Journal of Business Research 154 (2023) 113377

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Do online review readers react differently when exposed to credible versus fake online reviews?

Jong Min Kim [a,1], Keeyeon Ki-cheon Park [b,1], Marcello M. Mariani [c,d,*]

[a] College of Business and Management, Wenzhou-Kean University, China
[b] Kedge Business School, 680 Cr de la Libération, 33405 Talence, France
[c] Henley Business School, University of Reading, Greenlands, Henley on Thames Oxfordshire, RG9 3AU, United Kingdom
[d] University of Bologna, Italy

ARTICLE INFO

Keywords:
Fake reviews
Review manipulation
Topic modelling
Latent Dirichlet Allocation
Movie
Revenue

ABSTRACT

Marketing research on online reviews has attempted to understand the antecedents and consequences of review manipulation. Building on the elaboration likelihood model (ELM), this study deploys a rare dataset that allows distinguishing credible from less credible (and likely fake) online reviews by means of the online review posting policy adopted by the movie review website Naver.com. We use text analysis entailing word embedding and topic modelling techniques such as Latent Dirichlet Allocation, to capture content depth across different types of online reviews (credible vs manipulated). Furthermore, we explore how differences in the textual content of credible vs manipulated online reviews affect customer purchase decisions. Our results highlight that less credible reviews tend to contain more superficial information compared to more credible reviews, and that different levels of source credibility lead to distinctively different impacts of online reviews on box office revenue.

1. Introduction

Digital technologies are radically changing the marketing landscape with the emergence of online tools and techniques facilitating the interaction of consumers with companies, brands and products (Bresciani et al., 2021; D'Ambra et al., 2022; Mariani et al., 2022). In this context, online consumer reviews have become one of the most crucial sources of information about products because reviews help consumers identify unobserved product quality traits and obtain quality cues (Lappas et al., 2016) at a low cost, and almost in real time. Scholarly research in online reviews has found that online reviews significantly influence consumer awareness and attitude toward firms and brands (Vermeulen and Seegers, 2009), and product sales (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Mariani and Borghi, 2020). Industry research indicates that 9 out of 10 consumers read reviews before making a purchase (Trustpilot, 2020). Such importance of online reviews induces firms to be tempted to produce fake reviews to deceive reviewers and persuade them to buy (Luca and Zervas, 2016). In addition, rapid technological development encourages the creation of fake reviews for product promotion (Floridi, 2018). Previous studies suggest that review manipulation is a deceptive practice that is aimed at misleading consumers, leading them to make unintended purchase decisions (Dellarocas, 2006; Kumar et al., 2018). Thus, manipulation can affect consumers' trust and uncertainty (Ma and Lee, 2014; Zhao et al., 2013). Furthermore, it influences the credibility of online platforms in the eyes of consumers (Dwivedi et al., 2020).

The rise of such deceptive reviews is encouraging scholars to investigate the diverse aspects of credibility in online reviews from an academic perspective (Cox et al., 2009; Filieri et al., 2015). Research on online reviews has attempted to focus on review manipulation with the objective of detecting fake reviews on online review sites, such as Yelp, Amazon, and Trip Advisor, using various algorithms (Zhang et al., 2016; Cui et al., 2012; Kwark et al., 2014). Most existing studies focus on several superficial attributes of online reviews, such as the number of words in a document and review ratings, to distinguish fake reviews from authentic reviews (Mayzlin et al., 2014; Banerjee and Chua, 2017a). However, there is still a need for an in-depth investigation of consumer perceptions of the credibility of online reviews. Indeed, there is a dearth of studies exploring consumer information processing of credible vs less credible/fake online reviews. Therefore, this study aims

* Corresponding author.
E-mail addresses: jokim@kean.edu (J.M. Kim), parkky88@kaist.ac.kr (K.K.-c. Park), m.mariani@henley.ac.uk (M.M. Mariani).
[1] Jong Min Kim and Keeyeon Ki-cheon Park are co-first authors and contributed equally to the paper.

https://doi.org/10.1016/j.jbusres.2022.113377
Received 4 January 2022; Received in revised form 3 October 2022; Accepted 9 October 2022
Available online 21 October 2022

to fill this gap and investigates how consumers assess online reviews based on source credibility. More specifically, the objective of this work is to investigate whether online review readers process information differently when they choose to read reviews displaying different levels of source credibility.

In order to obtain an in-depth understanding of consumer information processing, this study adopts the dual-process theory, in particular the elaboration likelihood model (ELM) (Petty and Cacioppo, 1986). The ELM defines two ways through which individuals process information which entails two different routes: central vs peripheral routes. The central route is based on relatively high degrees of thinking, while the peripheral route occurs with relatively little thinking. This study explores how individuals process information in online reviews based on the levels of source credibility determined by fake reviews that they choose to evaluate.

To distinguish between credible and less credible (and likely fake) online reviews, we examine the extent to which the design of the review posting policy on a website can discourage or encourage manipulation. The empirical setting is similar to that used by Mayzlin et al. (2014), which exploited the differences in review website designs to identify unbiased (credible) vs fake (less credible) reviews. More specifically, this study deploys a rare dataset that allows distinguishing credible and less credible (and likely fake) online reviews by means of the online review posting policy adopted by a movie online review website, namely Naver.com. Naver.com separates customer reviews into two types (viewer-type versus netizen-type) based on the level of credibility determined by purchase verification to avoid review manipulation that lowers the credibility of online reviews (Ma et al., 2019). For instance, if a customer posts a review with a confirmed movie ticket through the website, the review is classified as viewer-type. Then, the customer who reads such a review knows if the review was written by an unbiased customer, so it is considered relatively credible. Otherwise, reviews without purchase confirmation are classified as relatively less credible (netizen-type). The website lets reviewers/consumers know what the difference is between viewer-type and netizen-type reviews. With this unique set of data, we examine online reviews' textual characteristics, mainly related to movie content, that we use as attributes that differentiate less credible reviews from credible reviews. Then, we explore how such differences in the textual content of online reviews would affect customer purchase decisions.

Our results highlight that less credible reviews (netizen-type) tend to contain more superficial information compared to more credible reviews (viewer-type) in terms of movie content analysis. In addition, our findings demonstrate that such different levels of source credibility lead to distinctively different impacts of online reviews on box office revenue. Based on the results, this study contributes to the literature revolving around fake reviews in different ways. First, this study uncovers how customers perceive manipulation of online reviews by assessing different levels of source credibility with different information processing methods – an important extension to the existing literature addressing how customers process online reviews based on credibility. Second, this work explains the impacts of textual attributes on customer purchase decisions at different credibility levels.

The rest of the paper is structured as follows. In the next section, we illustrate the theoretical underpinnings of studies pertaining to information processing and source credibility and review the extant literature on review manipulation to construct and develop our hypotheses. In the third section, we describe our research design, data, and model. In the fourth and fifth sections, we present respectively a detailed methodology and the empirical results. In the sixth section, we discuss the findings, illustrate the implications of the study, and point to limitations and future research directions.

2. Theoretical background and hypotheses development

2.1. Cognitive information processing

The dual-process theory describes two different and alternative types of cognitive information processing in the decision-making process (Evans, 2008; Evans and Stanovich, 2013). The elaboration likelihood model (ELM) is the reference model used in this study, and it comes from the dual-process approach, which has been broadly used to investigate how information processing by individuals leads to their decisions in online environments (Lee et al., 2008; Park and Kim, 2008). The ELM identifies two routes of cognitive information processing: the central route and the peripheral route (Petty and Cacioppo, 1986), assuming the routes as mutually exclusive. Individuals who engage in the central route are likely to adopt a "maximization" approach whereby they rationally collect and analyze the maximum amount of information available very carefully, while those who engage in the peripheral route tend to deploy shortcuts and pieces of information (e.g., the online review rating only) (Mariani and Borghi, 2020) to make their decisions.

The mode of processing selected depends on internal and external factors (Wirth et al., 2007). Internal factors consist of the individual's cognitive abilities, such as prior knowledge or motivation to invest time. The ELM suggests that there exist capacity and inspiration in "central" processing but not in "peripheral" (Chen and Chaiken, 1999). For instance, when the message's recipient or review reader has the motivation or can think on the message, they are likely to use the central route. External factors involve the complexity of information and other information-inherent and situational characteristics (Chaiken et al., 1989; Petty and Cacioppo, 1990). Furthermore, the characteristics of the social context, such as accountability and the risk of false decisions, can externally affect how individuals select the mode of information processing (Payne et al., 1993). This study aims to understand an external factor that may influence consumers' processing mode selection.

2.2. Credibility theory in information processing

Credibility is a multidimensional concept that results from an interaction of several dimensions, including source characteristics, message characteristics, receiver characteristics, and the media (Wathen and Burkell, 2002). In this study, we focus on source credibility, which is an important influencer of consumer decisions in the online context (Watts and Zhang, 2008). Source credibility refers to the extent to which a consumer perceives the source of information they obtain online as trustworthy and expert (Coursaris and Osch, 2016). It is determined by two underlying factors such as expertise and trustworthiness (Hovland et al., 1953). Expertise refers to the extent to which the source or speaker is considered capable of providing valid assertions, whereas trustworthiness is defined as the extent to which an individual perceives the sender or speaker to be trustful, fair, and honest (Hovland et al., 1953).

This study emphasizes the effect of source credibility as a factor that influences readers' information processing routes. Given the nature of online contexts (such as lack of tangible cues), credibility is a crucial driver in reducing any associated risks (Bart et al., 2005), and reduces the likelihood of biased decision making. Then, determining which sources to use depends on information-seeking information (Sweetser et al., 2008; Johnson and Kaye, 2002). Therefore, if individuals are highly motivated to process information to make unbiased decisions, they look for information sources with a higher level of credibility. In other words, with a high level of motivation, they assess credible information through an extensive and detailed process. Therefore, the likelihood of elaboration is determined by the motivation to engage in evaluating the information. In this study, we examine how customers process online reviews in their decision-making processes, depending on the level of source credibility they are motivated to engage.

2.3. Hypothesis development

Previous literature in many different fields has examined online review manipulation across a number of products such as books, travel services, and music (Dellarocas, 2006; Heydari et al., 2015; Banerjee and Chua, 2017b). Compared to face-to-face communication, online communication displays multiple limitations because non-verbal communication cues such as facial expression, body gestures, or voice tone cannot be used. So far, the literature concerning online review manipulation has explored several online review features that help distinguish fake reviews from authentic reviews, such as text features like word frequency and length (Fei et al., 2021; Banerjee and Chua, 2014). However, text features are not sufficient to define the specific characteristics of fake reviews. In this study, we focus on a specific subject in reviews, namely movie-story-related content, to distinguish online reviews subject to manipulation versus those that are authentic.

Review manipulators have a tendency to imitate authentic reviews to avoid detection, such as using similar language to that deployed in genuine reviews to enhance their credibility (Luppas, 2012; Chen and Chen, 2015). This happens because writing one's imagined experience is difficult. Hence, manipulators may choose to copy other existing reviews or release information with minor changes. One of the public-released information in the movie industry is a movie summary, which shortly describes movie content for advertisement. Then, manipulators may duplicate the released movie summary and then post it in the form of a review with associated high ratings to lure the purchase decision of potential customers with credibility. As a consequence, these fake reviews tend to be based on superficial information related to movie content.

In contrast, genuine consumers who really watch movies before posting their opinions online may write a review of the movie they actually watched with more effort. Accordingly, compared to fake reviews, genuine reviews tend to display more detailed information about movie content. In summary, even though a review subject is similar for both fake and authentic reviewers, the depth of the analysis contained in the reviews would be different. More specifically, fake reviewers would provide more superficial and less informative reviews than authentic reviewers. In this research, we differentiate the level of information depth in online reviews by building on two different measures: (1) semantic similarity between the movie summary published by the movie company and online reviews, (2) topic analysis in online reviews. For instance, an online review with high semantic similarity covers superficial information that requires less effort to receive the message. On the other hand, an online review that is analyzed in connection with various topics represents in-depth analysis of movie content. Then, we use these measures to distinguish the characteristics between fake and authentic reviews in terms of the level of information depth. Consequently, we develop the following hypotheses:

H1a. *Fake reviews tend to contain more superficial information of movie content than credible reviews.*

H1b. *Credible reviews tend to contain more in-depth analysis of movie content than fake reviews.*

Review credibility has been defined as a reader's trust in the review being read (Cheung et al., 2012; Filieri, 2016). The credibility of online reviews is a fundamental component that values WOM and influences the final decision of the review readers. In the online context, credibility is important to build customer trust and reduce the perceived inherent risk in online feedback (Brown et al., 2007). For instance, online reviews become more persuasive if the sources display higher levels of credibility. However, one factor that affects the level of credibility is manipulation of reviews (Dwivedi et al., 2021), which increases consumers' distrust and uncertainty (Filieri et al., 2015). According to the source credibility theory, source credibility provides a huge influence on message acceptance; furthermore, readers' intentions and behaviors, such as purchase decisions, intention to revisit, and willingness to share, are influenced by source credibility as well (Ayeh, 2015; Fan et al., 2018; Hautz et al., 2014; Hsieh and Li, 2020; Mariani et al., 2019). In this research, we attempt to explore how source credibility influences consumers' information processing in the online review context.

This study uses the dual-process theory, particularly the ELM, as the conceptual foundation to investigate how customers process the information in online reviews based on the level of credibility of the reviews, which is measured through the level of online review manipulation. According to the ELM, individuals can process the information of communication with varying levels of elaboration that is leveraged by different motivations or willingness to engage in information (Turner et al., 2011). Then, the motivation level can depend on individuals' choice of which source they will use. For instance, if individuals choose more credible sources to read reviews, they are likely to have higher motivations to seek or process information than those who prefer a source with lower credibility. Then, under the conditions of high motivation, individuals are more likely to perform rigorous information evaluation, so they use the central processing that entails a relatively high degree of cognitive effort. In other words, when review readers select highly credible sources with limited risk of review manipulation, they tend to elaborate on information through careful attention, deep and critical thinking, and intensive reasoning. For instance, individuals who seek information from more credible sources might devote more attention to reviews with analysis or critique. In the case of movie reviews, some reviewers posit an explanation on specific aspects of a movie, such as hidden, symbolic meanings in the movie.

In contrast, when individuals read reviews in a source with low credibility that can be easily exposed to manipulation, they tend to have a lower motivation to evaluate information. In other words, they are likely to avoid relying on reviews from such sources (Luca and Zervas, 2016). With a lower level of motivation, individuals then are more likely to use peripheral processing such as easily noticed and understood cues in reviews with relatively less cognitive effort. For instance, they process information unrelated to the stimulus's logical quality, such as simple movie summaries. For the movie industry, some reviewers provide a general description on a movie, which the movie distributors already provide. In this case, review readers do not need to process the information with rigorous evaluation. Based on the dual-process theory, we argue that individuals process information differently according to the levels of source credibility that they choose. Therefore, the following hypotheses are put forward:

H2a. *Online review readers exposed to credible reviews will be more affected by in-depth movie content analysis.*

H2b. *Online review readers exposed to fake reviews will be more affected by superficial information about movie content.*

3. Empirical approach

3.1. Data description

To explore the textual characteristics and consequences of fake reviews, we collected online reviews for movies from Naver.com, the leading portal website in South Korea. The search engine market share of Naver.com in 2020 is about 63 % in Korea.[2] We selected the top 50 financially successful movies in South Korea every year from 2017 to 2019. Then, we collected movie information, including online reviews written in Korean for 150 movies from Naver.com. Each online review consists of review ratings and textual content. We excluded movies that had run for 5 weeks in movie theaters to analyze the impact of the promotional periods in the movie industry. So, the final dataset includes 139 movies. Based on the online review data, we merged daily box office

[2] https://www.fntoday.co.kr/news/articleView.html?idxno=233242.

revenue data from the Korean Film Council.[3]

3.1.1. Summary statistics of individual-level online reviews

Naver.com provides prospective customers with two types of reviews: viewer-type, and netizen-type. If a customer posts a review after booking a movie ticket through the, a review posted by this customer is classified as a viewer-type review. Otherwise, it is categorized as a netizen-type review. The netizen-type review refers to the reviews that anyone can share their opinions on a movie without verifying their movie tickets. In other words, netizen-type reviews are vulnerable to review manipulation (Mayzlin et al., 2014). Therefore, netizen-type reviews have a lower level of credibility. In sum, viewer-type reviews only include the reviews posted by movie viewers. In contrast, netizen-type reviews include the reviews posted by movie viewers, review manipulators, and prospective customers who have not yet watched the movie. Table 1 shows the summary statistics of the ratings for the viewer- and netizen-type reviews. The average review rating of netizen-type reviews is significantly lower than that of viewer-type reviews ($7.69_{\text{Netizen-type}} < 8.74_{\text{Viewer-type}}$). In line with Mayzlin et al. (2014), which found unverified reviews to be more extreme, netizen-type reviews display more extreme ratings, such as 10 or less than or equal to 4. Table 2..

3.1.2. Summary statistics of weekly online reviews

To merge individual online review data with daily box office data, we aggregate the individual online review data into daily data. The average daily rating of netizen-type reviews was 7.50, while that of viewer-type reviews was 8.44. The average of daily posted netizen-type reviews was 47.11, but that of daily posted viewer-type reviews was 137.53. The review volume of netizen-type considerably exceeds that of viewer-type and this might be due to the fact that Naver.com allows anyone to post their online reviews for movies without purchasing movie tickets on the site and those reviews are categorized as netizen-type reviews. According to prior literature (Ma et al., 2019), review manipulation concentrates on the first two weeks after movie release in South Korea. There remain no significant incentives to be engaged in manipulating online reviews because box office revenue decreases significantly after the two weeks after the release date. Due to this, we split the sample period into the "promotional period (the first two weeks after release, from week 1 to week 2)" and "post period (the last three weeks, from week 3 to week 5)". For the first two weeks, the average daily rating of daily posted netizen-type reviews was 7.73, decreasing to 7.34 during the post-period. The same phenomenon also happens to viewer-type reviews. The average daily rating of viewer-type reviews was 8.53, dropping to 8.38 during the post-period.

Table 1
Summary statistics of individual online reviews.

	Netizen-type			Viewer-type	
Average of Review Ratings	7.69		Average of Review Ratings	8.74	
Distribution of ratings	Freq.	Percent	Distribution	Freq.	Percent
1	184,892	14.05	1	6,333	1.00
2	52,191	3.97	2	5,138	0.81
3	13,155	1.00	3	3,019	0.48
4	29,579	2.25	4	7,293	1.15
5	24,354	1.85	5	10,937	1.73
6	49,451	3.76	6	32,771	5.19
7	36,861	2.80	7	33,780	5.35
8	83,518	6.35	8	127,962	20.25
9	83,621	6.35	9	85,673	13.56
10	758,395	57.63	10	319,027	50.48
Total	1,316,017	100.00	Total	631,933	100.00

Table 2
Summary statistics of weekly online reviews.

	Netizen-type	Viewer-type
Daily review rating	7.50	8.44
Daily number of posted reviews	137.53	47.11
	Promotional period	Promotional period
Daily review rating	7.73	8.53
Daily number of posted reviews	284.02	78.30
	Post-period	Post-period
Daily review rating	7.34	8.38
Daily number of posted reviews	37.57	25.70

3.1.3. Summary statistics of weekly box office revenue

Table 3 shows summary statistics of weekly box office revenue. For five weeks, the log-transformed box office revenue is 19.16, and the log-transformed number of moviegoers is 10.18. The values of the two dropped during the post-period compared to those during the promotional period.

3.2. Mining the characteristics of textual content

To explore different characteristics between less credible and credible reviews, this paper attempts to find both less-demanding cues (peripheral route) and the cues that require careful attention and deep thinking with cognitive efforts (central route) from the textual content in online reviews. We use two different measures to distinguish online reviews aligned with the central vs peripheral routes. First, we use the semantic similarity between online reviews and movie summaries that are released to the public before the movie release date to measure the level of information processing of review readers. This measure refers to whether online reviewers copy the movie summary, which represents the superficial information that can be understood without sufficient effort (peripheral route). Second, we adopt topic analysis using Latent Dirichlet Allocation. This analysis can classify online reviews that include an in-depth analysis of topics which need to use the central route to receive the messages.

3.2.1. Semantic similarity analysis

Movie interest parties are known to hire viral marketing companies in South Korea. Those companies are known to use macro-programs to generate manipulated online reviews.[4] They intend to increase box office revenue by manipulating online reviews. To do this, they have to make the manipulated reviews not distinguishable from credible reviews. This phenomenon has also been observed by Lappas (2012), who

Table 3
Summary statistics of box office revenue.

	log(box office revenue)	log(the number of moviegoers)
Sample period	19.16	10.18
Promotional period	20.87	11.86
Post period	18.02	9.06

[3] The Korean Film Council is a special organization established in 1973, which is delegated by by the Ministry of Culture, Sports and Tourism, the ROK government. It plays the role of improving the quality of Korean films and therefore growing the film industry.

[4] https://m.cine21.com/news/view/?mag_id=90596.

showed that manipulated reviews tend to look as similar as possible to credible reviews so that they could go unnoticed by review readers. For instance, manipulators can copy a movie summary, which is usually open to the public from the movie release, to pretend that they watch a movie to increase the credibility of their reviews. However, the information reflected in the reviews tends to be superficial rather than include personal experiences. To capture this aspect, we examine the semantic similarity between online reviews and movie summaries to distinguish the characteristics of manipulated reviews.

To examine the similarity, we use textual embedding techniques. First, we apply a pre-trained word embedding technique, the fastText word embedding technique (Facebook I, 2016; Bojanowski et al., 2017; Joulin et al., 2016) for Korean to vectorize all words. fastText is a neural network-based learning model that is relatively novel in the marketing field (Alantari et al., 2021). It was originally created by Facebook's AI research lab, and it allowed us to build a machine-learning algorithm to obtain a vector representation of tokens in the text for diverse languages, including Korean. By using fastText word embedding, words in both reviews and movie summaries are converted into 300-dimensional vectors. Then, we use the cosine similarity, a popular similarity measure (Zhelezniak et al., 2019), to quantify how similar reviews are with the movie summary. We calculate cosine similarity between two-word vectors across online reviews and movie summaries. As a result, we obtain the cosine similarities as a measure to examine the semantic similarity between online reviews and movie summaries. Based on the analysis, we create a binary variable: semantic similarity. If the semantic similarity score is greater than the average semantic similarity score, then the semantic similarity variable gets 1. Otherwise, it gets 0.

3.2.2. Topic modeling - Latent Dirichlet Allocation

To capture diverse interests or topics in online reviews, we conduct topic modeling using the Latent Dirichlet Allocation (LDA) technique (Blei et al., 2003). LDA is a popular method for topic discovery (Calheiros, Moro, & Rita, 2017; Jelodar et al., 2019; Mariani and Baggio, 2022), which has been the most applied in the marketing field (Jacobs et al., 2016; Puranam et al., 2017; Tirunillai and Tellis, 2014). This method has the potential to gather words that reflect topics of latent interest to marketers (Büschken and Allenby, 2016). In particular, the method is widely used to examine online reviews because there is no assumption about text structure or grammar (Blei, 2012), so it can embody unstructured text data. Also, the model is useful for analyzing and organize an extensive amount of data into the limited number of discovered topics (Blei, 2012). Therefore, we apply the LDA model to extract different movie review topics in the online reviews analyzed.

The LDA model assumes that there are a limited number of latent topics that appear across textual documents that are represented by online reviews in our dataset. Each document is a mixture of topics, and each topic is considered as a discrete probabilistic distribution of multiple words. In other words, there exists a dictionary of words for all documents, and the distribution of words used characterizes each topic. In particular, the words with higher probability are used to define the latent topics. Topic modeling is applied to each review as a document. For each document, we constructed a dictionary reporting how many words and how many times such words appear. Then, we identified the words occurring in each topic and their relative weights. The documents are subsequently assigned to the part of a particular topic that has the highest probability based on the analysis.

To identify the appropriate topic number, we use one of the metrics for evaluating the topic model, the coherence score. We selected the number 16 as the threshold input for topic modeling based on the coherence scores. Table 4 presents the topic modeling results (translated from Korean into English), with the top 10 words in decreasing order of posterior probability of being in the 16 topics. Based on the review characteristics and the conceptualization of word-of-mouth literature, we interpret the topics and name each topic. For instance, the terms belonging to topic number 2 include "action," "in-between," "one,"

Table 4
Topic Classification.

ID	Group Name	Topic Name	Topic proportion (%)	Keywords
1	Impression	Regret	0.0797	watch, first, image, theater, regret, cookie, cinema, today, release, not-watch
2	Impression	Satisfaction	0.0461	movie, life, best, most, awhile, meaning, entertainment, recent, nowadays, rightly
3	Movie story analysis	Story-laughing point	0.068	action, in-between, one, story, not-really, laugh, character, comic, appeal, dialogue
4	Movie story analysis	Connection with history	0.0811	history, our, heart, now, truth, country, period, if, for, Korea
5	Impression	Aftertaste	0.0583	last, movie, scene, tear, really, continue, goose-bump, aftertaste, memory, mood
6	Evaluation - Negative	No fun	0.0504	movie, just, degree, no-fun, self, strange, because, level, audience, feminist
7	Evaluation - Negative	Worst evaluation	0.0634	person, rating, understand, part-time, worst, watch, this-movie, because, trash, review
8	Movie director	Movie direction	0.0638	director, directing, film, Korea, likelihood, Korean-movie, subject, forced, new-school, comedy
9	Actors	Acting/Chemistry	0.0914	acting, actor, performance, Hyunbin, Dongsuk Ma, Haehin Yoo, Gangho Song, chemistry, leading-actor, Woosung Jung
10	Particular movie - marvel	Marvels	0.0746	as-expected, expectation, marvels, series, next, disappointment, hero, this, avengers, convenience
11	Particular movie - Disney	Disney	0.0602	touching, interest, for-all, kid, music, song, really, flavor, Disney, movie
12	Movie story analysis	Connection to reality	0.0542	reality, story, main-character, sympathy, love, woman, Korean, man, look, human
13	Evaluation - Positive	Recommendation	0.0527	authentic, best, really, completely, big-hit, very-fun, this-year, strongly-recommended, of-all-time, masterpiece
14	Movie story analysis	Story development	0.0589	story, feeling, content, surprised, moment, little, development, ending, beginning, little
15	Evaluation - Positive	Second trial recommendation	0.052	thinking, movie, again, one-more, recommend, watch,

(continued on next page)

Table 4 (*continued*)

ID	Group Name	Topic Name	Topic proportion (%)	Keywords
16	Impression	Immersion	0.0452	family, really, mother, friend time, movie, immersion, for-whole-time, story, original-work, degree, concentration, different, tension

"story," "not-really," "laugh," "character," "comic," "appeal," "dialogue," which could be summarized as laughing points in movie story. Then, we group several topics into a limited number of groups. First, we find that a substantial number of topics focus on movie story analysis (e.g., story laughing point, connecting with history, connecting with the reality, and story development). Second, several topics focus on evaluations, including both positive and negative feedback. We expect that these two topics could be associated with review manipulation because movie story analysis is associated with deeper experiences of review posters, and therefore, it is beyond a simple story description (semantic similarity). Review manipulation could consist more likely of a simple story description. In addition, review manipulation could focus more on evaluations, including sentiment. Therefore, we focus on the two groups of topics to distinguish manipulated reviews from credible reviews. Based on the topic modeling, we create two binary variables, movie story analysis, and movie evaluation. If a review includes movie story analysis in the review, then the review gets 1. Otherwise, it gets 0. Similarly, we define movie evaluation as a binary variable.

3.2.3. Summary statistics of the characteristics of textual content

Based on Semantic Similarity Analysis and Topic Modeling Analysis, we pay attention to the 3 topics as mentioned above: movie story analysis, movie evaluation, and movie similarity. After coding these variables, we aggregate these individual data into daily data. By doing this, we create three percentage variables. For example, suppose 10 movie story analysis-related reviews were posted for a day by netizens, and there were 100 reviews posted on the day by netizens. In that case, the movie story analysis percentage is 0.01 (10/100). Because the two analyses are administered independently, the total percentage of the three variables could be over 100.

Table 5 shows the comparison between netizen-type and viewer-type reviews regarding the characteristics of textual content. Movie similarity reflects the extent to which review posters copy the released movie summary. In other words, high movie similarity represents superficial knowledge of the movie contents without thorough analysis and evaluations. Netizen-type reviews are more likely to include this type of textual characteristic. However, we cannot confirm that the movie similarity percentage of netizen-type reviews is greater than that of viewer-type reviews from the table (Netizen-type$_{\text{Movie similarity percentage}}$ = 0.55, Viewer-type$_{\text{Movie similarity percentage}}$ = 0.55, respectively). This is different from our expectations (H1a). However, our hypothesis could be supported when we find that there exists a significant difference in the percentage during the promotional period because fake reviews are mostly posted during the period. To confirm this, we use a more sophisticated approach in the next section (4.1). The movie story analysis percentage of netizen-type reviews is about 24 %, while that of viewer-type reviews is about 28 %. We further analyze these aspects in the empirical analysis by considering time- and movie-specific effects. Considering the fact that movie story analysis is associated with deeper experiences of review posters, it is expected to add what is expected here. The movie evaluation percentage of netizen-type reviews is greater than that of viewer-type reviews (Netizen-type$_{\text{Movie evaluation percentage}}$ = 0.23 > Viewer-type$_{\text{Movie evaluation percentage}}$ =.18$_{\text{Viewer-type}}$). These three variables are used for the dependent variables in Study 1.

Table 5
Summary statistics of the characteristics of textual content.

	Netizen-type	Viewer-type
Movie similarity percentage	0.55	0.55
Movie story analysis percentage	0.24	0.28
Movie evaluation percentage	0.23	0.18

4. Empirical studies and findings

4.1. Study 1: Characteristics of fake reviews

4.1.1. Model specification

In the first study (Study 1), we explore the characteristics of fake reviews. To do this, we exploit the differences in the characteristics of textual content between viewer-type and netizen-type reviews. Mayzlin et al. (2014) used the difference in review policy between Expedia.com and TripAdvisor.com to explore promotional reviews. Expedia.com adopts a review policy to only allow customers who book a hotel room via the website to share their experiences with hotel services. On the other hand, TripAdvisor.com implements a review policy allowing anyone who wants to post opinions to post reviews. Due to the difference in the online review policy, online reviews on TripAdvisor.com are more vulnerable to review manipulation. To capture the impacts of review manipulation, they exploit the differences in the characteristics of online reviews such as review ratings or extreme reviews posted on TripAdvisor.com and Expedia.com. Following the lead of their model specification, we develop the following model specification:

$$\frac{\#ofSpecificContent_{it}^{Netizen}}{TotalReview_{it}^{Netizen}} - \frac{\#ofSpecificContent_{it}^{Viewer}}{TotalReview_{it}^{Viewer}} = \alpha + \beta^{*}PromotionalPeriod_{it} + \gamma^{'}{}^{*}Controls_{it} + \sum \delta_i + \varepsilon_{it} \tag{1}$$

where i is a movie and t is a day. Specific content includes the three types of characteristics of textual content: movie story analysis, movie evaluation, and movie similarity. Controls include monthly and day of the week dummy variables to control seasonality and day of the week effects on the online review generation. δ_i controls movie-level heterogeneity. ε_{it} is a random error.

As is mentioned previously, review manipulation concentrates on the first two weeks in South Korea (Ma et al., 2019). Considering the dynamics of review manipulation, we use the promotional period (first two weeks) as the independent variable. In the above model specification, the estimated coefficient of the constant represents the difference in the specific content between netizen- and viewer-type. Our primary interest is placed on the estimated coefficient of the promotional period. This would capture the impact of review manipulation on the difference in the textual content between netizen- and viewer-type reviews.

4.1.2. Empirical results

Table 6 shows the empirical results of the model specification in Equ. (1). Across the three columns (1), (2), and (3), we include the same control variables such as time-fixed (monthly dummy and day of the week dummy variables) and movie-fixed effects (movie-fixed dummy variables). The estimated coefficients of the constants over the three columns turn out to be insignificant (β_{Constant} = -0.050, *p-value* > 0.10, β_{Constant} = -0.064, *p-value* > 0.10, and β_{Constant} = 0.017, p-value < 0.01, respectively). This means that there exist no differences in the three textual characteristics between netizen- and viewer-type reviews. On the other hand, in the first column (1), we explore the impacts of the promotional period on the differences in the percentage of movie similarity. As expected, the promotional period's estimated coefficient is significantly positive ($\beta_{\text{Promotional Period}}$ = 0.012, *p-value* < 0.01). This shows that netizen-type reviews are more likely to include movie similarity in

Table 6
The impacts of review manipulation on online reviews.

	Difference in percentage of movie similarity (1)	Difference in percentage of movie story analysis (2)	Difference in percentage of movie evaluation (3)
Promotional Period	0.012** (0.005)	-0.008 (0.005)	0.014*** (0.004)
Constant	-0.050 (0.046)	-0.064 (0.044)	0.017 (0.040)
Monthly Dummy	Included	Included	Included
Day of the Week Dummy	Included	Included	Included
Movie-fixed effects	Included	Included	Included
Observations	4,646	4,646	4,646
R^2	0.038	0.065	0.075

Notes: ***/**/* indicates significance at the 1%/5%/10% level. Standard errors are in parentheses.

the textual content during the promotional period. Different from the expectation on movie story analysis, review manipulation is not apparent with this aspect ($\beta_{\text{Promotional Period}}$ = -0.008, *p-value* > 0.10) in the second column (2). Netizen-type reviews tend to include more movie evaluation in the textual content during the promotional period ($\beta_{\text{Promotional Period}}$ = 0.014, *p-value* < 0.01) in the third column (3). Because review manipulation could concentrate on either the first week or the second week, we explore the differential impact of the promotional period in the next table (Table 7) by splitting the period into two: promotional period 1 and 2.

Table 7 shows the differential impacts of two promotional periods on the differences in the differences in the percentages of movie similarity, movie story analysis, and movie evaluation. In the first column (1), the estimated coefficients of the promotional periods are both significantly positive ($\beta_{\text{Promotional Period 1}}$ = 0.015, *p-value* < 0.01, $\beta_{\text{Promotional Period 2}}$ = 0.010, *p-value* < 0.10, respectively). In the case of movie story analysis, the estimated coefficient of promotional period 2 is significantly negative ($\beta_{\text{Promotional Period 2}}$ = -0.010, *p-value* < 0.10), though the estimated coefficient of promotional period 1 is insignificantly negative ($\beta_{\text{Promotional Period 1}}$ = -0.005, *p-value* > 0.10). As confirmed in Table 6, the estimated coefficients of promotional periods are significantly positive ($\beta_{\text{Promotional Period 1}}$ = 0.08, *p-value* < 0.10, $\beta_{\text{Promotional Period 2}}$ = 0.020, *p-value* < 0.01, respectively). The degree of the impacts becomes more evident in the promotional period 2. From the empirical results, we can conclude that review manipulation would happen by increasing the characteristics of textual content such as movie similarity and movie evaluation reflected in online reviews, while manipulated reviews would seem to reflect superficial or limited information in the textual content in terms of movie story analysis.

4.2. Study 2: Consequences of fake reviews

4.2.1. Model specification

In Study 2, we explore how the characteristics of texual content would affect box office revenue. To do it, we develop our empirical model specification (dynamic regression model) based on Duan et al. (2008):

Table 7
The impacts of review manipulation on online reviews–(1st and 2nd promotional period).

	Difference in percentage of movie similarity (1)	Difference in percentage of movie story analysis (2)	Difference in percentage of movie evaluation (3)
Promotional Period-1	0.015*** (0.005)	-0.005 (0.005)	0.008* (0.005)
Promotional Period-2	0.010* (0.006)	-0.010*(0.005)	0.020***(0.005)
Constant	-0.050(0.046)	-0.063 (0.044)	0.017(0.040)
Monthly Dummy	Included	Included	Included
Day of the Week Dummy	Included	Included	Included
Movie-fixed effects	Included	Included	Included
Observations	4,646	4,646	4,646
R^2	0.038	0.065	0.076

Notes: ***/**/* indicates significance at the 1%/5%/10% level. Standard errors are in parentheses.

$$\log(\text{Box office revenue})_{it} = \alpha + \beta_1 * \log(\text{Box office revenue})_{it-1} + \beta_2 * Dailyrating_{it-1} + \beta_3 * \log(Numberofreviews)_{it} + \beta_4 * Contentpercentage_{it} + \beta_5 * Evaluationpercentage_{it} + \beta_6 * Similaritypercentage_{it} + \gamma' * Controls_{it} + \sum \delta_i + \varepsilon_{it} \quad (2)$$

where *i* is a movie and *t* is a day. Controls contain monthly and day of the week dummy variables to control seasonality and day of the week effects on box office revenue. δ_i controls movie-level heterogeneity. And ε_{it} is a random error.

According to prior literature (Duan et al., 2008), because responding to the change in demand takes time, including the previous box office in the equation for box office revenue would be appropriate. However, the above model specification includes an endogenous lagged variable. If we use ordinary least squares estimation, it causes an endogeneity issue in the estimation. Therefore, we use Arellano and Bond GMM-based estimation to address the endogeneity issue. In Eq. (2), we assume that review consumers use both netizen-type and viewer-type reviews as primary information sources. Because of the assumption, we include textual characteristics such as movie story analysis as independent variables. Together with these, we control lagged daily ratings and the number of posted reviews based on Duan et al. (2008).

The estimated coefficient of viewer movie analysis percentage is significantly positive ($\beta_{\text{Viewer movie story analysis percentage}}$ = 0.173, *p-value* < 0.01). In contrast, that of netizen movie analysis percentage is not significant ($\beta_{\text{Viewer movie story analysis percentage}}$ = 0.006, *p-value* > 0.10) in column (1). This means that deep experiences reflected in viewer-type reviews have a positive impact on box office revenue, but those in netizen-type reviews do not have any significant impact on the revenue. This is also confirmed in column (2) considering the number of moviegoers as the dependent variable. The estimated coefficient of viewer movie analysis percentage is significantly positive ($\beta_{\text{Viewer movie story analysis percentage}}$ = 0.166, *p-value* < 0.01), but that of netizen movie analysis percentage is insignificant ($\beta_{\text{Viewer movie story analysis percentage}}$ = 0.019, *p-value* > 0.10).

The estimated coefficients of viewer and netizen movie evaluation percentage are both significantly positive ($\beta_{\text{Viewer movie evaluation percentage}}$ = 0.198, *p-value* < 0.01, $\beta_{\text{Viewer movie evaluation percentage}}$ = 0.107, *p-value* < 0.01, respectively) in column (1). In column (2), where the number of moviegoers is the dependent variable, the positive impacts of movie evaluation are also confirmed.

Differently from these, the estimated coefficient of viewer movie similarity percentage is significantly negative ($\beta_{\text{Viewer movie similarity percentage}} = -0.139$, $p\text{-value} < 0.01$), meaning that if the percentage of movie similarity reflected in online reviews increases, it has a negative impact on box office revenue. As is expected, review consumers expect deeper information rather than superficial information from the more credible information source. However, the estimated coefficient of netizen movie similarity is significantly positive ($\beta_{\text{Viewer movie similarity percentage}} = 0.042$, $p\text{-value} < 0.01$), showing that review consumers demand a lower level of information depth from less credible information sources. These phenomena are also confirmed in the second column (2).

Interestingly, an increase in netizen daily ratings has a negative impact on box office revenue ($\beta_{\text{Viewer daily rating}} = -0.012$, $p\text{-value} < 0.01$) but the impact of viewer daily ratings is not significant in column (1). In column (2), the positive impact of an increase in viewer daily ratings is confirmed ($\beta_{\text{Viewer daily rating}} = 0.035$, $p\text{-value} < 0.01$). On the other hand, the numbers of posted viewer and netizen type reviews have positive impacts on box office revenue ($\beta_{\text{Viewer daily number}} = 0.121$, $p\text{-value} < 0.01$, $\beta_{\text{Netizen daily number}} = 0.153$, $p\text{-value} < 0.01$, respectively). It is also confirmed in column (2), where the number of moviegoers is the dependent variable.

For further analysis, we consider cumulative ratings instead of daily ratings in the first column (1) of Table 9 because review consumers could use cumulative review ratings rather than daily review ratings as the review valence. All estimated coefficients are basically the same as those of Table 8, except that the estimated coefficient of netizen cumulative ratings is insignificant.

The second column assumes that review consumers could place different weights between credible and less credible information sources. That is, review consumers could place a higher weight on credible information sources (viewer-type reviews) than less credible information sources (netizen-type reviews). They could only consider the differences between viewer-type and netizen-type reviews regarding review characteristics. Therefore, we create different variables between netizen-type and viewer-type reviews.

Based on the model specification, the estimated coefficient of viewer movie story analysis percentage turns out to be significantly positive

Table 8
The impact of online reviews on box office revenue.

	log(box office revenue)$_{it}$ (1)	log(the number of moviegoers)$_{it}$ (2)
log(box office revenue)$_{it-1}$	0.792*** (0.012)	0.782*** (0.008)
Viewer_daily_rating$_{it-1}$	0.026 (0.005)	0.035*** (0.007)
Netizen_daily_rating$_{it-1}$	-0.012*** (0.003)	-0.013*** (0.003)
log(Viewer_daily_Num)$_{it}$	0.121*** (0.007)	0.125*** (0.007)
log(Netizen_daily_Num)$_{it}$	0.153*** (0.009)	0.164*** (0.008)
Viewer_movie story analysis_percentage$_{it}$	0.173*** (0.022)	0.166***(0.019)
Netizen_movie story analysis_percentage$_{it}$	0.006 (0.033)	0.019(0.029)
Viewer_movie evaluation_percentage$_{it}$	0.198***(0.027)	0.202***(0.024)
Netizen_movie evaluation_percentage$_{it}$	0.107***(0.025)	0.109***(0.021)
Viewer_movie similarity_percentage$_{it}$	-0.139***(0.023)	-0.161***(0.024)
Netizen_movie similarity_percentage$_{it}$	0.042***(0.017)	0.041*** (0.014)
Monthly Dummy	Included	Included
Day of the Week Dummy	Included	Included
Constant	Included	Included
Observations	4,285	4,285
Wald chi2	40560567.625	4343337.457
Probability	<0.01	<0.01

Notes: ***/**/* indicates significance at the 1%/5%/10% level. Standard errors are in parentheses.

Table 9
The impact of online reviews on box office revenue.

	log(box office revenue)$_{it}$ (1)	log(box office revenue)$_{it}$ (2)
log(box office revenue)$_{it-1}$	0.785*** (0.011)	0.801*** (0.013)
Viewer_cumlative_rating$_{it-1}$	-0.205 (0.185)	Not included
Netizen_cumulative_rating$_{it-1}$	0.073 (0.236)	Not included
Viewer_daily_rating$_{it-1}$	Not included	0.014** (0.007)
dif(Viewer_daily_rating$_{it-1}$- Netizen_daily_rating$_{it-1}$)	Not included	-0.015*** (0.003)
log(Viewer_daily_Num)$_{it}$	0.127*** (0.008)	0.271*** (0.014)
log(Netizen_daily_Num)$_{it}$	0.171*** (0.010)	Not included
dif(log(Viewer_daily_Num)$_{it}$- log (Netizen_daily_Num)$_{it}$)	Not included	0.153*** (0.009)
Viewer_movie story analysis_percentage$_{it}$	0.181*** (0.021)	0.197*** (0.037)
Netizen_movie story analysis_percentage$_{it}$	-0.006 (0.028)	Not included
dif(Netizen_movie story analysis_percentage$_{it}$- Viewer_movie story analysis_percentage$_{it}$)	Not included	0.011 (0.028)
Viewer_movie evaluation_percentage$_{it}$	0.247*** (0.025)	0.350*** (0.037)
Netizen_movie evaluation_percentage$_{it}$	0.115***(0.020)	Not included
dif(Netizen_movie evaluation_percentage$_{it}$ - Viewer_movie evaluation_percentage$_{it}$)	Not included	0.134***(0.022)
Viewer_movie similarity_percentage$_{it}$	-0.185***(0.020)	-0.121*** (0.028)
Netizen_movie similarity_percentage$_{it}$	0.046**(0.021)	Not included
dif(Netizen_movie similarity_percentage$_{it}$- Viewer_movie similarity_percentage$_{it}$)	Not included	0.033*(0.018)
Monthly Dummy	Included	Included
Day of the Week Dummy	Included	Included
Constant	Included	Included
Observations	4,289	4,285
Wald chi2	12418899.471	6507377.655
Probability	<0.01	<0.01

Notes: ***/**/* indicates significance at the 1%/5%/10% level. Standard errors are in parentheses.

($\beta_{\text{Viewer movie story analysis percentage}} = 0.197$, $p\text{-value} < 0.01$). But the difference in the movie story analysis percentage between netizen-type and viewer-type reviews is insignificant ($\beta_{\text{dif(Netizen\_movie story analysis\_percentage-Viewer\_movie story analysis\_percentage)}} = 0.011$, $p\text{-value} > 0.10$). This means that when netizen movie story analysis percentage exceeds viewer movie story percentage, it has no impact on box office revenue.

The estimated coefficient of viewer movie evaluation percentage is significantly positive ($\beta_{\text{Viewer movie evaluation percentage}} = 0.350$, $p\text{-value} < 0.01$). The difference between netizen movie evaluation percentage and viewer movie evaluation percentage is also significantly positive ($\beta_{\text{dif (Netizen\_movie evaluation\_percentage-Viewer\_movie evaluation\_percentage)}} = 0.134$, $p\text{-value} < 0.01$). Movie evaluation has a positive impact on the box office irrelevant of the types of reviews. On the other hand, viewer movie similarity has a negative impact on box office revenue ($\beta_{\text{Viewer movie similarity percentage}} = -0.121$, $p\text{-value} < 0.01$). However, when the percentage of netizen-type reviews exceeds that of viewer-type reviews, it has a positive impact on box office revenue ($\beta_{\text{dif(Netizen\_movie similarity\_percentage-Viewer\_movie similarity\_percentage)}} = 0.033$, $p\text{-value} > 0.10$).

5. Conclusion and discussion

5.1. Discussion of key findings

In this study, we explore the different impacts of textual characteristics reflected in online reviews on box office revenue depending on the level of source credibility. First, we examine how fake reviews (i.e., likely manipulated reviews) are different in the textual characteristics from credible customer reviews. To do this, we analyze online reviews for movies posted on Naver.com, a leading portal website in South Korea. Considering the importance of review volume and credibility, the website tries to increase review volume while maintaining review credibility by adopting a review policy (Ma et al., 2020), which allows two types of customer reviews, viewer-type (more credible) and netizen-type (less credible). Netizen-type reviews are known to be vulnerable to review manipulation, and therefore they are considered less credible (Ma et al., 2019). As a result, our findings show that netizen-type reviews tend to be more superficial in information sharing, while viewer-type reviews are more likely to contain in-depth movie analysis. Second, we find that the level of source credibility plays a different role in determining customer decision making. In other words, different levels of source credibility would affect box office revenue differently. As authentic (i.e., credible) reviews contain more in-depth analysis of movie content, they have a positive impact on box office revenue; On the other hand, fake reviews (i.e., likely manipulated reviews) include more superficial information about a movie, and this has a negative impact on box office revenue. On the other hand, even when less credible reviews (netizen-type) contain superficial information, they positively impact box office revenue.

5.2. Theoretical implications

This study provides significant theoretical contributions. First, our study is the first to explore how online review consumers process information differently when they are exposed to different levels of source credibility. Our findings provide an extension to the literature concerning how credibility changes customer responses (Filieri et al., 2015; Lee and Lin, 2005). Secondly and related to the previous point, the findings suggest that source credibility affects what types of cues customers focus on before making purchase decisions. In other words, the degree of influence of textual cues in online reviews would be determined by the source credibility. We extend the findings of prior literature concerning the influence of source credibility on the message (Ayeh, 2015; Fan et al., 2018). Our findings further show that the source credibility determines which textual characteristics in the message consumers focus on.. Third, we show that the textual characteristics as well as the level of source credibility impact customer decision making. The impacts are determined by the combination between textual characteristics and the level of source credibility. This extends previous research (Singh et al., 2017) that found that textual characteristics are closely related to the usefulness of online reviews. Fourth, we conduct an in-depth investigation of the differences in textual characteristics between fake and authentic online reviews. Mayzlin et al. (2014) focused on the differences in quantitative features (such as review ratings) of online reviews between credible and less credible online reviews to examine review manipulation. According to Hu et al. (2012), review manipulation could also happen to textual comments. We, therefore, extend previous literature (Hu et al., 2012; Mayzlin et al., 2014) by suggesting that the subtle differences in reviews' textual characteristics can bring about different levels of information depth which generates differentiated consumers' attitudes, ultimately impacting product commercial performance.

5.3. Practical and managerial implications

Our findings provide practical business implications for online review platform managers and customers relying on online reviews, particularly relevant in the movie industry. First, review platform managers face increasing difficulty detecting manipulated online reviews because review manipulators tend to emulate authentic reviews to avoid detection. Review manipulators are likely to use similar language to genuine reviews for their credibility (Luppas, 2012; Chen and Chen, 2015). According to our findings, even when manipulated reviews contain movie content, the information itself is likely to be non-specific with only superficial messages. Differently from this, credible reviews tend to contain more in-depth information that needs thorough thinking. This means that review platform managers of movie review websites could successfully develop a detecting method by differentiating authentic reviews from manipulated reviews based on the information depth reflected in the textual content. Second, customers relying on online reviews before purchasing a movie ticket need to know how credible and less credible reviews are different in the textual content. As was found by Hu et al. (2012), review manipulation on textual content would significantly affect consumer purchase decisions because consumers cannot detect manipulation through textual characteristics. Consumers need to know that manipulated reviews contain superficial movie content and recommendation. Those reviews are less likely to include in-depth analysis of movies related to cultural or historical context. By acknowledging the differences, they could avoid uninformed and unintended purchase decisions.

5.4. Limitations and future research directions

Like other research, our study is not free from some limitations. Consistently with prior literature (Mayzlin, 2014), we assume that the differences in textual content between credible and less credible reviews are caused by review manipulation. However, as is mentioned previously, in our study, less credible reviews could be also posted by prospective customers who have not yet watched the movie. The differences could be also caused by those prospective reviews. To address this issue, we sampled the period into "promotional period" and "post period" based on prior literature (Ma et al., 2018) and find that there are no differences in textual characteristics between moviegoers and prospective customers after the promotional period. However, there is no guarantee that review manipulation only concentrates on the promotional period. A more accurate measure to detect the review manipulation period needs to be developed. Second, to we explore how online review consumers process information differently when exposed to different level of source credibility, we use box office revenue. We infer the impacts of source credibility by relying on the revealed customer choice (box office revenue). Therefore, in the future experimental studies might be conducted in order to understand how consumers perceive different levels of source credibility and respond to them. Such an experimental approach might potentially reveal if the relationship between the differences in source credibility mingled with different textual characteristics and different customers' reactions. Lastly, the evaluation of movies reflected in online reviews could be potentially more subjective than the evaluation of other products because movies are artistic products (Ulker-Demirel et al., 2018). Therefore, while the marketing literature has significantly legitimized research on online reviews in the movie context (Chintagunta et al., 2010), future studies might seek to validate our findings for other products and in other industries in future research.

CRediT authorship contribution statement

Jong Min Kim: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Keeyeon Ki-cheon Park:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marcello M. Mariani:** Supervision, Investigation, Conceptualization, Formal analysis, Project administration, Validation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Alantari, H. J., Currim, I. S., Deng, Y., & Singh, S. (2021). An Empirical Comparison of Machine Learning Methods for Text-based Sentiment Analysis of Online Consumer Reviews. *International Journal of Research in Marketing, 39*(1), 1–19.

Ayeh, J. K. (2015). Travellers' acceptance of consumer-generated media: An integrated model of technology acceptance and source credibility theories. *Computers in Human Behavior, 48*, 173–180.

Bart, Y., Shankar, V., Sultan, F., & Urban, G. L. (2005). Are the drivers and role of online trust the same for all web sites and consumers? A large-scale exploratory empirical study. *Journal of Marketing, 69*(4), 133–152.

Banerjee, S., & Chua, A. Y. (2014). A theoretical framework to identify authentic online reviews. *Online Information Review., 38*(5), 634–649.

Banerjee, S., & Chua, A. Y. (2017a). Theorizing the textual differences between authentic and fictitious reviews: Validation across positive, negative and moderate polarities. *Internet Research, 27*(2), 321–337.

Banerjee, S., & Chua, A. Y. (2017b). Authentic versus fictitious online reviews: A textual analysis across luxury, budget, and mid-range hotels. *Journal of Information Science, 43*(1), 122–134.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *The Journal of Machine Learning Research, 3*, 993–1022.

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM, 55*(4), 77–84.

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics, 5*, 135–146.

Bresciani, S., Ferraris, A., Romano, M., & Santoro, G. (2021). Shifting Paradigms in Modern Marketing1. In *Digital Transformation Management for Agile Organizations: A Compass to Sail the Digital World*. Emerald Publishing Limited.

Brown, J., Broderick, A. J., & Lee, N. (2007). Word of mouth communication within online communities: Conceptualizing the online social network. *Journal of Interactive Marketing, 21*(3), 2–20.

Büschken, J., & Allenby, G. M. (2016). Sentence-based text analysis for customer reviews. *Marketing Science, 35*(6), 953–975.

Calheiros, A. C., Moro, S., & Rita, P. (2017). Sentiment classification of consumer-generated online reviews using topic modeling. *Journal of Hospitality Marketing & Management, 26*(7), 675–693.

Chaiken, S. (1989). Heuristic and systematic information processing within and beyond the persuasion context. *Unintended thought*, 212–252.

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

Chen, S., & Chaiken, S. (1999). The heuristic-systematic model in its broader context. In S. Chaiken, & Y. Trope (Eds.), *Dual-process theories in social psychology* (pp. 73–96). The Guilford Press.

Chen, Y. R., & Chen, H. H. (2015, May). Opinion spam detection in web forum: a real case study. In *Proceedings of the 24th International Conference on World Wide Web* (pp. 173-183).

Cox, C., Burgess, S., Sellitto, C., & Buultjens, J. (2009). The role of user-generated content in tourists' travel planning behavior. *Journal of Hospitality Marketing & Management, 18*(8), 743–764.

Cheung, C. M. Y., Sia, C. L., & Kuan, K. K. (2012). Is this review believable? A study of factors affecting the credibility of online consumer reviews from an ELM perspective. *Journal of the Association for Information Systems, 13*(8), 618–635.

Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science, 29*(5), 944–957.

Coursaris, C. K., & Van Osch, W. (2016, July). Exploring the effects of source credibility on information adoption on YouTube. In *International Conference on HCI in Business, Government, and Organizations* (pp. 16–25). Cham: Springer.

Cui, G., Lui, H. K., & Guo, X. (2012). The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce, 17*(1), 39–58.

D'Ambra, J., Akter, S., & Mariani, M. (2022). Digital transformation of higher education in Australia: Understanding affordance dynamics in e-textbook engagement and use. *Journal of Business Research, 149*, 283–295.

Dellarocas, C. (2006). Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management science, 52*(10), 1577–1593.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing, 21*(4), 23–45.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter?—An empirical investigation of panel data. *Decision Support Systems, 45*(4), 1007–1016.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., … Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 59*, Article 102168.

Evans, J. S. B. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology., 59*, 255–278.

Evans, J. S. B., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science, 8*(3), 223–241.

Facebook I (2016). fastText: Library for fast text representation and classification. https://github.com/facebookresearch/fastText.

Fan, A., Shen, H., Wu, L., Mattila, A. S., & Bilgihan, A. (2018). Whom do we trust? Cultural differences in consumer responses to online recommendations. *International Journal of Contemporary Hospitality Management, 30*(3), 1508–1525.

Fei, G., Mukherjee, A., Liu, B., Hsu, M., Castellanos, M., & Ghosh, R. (2021). Exploiting Burstiness in Reviews for Review Spammer Detection. *Proceedings of the International AAAI Conference on Web and Social Media, 7*(1), 175-184. Retrieved from https://ojs.aaai.org/index.php/ICWSM/article/view/14400.

Filieri, R., Alguezaui, S., & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management, 51*, 174–185.

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research, 58*, 46–64.

Floridi, L. (2018). Artificial intelligence, deepfakes and a future of ectypes. *Philosophy & Technology, 31*(3), 317–321.

Hautz, J., Füller, J., Hutter, K., & Thürridl, C. (2014). Let users generate your video ads? The impact of video source and quality on consumers' perceptions and intended behaviors. *Journal of Interactive Marketing, 28*(1), 1–15.

Heydari, A., Ali Tavakoli, M., Salim, N., & Heydari, Z. (2015). Detection of review spam: A survey. *Expert Systems with Applications, 42*(7), 3634–3642.

Hsieh, J. K., & Li, Y. J. (2020). Will you ever trust the review website again? The importance of source credibility. *International Journal of Electronic Commerce, 24*(2), 255–275.

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). *Communication and persuasion*. Yale University Press.

Hu, N., Bose, I., Koh, N. S., & Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems, 52*(3), 674–684.

Jacobs, B. J., Donkers, B., & Fok, D. (2016). Model-based purchase predictions for large assortments. *Marketing Science, 35*(3), 389–404.

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. (2019). Latent Dirichlet allocation (LDA) and topic modeling: Models, applications, a survey. *Multimedia Tools and Applications, 78*(11), 15169–15211.

Johnson, T. J., & Kaye, B. K. (2002). Webelievability: A path model examining how convenience and reliance predict online credibility. *Journalism & Mass Communication Quarterly, 79*(3), 619–642.

Joulin, A., Grave, E., Bojanowski, P., & Mikolov, T. (2016). Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.

Kumar, N., Venugopal, D., Qiu, L., & Kumar, S. (2018). Detecting review manipulation on online platforms with hierarchical supervised learning. *Journal of Management Information Systems, 35*(1), 350–380.

Kwark, Y., Chen, J., & Raghunathan, S. (2014). Online product reviews: Implications for retailers and competing manufacturers. *Information Systems Research, 25*(1), 93–110.

Lee, J., Park, D. H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications, 7*(3), 341–352.

Lee, G. G., & Lin, H. F. (2005). Customer perceptions of e-service quality in online shopping. *International Journal of Retail & Distribution Management, 33*(2), 161–176.

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science, 62*(12), 3412–3427.

Ma, Y. J., & Lee, H. H. (2014). Consumer responses toward online review manipulation. *Journal of Research in Interactive Marketing., 8*(3), 224–244.

Ma, H., Kim, J. M., & Lee, E. (2019). Analyzing dynamic review manipulation and its impact on movie box office revenue. *Electronic Commerce Research and Applications, 35*, Article 100840.

Ma, H., Kim, J. M., & Lee, E. (2020). A 2020 perspective on "Analyzing dynamic review manipulation and its impact on movie box office revenue". *Electronic Commerce Research and Applications, 41*, Article 100950.

Mariani, M., & Baggio, R. (2022). Big data and analytics in hospitality and tourism: A systematic literature review. *International Journal of Contemporary Hospitality Management, 34*(1), 231–278.

Mariani, M., & Borghi, M. (2020). Online review helpfulness and firms' financial performance: An empirical study in a service industry. *International Journal of Electronic Commerce, 24*(4), 421–449.

Mariani, M., Styven, M. E., & Ayeh, J. K. (2019). Using Facebook for travel decision-making: An international study of antecedents. *International Journal of Contemporary Hospitality Management, 31*(2), 1021–1044.

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2022). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology & Marketing, 39*(4), 755–776.

Mayzlin, D., Dover, Y., & Chevalier, J. (2014). Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review, 104*(8), 2421–2455.

Park, D. H., & Kim, S. (2008). The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. *Electronic commerce research and applications, 7*(4), 399–410.

Payne, J. W., Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge: Cambridge University Press.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion* (pp. 1–24). New York, NY: Springer.

Petty, R. E., & Cacioppo, J. T. (1990). *Involvement and persuasion*. Tradition versus integration.

Puranam, D., Narayan, V., & Kadiyali, V. (2017). The effect of calorie posting regulation on consumer opinion: A flexible latent Dirichlet allocation model with informative priors. *Marketing Science, 36*(5), 726–746.

Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Roy, P. K. (2017). Predicting the "helpfulness" of online consumer reviews. *Journal of Business Research, 70*, 346–355.

Sweetser, K. D., Porter, L. V., Chung, D. S., & Kim, E. (2008). Credibility and the use of blogs among professionals in the communication industry. *Journalism & Mass Communication Quarterly, 85*(1), 169–185.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using Latent Dirichlet Allocation. *Journal of Marketing Research, 51*(4), 463–479.
Trustpilot (2020). the critical role of reviews in Internet trust. Retrieved on the 19.12.2021 from: https://business.trustpilot.com/guides-reports/build-trusted-brand/the-critical-role-of-reviews-in-internet-trust.
Turner, J. C., Reynolds, K. J., Van Lange, P. A. M., Kruglanski, A. W., & Higgins, E. T. (2011). Handbook of Theories of Social Psychology.
Ulker-Demirel, E., Akyol, A., & Simsek, G. G. (2018). Marketing and consumption of art products: The movie industry. *Arts and the Market, 8*(1), 80–98.
Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management, 30*(1), 123–127.
Wathen, C. N., & Burkell, J. (2002). Believe it or not: Factors influencing credibility on the Web. *Journal of the American society for information science and technology, 53*(2), 134–144.
Watts, S. A., & Zhang, W. (2008). Capitalizing on content: Information adoption in two online communities. *Journal of the Association for information Systems, 9*(2), 73–94.
Wirth, W., Böcking, T., Karnowski, V., & Von Pape, T. (2007). Heuristic and systematic use of search engines. *Journal of Computer-Mediated Communication, 12*(3), 778–800.
Zhang, D., Zhou, L., Kehoe, J. L., & Kilic, I. Y. (2016). What online reviewer behaviors really matter? Effects of verbal and nonverbal behaviors on detection of fake online reviews. *Journal of Management Information Systems, 33*(2), 456–481.
Zhao, Y., Yang, S., Narayan, V., & Zhao, Y. (2013). Modeling consumer learning from online product reviews. *Marketing Science, 32*(1), 153–169.
Zhelezniak, V., Savkov, A., Shen, A., & Hammerla, N. Y. (2019). In *Correlation coefficients and semantic textual similarity* (pp. 951–962). Association for Computational Linguistics.

Jong Min Kim, Ph.D. is Assistant Professor at the College of Business and Public Management, Wenzhou-Kean University, China. His research interests include online word-of-mouth, management response, promotional reviews, mobile marketing, and corporate social responsibility. In terms of methodology, Dr. Kim focuses on quasi-experimental approaches based on Econometrics. His research has appeared in the *Journal of Business Research*, *Journal of Interactive Marketing*, *International Journal of Electronic Commerce*, and *Tourism Management*.

Keeyeon Park, Ph.D., is a Lecturer at the Wenzhou-Kean University. His research interests span marketing applications of Machine Learning, Natural Language Processing, Network Analysis, Digital Transformation, Mobile Applications.

Marcello Mariani is a Professor of Management at the University of Reading (UK) and University of Bologna (Italy), member of the Henley Center for Entrepreneurship, the Academy of Management and the European Institute for Advanced Studies in Management. His current research interests include big data and analytics, eWOM, digital business models, AI, IoT, automation and coopetition strategies in service industries. His researches have been published in *Journal of Business Research, MIT Sloan Management Review*, *Industrial Marketing Management, Journal of Advertising, Harvard Business Review, International Marketing Review, Psychology & Marketing, Industrial and Corporate Change, Long Range Planning, Technological Forecasting and Social Change, International Journal of Electronic Commerce, Tourism Management, Annals of Tourism Research, Journal of Travel Research, International Journal of Contemporary Hospitality Management, International Journal of Hospitality Management, European Management Journal*, *Production Planning & Control, European Accounting Review, International Studies in Management and Organizations, Journal of Destination Management and Marketing, International Studies in Management and Organizations* and more.