office rankings. These selections accounted for 98.02% of the film market share in the US and 97.18% of the Korean market in 2017, as detailed (Table 2). Therefore, it can be asserted that the sample selection for this analysis effectively mirrors the domestic movie markets of both countries for the specified year.

Second, the analysis of films from the US and Korea was subject to potential selection bias. The influence of eWOM on consumer choices could differ across various film genres or audience characteristics. To reduce such bias, this research employed propensity score matching for movie genre and ratings. Through this approach of matching subgroups, 131 American and 105 Korean movies were matched. The findings are presented in Table 3.

Next, average difference testing was conducted to determine if there were any differences between the set of movies from each country selected through propensity score matching (Table 4). Statistical analysis revealed no significant variations in the features (i.e., genre and movie ratings) of the films selected from both the US and Korea. Hence, the samples from the US and Korea utilized in this research were deemed suitable for a comparative study.

Third, the potential audience size for the film industries in the US and South Korea could vary, potentially affecting the impact of eWOM. To account for this, the present study incorporated the size of the film market and the volume of films released in both the US and Korea as control variables. These variables were measured on a monthly basis to adjust for the distinctive seasonal fluctuations observed in the film markets of the two countries.

Table 4. Balance testing results.

Variables	US	KOR	F	p
Horror	.0611 (.240)	.0286 (.167)	1.382	.241
Drama	.237 (.427)	.210 (.409)	.244	.622
Crime	.045 (.210)	.105 (.308)	3.045	.082
Comic	.130 (.337)	.057 (.233)	3.518	.062
Animation	.107 (.310)	.124 (.331)	.164	.686
Action	.336 (.474)	.257 (.439)	1.716	.192
R	.443 (.449)	.419 (.496)	.132	.716
NC-17	.122 (.329)	.133 (.342)	.065	.799
G	.130 (.337)	.133 (.342)	.006	.939

Fourth, we analyzed the frequency of keywords through text mining to assess the differences between movie reviews in the United States and Korea (Fig. 2). Positive words (e.g., great, good, best, see, really) were found in both the United States and Korea, with no significant difference in the words used. Therefore, the words used in the movie reviews of the two countries are not significantly different, making comparing cultural differences appropriate in this study.

4.2. Measurements

The movie industry typically features a short product lifecycle. Acknowledging this, Duan, Gu, and Whinston (2008) examined daily movie sales and eWOM data over 42 days post-release. To delve deeper into eWOM dynamics and competition, this study extended data collection to 45 days, allowing for a granular daily analysis. However, due to the risk of biased estimates in unbalanced panel data (Wooldridge 2013), films screened for less than 45 days were excluded.[3] Consequently, data on 163 movies released in Korea and the US in 2019 were collected, amassing a total of 7,335 screening days.

The target eWOM variables were measured using three methods. The eWOM volume, valence, and variance of the movie reviews were initially measured as a cumulative value up to the date of measurement and was used for hypothesis testing in the main model. These variables were then measured in two different ways to test the robustness of the estimates. First, the

[3] In order to reduce the bias of the estimates, films that were not in release for at least 45 days were excluded from the analysis, but all of the selected movies were included in the calculation of the variables related to competition, i.e., the number and eWOM valence of competing films.

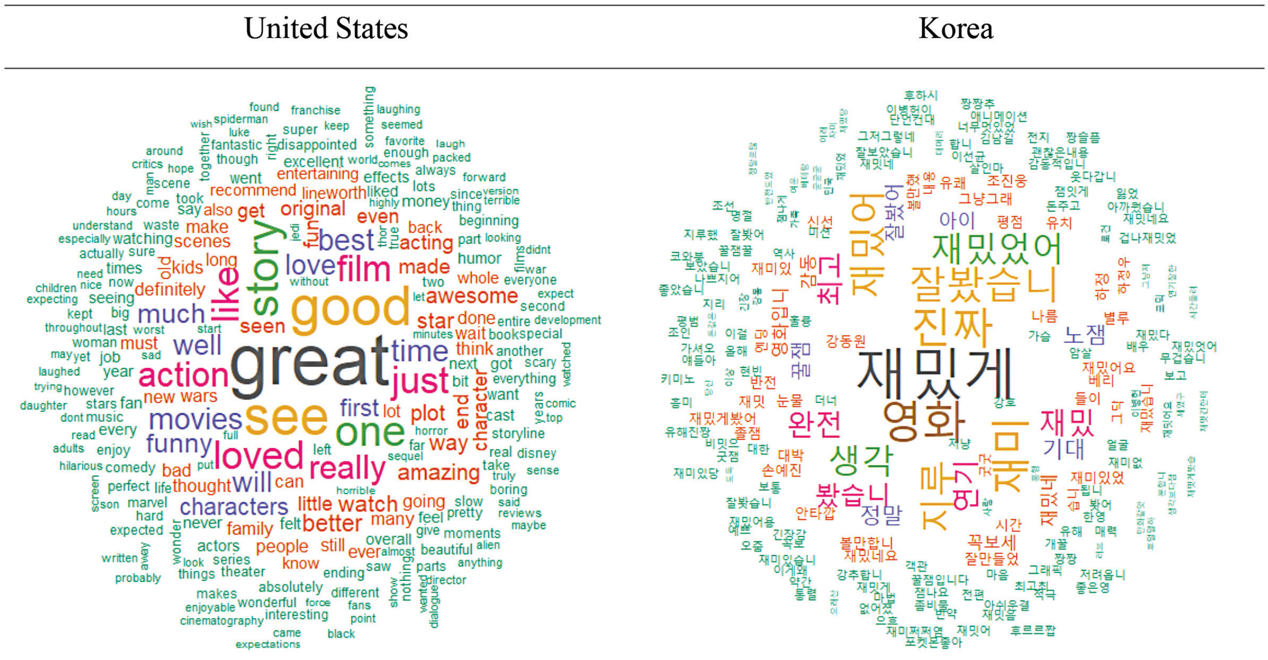

Fig. 2. Key words used in the movie reviews.

negative and positive reviews were identified using an emotional analysis method with text mining, and the cumulative negative eWOM volume and the cumulative positive eWOM volume until the measurement date were measured. Second, we observed Facebook posts and measured the number of likes using a crawling program that summed the number of likes on all posts, excluding those made by celebrities or distributors, after searching for a movie on Facebook.[4]

To assess the effect of competition, the number and average score of competing films were assessed. The number of competing movies was defined by the count of films released on the measurement day. The eWOM valence of competing movies was calculated by weighting the average eWOM valence of all movies released that day against their screen count, which significantly affects sales within the film industry (e.g., Liu 2006).

In addition, the size of the movie market per month, the number of films released per month, the release date, the number of screens, critic ratings, genre, and movie ratings were used as control variables. The tracking of the release date spanned from day 1 to day 45 post-release, and it was squared to account for the nonlinear decline in movie sales. Additionally, independent of eWOM's impact, film revenues are notably higher during weekends (Duan, Gu, and Whinston 2008); hence, data collected on Fridays, Saturdays, and Sundays were used as a dummy variable. The number of screens was recorded as the as the number of movie screens each day, while critic ratings for Korean movies were sourced from Naver and for US films from Metacritic. Moreover, a dummy variable was assigned to indicate the country (1 for Korea and 0 for the US), and movie ratings were also measured as dummy variables (G, PG, PG-13, R, and NC-17). A natural logarithm transformation was applied to all non-dummy variables (e.g., Duan, Gu, and Whinston 2008; Liu 2006). A summary of the variables analyzed is presented in Tables 5 and 6.

4.3. Analysis method

Panel regression analysis was conducted for hypothesis testing. Panel regression analysis combines cross-sectional and time series data to uncover insights not obtainable through purely cross-sectional or time series methodologies alone (Wooldridge 2013). This analytical approach offers a more rigorous examination than ordinary least squares (OLS) regression by assessing the dynamic interactions among variables and accounting for unobserved variations.

[4] Online content posted by celebrities (e.g., actors) and movie distributors could be included in eWOM, but the present study excluded this because it focuses on the effect of pure consumer-earned media (Stephen and Galak 2012). Facebook uses a blue badge to identify celebrities, so it was possible to distinguish posts from celebrities from those of consumers.

Table 5. Measurements used in the research model.

Variables	Measurement
VOL	The volume of reviews accumulated from the date of release to the measurement date
VAL	Mean of the reviews accumulated from the date of release to the measurement date
VAR	Standard deviation of the reviews accumulated from the date of release to the measurement date
NEGA	The volume of negative reviews accumulated from the date of release (the valence of the reviews was determined by sentiment analysis)
POSI	The volume of positive reviews accumulated from the date of release (the valence of the reviews was determined by sentiment analysis)
LIKE	The number of Facebook likes accumulated from the date of release to the measurement date
COMPE	Number of movies playing on the measurement date
W_COMPA	Average review rating for competing movies playing on the measurement date ($Review\ Rating * \frac{1+SCREEN}{1+TOTAL\,SCREEN}$)
M_GROSS	Measured monthly movie market size by country
M_RELEASE	Measured monthly releases by country
NATION	Dummy variable with US = 0, Korea = 1
WEEK	Weekend (Fri, Sat, and Sun) measurements with dummy variables
AGE	Measures the days elapsed between the release date and the measurement date
SCREEN	The number of screens on the measurement date
GROSS	Sales on the measurement date
CRITIC	Average rating of critics
GENRE	Divided into 8 movie genres (comedy, horror, romance, action, drama, animation, and fantasy)
PG	Divided into 5 movie ratings (G, PG, PG-13, R, and NC-17)

For these reasons, panel regression analysis is extensively applied in eWOM studies (e.g., Saboo, Kumar, and Ramani 2016). Both fixed effects and random effects models can be used with the panel regression approach. In this study, a random effects model was used to analyze the country dummy variable.

5. Results

5.1. Verification of the measurement model

Two tests were performed to verify the measurement model. First, because multicollinearity may arise due to strong correlations between variables, the variation index factor of each variable was analyzed. The variance expansion factor of the variable with the highest VIF did not exceed 10 (6.73), which is the threshold for possible multicollinearity. Second, to ensure that each variable exhibited a stable time series, a unit root test was performed. In the present study, the Phillips–Perron and augmented Dickey-Fuller tests were utilized (Schwert 1987). The significance of the test statistics for all variables suggested the absence of unit roots, affirming their stability over time.

5.2. Hypothesis testing

The analysis results are shown in Table 7. The homogeneous model (1) without the national dummy variable revealed that the three eWOM characteristics and the two competition variables had a positive effect on movie sales: eWOM volume ($\beta = 0.2882$; $p < .001$), eWOM valence ($\beta = 0.5778$; $p < .05$), and eWOM variance ($\beta = 1.0282$; $p < .001$), the number of competing films ($\beta = 0.6317$; $p < .05$), and the eWOM valence of competing films ($\beta = 0.6536$; $p < .001$). However, the addition of the country dummy variable to model (2) led to eWOM variance having a negative effect on sales ($\beta = -.0.013$; $p < .001$). Therefore, eWOM variance is highly likely to be affected by cultural differences between countries.

Second, in the competition model (3), we analyzed how the effects of eWOM characteristics differed according to competition. The results of the analysis revealed that competition enhanced the effects of the eWOM characteristics. In particular, the number of competing films exhibited a strong positive moderating effect on eWOM variance ($\beta = 0.1088$; $p < .001$), eWOM volume ($\beta = 0.0076$; $p < .001$), and eWOM valence ($\beta = 0.0168$; $p > .05$). In terms of the eWOM valence of competing movies, eWOM volume ($\beta = 0.6370$; $p < .001$), eWOM variance ($\beta = 0.3171$; $p < .001$), and eWOM valence ($\beta = 0.0348$; $p < .001$) were all positively moderated by this factor. Therefore, Hypothesis 1 was partially supported. The reason why the moderating effect on eWOM volume was stronger than that on variance is that, when the eWOM valence of competing movies increases, the relative importance of quality (i.e., volume) decreases in the decision-making process but, at the same time, as the average quality increases, the risk of a mismatch, which is a negative effect of eWOM variance, also increases.

Third, the cultural difference model (4) analyzed whether the effects of eWOM characteristics differed according to the cultural differences between the

Table 6. Descriptive statistics and correlation analysis of the variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. VOL	1															
2. VAL	.141**	1														
3. VAR	−.138**	−.687**	1													
4. NEGA	.441**	−.010	−.052**	1												
5. POSI	.531**	.204**	−.121**	.531**	1											
6. LIKE	.015	.070**	−.102**	.030**	−.013	1										
7. COMPE	−.069**	−.130**	.264**	−.149**	−.020*	−.072**	1									
8. W_COMPA	.078**	.253**	−.425**	.129**	−.022**	.118**	−.485**	1								
9. M_GROSS	−.054**	−.173**	.391**	−.114**	.071**	−.130**	.284**	−.459**	1							
10. M_RELEASE	−.018*	−.147**	.258**	−.174**	−.031**	−.086**	.343**	−.367**	.111**	1						
11. NATION	.090**	.251**	−.530**	.211**	−.059**	.157**	−.519**	.680**	−.715**	−.495**	1					
12. WEEK	−.007	−.002	.008	−.008	−.005	−.020	.053**	−.016	.010	.012	−.012	1				
13. AGE	.226**	−.035**	.017*	.227**	.226**	−.056**	.000	.009	−.009	.028**	0.000	−.009	1			
14. SCREEN	.004	−.013	.206**	−.083**	.143**	−.041**	.249**	−.366**	.390**	.274**	−.554**	−.004	−.344**	1		
15. GROSS	−.021**	−.058**	.271**	−.132**	.116**	−.070**	.355**	−.459**	.499**	.325**	−.688**	.059**	−.271**	.767**	1	
16. CRITIC	.195**	.255**	−.296**	.214**	.133**	.073**	−.170**	.200**	−.199**	−.166**	.286**	−.003	.000	−.093**	−.129**	1
Mean	6.4	2.1	0.8	1.7	2.4	0.8	2.6	2.1	26.4	5.1	0.4	0.4	5.8	6.2	16.3	4.0
SD	1.3	0.2	0.3	0.6	0.6	1.9	0.3	0.1	1.3	0.2	0.5	0.5	1.7	2.1	5.5	0.3

*$p < 0.05$; **$p < 0.01$.

countries. The results showed that eWOM volume ($\beta = 0.0450$; $p < .05$), eWOM valence ($\beta = 4.1467$; $p < .001$), and eWOM variance ($\beta = 0.8730$; $p < .001$) were stronger in Korea than in the US. Thus, Hypothesis 2 was supported.

5.3. Robustness check

The robustness of our results needed to be checked because these characteristics can be influenced by various factors. To begin with, audience reviews were analyzed to measure the volume of cumulative emotionally negative and positive eWOM. To verify that Korean consumers process reviews more carefully than do US consumers, the eWOM characteristics were measured based on an emotional analysis of the text of reviews, while disregarding the rating (Deng 2020). To achieve this, a linguistic inquiry and word count approach was employed to measure the ratio of positive to negative words. This analysis thus enabled the effect of eWOM valence on the sales of a movie to be measured based on the text of reviews. The analysis results are presented in Table 8.

Second, we analyzed whether the same results could be obtained when collecting eWOM data from social media (Table 9). Facebook has been investigated in this respect in number of previous studies (e.g., Colicev et al. 2018; Ilhan, Kübler, and Pauwels 2018), so it was used for the analysis in the present study. Python was used to collect Facebook posts based on a search of the title of the movie for specific dates and times (i.e., from the opening date until 45 days after release). After the posts had been collected, a researcher excluded those posts not related to the film and posts made by celebrities, and then measured the eWOM characteristics by summing the number of likes for all posts each day. The number of likes was employed as a measure of eWOM volume as in previous research (e.g., Colicev et al. 2018).

Third, we looked to eliminate endogeneity by using two-stage least squares (2SLS) analysis. In this study, the traditional method of measuring a lagged independent variable as an instrumental variable was used (Arellano and Bond 1991). Therefore, *t*-1 lagged independent variables VOL, VAL, VAR, COMPE, and W_COMPA, which represented the independent variables for each model, were employed as instrumental variables. This method of measuring instrumental variables is widely used in eWOM research (e.g., Jabr and Zheng 2014). Table 10 presents the results of the 2SLS analysis. Overall, based on the robustness checks described in this section, we believe that the findings of the present study are consistent even when different measurements and analytical methods are employed.

Table 7. Hypothesis testing.

	(1)	(2)	(3)	(4)
Variables	Homogeneous model	Nation model	Competitive model	Cultural model
(Intercept)	−82.3161***	1.1910	1.1023	2.7959
	(3.3180)	(3.1408)	(3.1269)	(3.0948)
VOL	0.2882***	0.2844***	0.2724***	0.2576***
	(0.0263)	(0.0184)	(0.0185)	(0.0225)
VAL	0.5778*	0.6257***	1.0030***	0.4551**
	(0.2522)	(0.1651)	(0.2013)	(0.1625)
VAR	1.0282***	−0.0103	0.0168	−0.1215
	(0.1161)	(0.0889)	(0.0907)	(0.1077)
W_COMPA	0.6317*	1.3374***	0.8231***	1.2243***
	(0.2547)	(0.2214)	(0.2374)	(0.2201)
COMPE	0.6536***	0.6336***	0.5591***	0.6203***
	(0.0492)	(0.0430)	(0.0449)	(0.0428)
NATION		−7.2091***	−7.1997***	−7.3050***
		(0.1141)	(0.1127)	(0.1134)
VOL*NATION				0.0450*
				(0.0220)
VAL*NATION				4.1467***
				(0.7293)
VAR*NATION				0.8730***
				(0.2140)
VOL*W_COMPA			0.6370***	
			(0.1891)	
VAL*W_COMPA			0.0348**	
			(0.0130)	
VAR*W_COMPA			0.3171***	
			(0.0834)	
VOL*COMPE			0.0076***	
			(0.0023)	
VAL*COMPE			0.0403	
			(0.0282)	
VAR*COMPE			0.1088***	
			(0.0149)	
M_GROSS	23.3659***	2.0382**	2.1265**	1.8535***
	(0.7704)	(0.7836)	(0.7770)	(0.7732)
M_RELEASE	8.4461***	−1.4456**	−1.2646**	−1.5486***
	(0.5340)	(0.4650)	(0.4658)	(0.4542)
AGE	−0.4676***	−0.4606***	−0.4589***	−0.4520***
	(0.0120)	(0.0091)	(0.0092)	(0.0095)
WEEK	0.5218***	0.5296***	0.5238***	0.5298***
	(0.0156)	(0.0141)	(0.0140)	(0.0141)
SCREEN	1.0918***	1.0722***	1.0721***	1.0740***
	(0.0080)	(0.0071)	(0.0073)	(0.0076)
CRITIC	−1.2045***	0.3916***	0.4013***	0.4048*
	(0.1958)	(0.0909)	(0.0876)	(0.0845)
GENRE	Yes	Yes	Yes	Yes
PG	Yes	Yes	Yes	Yes
Adj. R2	0.90263	0.94034	0.94232	0.94347
N	7,335	7,335	7,335	7,335

Note: Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

6. Discussions

6.1. Theoretical implications

eWOM has received significant attention from the service and film marketing literature. However, research on the moderating effects of competitive and cultural factors has been limited. In this context, this study offers theoretical contributions by empirically analyzing differences in the effects of eWOM volume, valence, and variance according to competitive and cultural factors based on the CUT.

Competitive factors have been identified as potential moderating factors by many eWOM researchers (Babić Rosario et al. 2016; You, Vadakkepatt, and Joshi 2015), but no specific mechanisms have yet been

Table 8. Review sentiment analysis model.

DV: GROSS	(1)	(2)	(3)
Variables	Nation model	Competitive model	Cultural model
(Intercept)	1.5741***	3.4848	0.8961
	(3.1612)	(3.1682)	(3.0550)
NEGA	−0.0005***	−0.0006***	−0.0280
	(0.0001)	(0.0001)	(0.0261)
POSI	0.0001***	0.0001***	0.3524***
	(0.0000)	(0.0000)	(0.0258)
W_COMPA	1.2015***	0.5938*	1.2112***
	(0.2233)	(0.2537)	(0.2175)
COMPE	0.5679***	0.4059***	0.6118***
	(0.0434)	(0.0482)	(0.0425)
NATION	−7.0176***	−6.9647***	−7.5530***
	(0.1112)	(0.1120)	(0.1132)
NEGA*NATION			−0.1096**
			(0.0368)
POSI*NATION			0.0973**
			(0.0333)
NEGA*W_COMPA		−0.00032*	
		(0.00016)	
POSI*W_COMPA		0.00012***	
		(0.00003)	
NEGA*COMPE		−0.00003*	
		(0.00002)	
POSI*COMPE		0.00003***	
		(0.00000)	
CONTROL	Yes	Yes	Yes
Adj. R2	0.93967	0.93969	0.94423
N	7,335	7,335	7,335

Note: Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 9. Social media eWOM model.

	(1)	(2)	(3)
Variables	Nation model	Competitive model	Cultural model
(Intercept)	−4.2586	−4.2426	−4.3499
	(3.4043)	(3.4080)	(3.4054)
Facebook_LIKE	0.0138**	0.0097*	−0.0006
	(0.0047)	(0.0051)	(0.0078)
W_COMPA	1.4903***	1.4105***	1.4802***
	(0.2479)	(0.2521)	(0.2480)
COMPE	0.6921***	0.6835***	0.6906***
	(0.0462)	(0.0479)	(0.0462)
NATION	−6.9804***	−6.9802***	−6.9990***
	(0.1224)	(0.1226)	(0.1228)
LIKE*NATION			0.0223*
			(0.0097)
LIKE*W_COMPA		0.0195*	
		(0.0098)	
LIKE*COMPE		0.0016	
		(0.0018)	
CONTROL	Yes	Yes	Yes
Adj. R2	0.89323	0.93238	0.93347
N	7,335	7,335	7,335

Note: Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

identified. In this study, we analyzed how competition moderates the effects of eWOM characteristics by applying the CUT. The subsequent results increase the understanding of how the effectiveness of eWOM is affected by competitive situations, but also how viewers respond to eWOM information as a signal in film industry. Past research has reported contradictory results for the effects of eWOM variance, and

Table 10. Two-stage least squares (2SLS) results.

	(1)	(2)	(3)	(4)
Variables	Homogeneous model	Nation model	Competitive model	Cultural model
(Intercept)	−163.7000***	4.4035*	5.8274**	8.1436***
	(1.8830)	(2.0596)	(2.0421)	(2.0546)
VOL	0.1225***	0.2050***	0.2156***	0.3014***
	(1.0170)	(0.0079)	(0.0080)	(0.0105)
VAL	1.0170***	0.4414***	0.7466***	0.4174***
	(0.1054)	(0.0683)	(0.1176)	(0.0693)
VAR	0.5833***	−0.2782***	−0.1923***	−0.2612***
	(0.0649)	(0.0428)	(0.0506)	(0.0556)
W_COMPA	−3.1080***	0.2232	−0.2238	0.5050**
	(0.2715)	(0.1784)	(0.1862)	(0.1847)
COMPE	0.7210***	0.2635***	0.1840***	0.5770***
	(0.0591)	(0.0384)	(0.0401)	(0.0445)
NATION		−6.9893***	−7.0783***	−7.3630***
		(0.0691)	(0.0689)	(0.0714)
VOL*NATION				−0.2053***
				(0.0144)
VAL*NATION				3.9571***
				(0.4264)
VAR*NATION				0.9523***
				(0.1284)
W_COMPA*NATION				−0.2232***
				(0.0390)
COMPE*NATION				−0.1205***
				(0.0077)
VOL*W_COMPA			0.0610***	
			(0.0108)	
VAL*W_COMPA			0.4082**	
			(0.1416)	
VAR*W_COMPA			0.2433***	
			(0.0651)	
VOL*COMPE			0.0065**	
			(0.0022)	
VAL*COMPE			0.0516	
			(0.0291)	
VAR*COMPE			0.1245***	
			(0.0144)	
M_GROSS	49.7600***	2.6715***	2.4508***	1.3014*
	(0.4746)	(0.5575)	(0.5528)	(0.5537)
M_RELEASE	6.0910***	−2.5103***	−2.5687***	−2.8755***
	(0.3818)	(0.2608)	(0.2578)	(0.2545)
AGE	−0.2328***	−0.3779***	−0.3960***	−0.4050***
	(0.016)	(0.0070)	(0.0070)	(0.0074)
WEEK	0.5424***	0.5418***	0.5335***	0.5314***
	(0.5425)	(0.0165)	(0.0162)	(0.0160)
SCREEN	1.4090***	1.1722***	1.1441***	1.1253***
	(1.4090)	(0.0070)	(0.0072)	(0.0074)
CRITIC	0.1717***	0.3520***	0.3699***	0.3176***
	(0.0460)	(0.0298)	(0.0297)	(0.0294)
GENRE	Yes	Yes	Yes	Yes
PG	Yes	Yes	Yes	Yes
Adj. R2	0.9611	0.9838	0.843	0.9848

Note: Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

the present study aimed to explain this by revealing that these effects can be moderated by competition (Clemons, Gao, and Hitt 2006; Sun 2012; Wang, Liu, and Fang 2015).

In addition, how the effects of eWOM characteristics differ according to cultural dimensions has not been studied in sufficient detail (Carrillat, Legoux, and Hadida 2017; King, Racherla, and Bush 2014). Past research has limited its focus to the cultural dimension to Hofstede's cultural theories, such as individualism–collectivism and the avoidance of uncertainty, and insufficient research has been conducted on eWOM variance compared to other eWOM characteristics (Chiu et al. 2019). This study contributes to eWOM literature by demonstrating that the effects of eWOM variance differ systematically in terms of the CV of the signals perceived by consumers in high- and low-context cultures (Hall 1989). Unlike previous studies that have focused on the importance of eWOM information in consumer decision-making, this study suggests a new research direction for the study of cultural differences in eWOM by focusing on cultural differences in the characteristics of information processing of eWOM signals by viewers.

Specifically, this study confirms some of the previous findings and further clarifies the impact of eWOM on consumer purchasing decisions in the international marketing context of the film industry. Our results improved the predictability of film sales across cultures by identifying the effects of various eWOM factors and the boundary conditions that govern these effects.

This study also expands the CUT by incorporating competition and cultural factors. Prior CUT research has focused on signals such as brand, price, advertising, store name, reputation, and guarantees (Purohit and Srivastava 2001). The present study reports the effects of eWOM signals in the CUT context, which is very important for consumer decision-making but has been neglected in previous CUT research. In addition, this study found that the PV of the eWOM signals may vary depending on competition, while the CV of eWOM signals may differ according to cultural factors. Thus, the empirical results expand the current knowledge of the CUT.

6.2. Practical implications

The present study also offers number of practical implications. For example, the results offer guidelines for global eWOM strategies. Table 11 presents the results of marginal effect analysis. Film distributors will thus be able to use the results of this marginal effect analysis in developing eWOM management strategies in various film markets.

Although not covered in the main research model, interaction effects were analyzed in the marginal effect analysis to determine additional practical implications. Because Korean consumers are relatively strongly affected by eWOM, it can be assumed that the negative effects of competition are stronger than the positive effects. For example, given the relatively low rating of films due to insufficient screenings, Korean consumers are more likely to consider ratings to be important than US consumers, so they will not select movies with low ratings but are likely to see highly rated movies. Therefore, it would be more effective for countries with Eastern cultures to invest more resources in managing online reviews than countries with Western cultures. In addition, in the case of eWOM variance, it is likely to have a relatively positive effect in Eastern countries such as Korea, but it is likely to be negative in Western countries such as the United States, so a culture-specific review management strategy is needed. For example, in Western cultures such as the United States, marketing communications are conducted targeting target consumers, and in countries such as Korea, the effect of eWOM variance is relatively positive, so a wider target customer can be selected.

Competitive factors were found to have a positive effect on movie sales. Film distributors often adjust release dates to avoid competition with major films. However, it was found in the present study that, as the number of competitive movies increased, overall market demand increased, thereby contributing to the sales of individual movies. This has important marketing implications because it contradicts traditional practice. It was also found that the positive effect of competition was focused on products with better eWOM characteristics. In addition, the positive effect of competition was found to be weaker in Korea, which has a higher tendency to avoid uncertainty than the US (Table 10). Therefore, the strategy for selecting the release date should differ between markets with different cultures. For example, in countries with Eastern culture, such as Korea, it may be effective to avoid competition with other films, while in countries with Western culture, a strategy to stimulate demand through competition with other films may be effective.

Film distributors should also emphasize eWOM information according to competition and cultural differences in their target markets. Although eWOM information cannot be directly manipulated, the effectiveness of marketing communication can be enhanced by selectively highlighting the characteristics of the eWOM according to competition. For example, if the variance of a movie is expected to be high and it is released at the same time as many other movies, highlighting high eWOM variance in promotional materials could take advantage of the positive effect of this variance. In particular, the effect of eWOM variance can be strengthened by introducing diverse perspectives on movies across multiple heterogeneous channels. On the other hand, if the variance is expected to be low, the movie should avoid competitive release windows and highlight other eWOM characteristics (i.e., volume and valence).

Table 11. Marginal effects of eWOM elasticities on movie sales.

Cultural interaction marginal effect					
	VOL	VAL	VAR	W_COMPA	COMPE
US	0	0	0	0	0
KOR	0.024	4.350	0.855	−0.133	−0.109

Competitive interaction marginal effect			
	VOL	VAL	VAR
W_COMPA 25th Percentile	0.071	1.318	0.656
W_COMPA 50th Percentile	0.074	1.363	0.678
W_COMPA 75th Percentile	0.076	1.403	0.698
COMPE 25th Percentile	0.015	0.083	0.225
COMPE 50th Percentile	0.016	0.086	0.232
COMPE 75th Percentile	0.017	0.088	0.239

6.3. Limitations of research and future directions

This study has limitations and associated future research directions that should be noted. First, it is necessary to analyze variables that moderate the effects of eWOM in various industries. Although propensity score matching was used to reduce the differences in the characteristics of the movies released in the two countries, we also considered control variables such as the market size and the number of movies released. However, in the future, verification with more countries and control variables is needed, while it is also necessary to analyze whether the same results are obtained in other industries. In particular, the film industry is a hedonic industry, so future research should look to analyze industries with utilitarian characteristics.

It is also necessary to analyze the linguistic characteristics of eWOM. In this study, we used emotional analysis, a text mining methodology, on the text of audience reviews. However, other linguistic features should be covered in future research using the recently proposed LIWC methodology. For example, it is necessary to analyze how cultural differences affect the writing of reviews and how these linguistic differences affect consumer decision-making.

The cultural factors that moderate the influence of reviewer characteristics on consumer decision-making also warrant investigation. In recent research on the effects of user reviews, the results of the reviewer's influence on review usability have been reported, but the analysis of cultural moderating effects has been limited.

Conflict of interest

There is no conflict of interest.

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