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Too Much Information – Trying to Help or Deceive? An Analysis of Yelp Reviews

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A B S T R A C T

The proliferation of online customer reviews has completely changed how consumers purchase. Consumers now heavily depend on authentic experiences shared by previous customers. However, deceptive reviews that aim to manipulate customer decision-making to promote or defame a product or service pose a risk to businesses and buyers. The studies investigating consumer perception of deceptive reviews found that one of the important cues is based on review content.

This study aims to investigate the impact of the information amount of review on the review truthfulness. This study adopted the Information Manipulation Theory (IMT) as an overarching theory, which asserts that the violations of one or more of the Gricean maxim are deceptive behaviors. It is regarded as a quantity violation if the required information amount is not delivered or more information is delivered; that is an attempt at deception. A topic modeling algorithm is implemented to reveal the distribution of each topic embedded in a text. This study measures information amount as topic diversity based on the results of topic modeling, and topic diversity shows how heterogeneous a text review is.

Two datasets of restaurant reviews on Yelp.com, which have Filtered (deceptive) and Unfiltered (genuine) reviews, were used to test the hypotheses. Reviews that contain more diverse topics tend to be truthful. However, excessive topic diversity produces an inverted U-shaped relationship with truthfulness. Moreover, we find an interaction effect between topic diversity and reviews' ratings. This result suggests that the impact of topic diversity is strengthened when deceptive reviews have lower ratings. This study contributes to the existing literature on IMT by building the connection between topic diversity in a review and its truthfulness. In addition, the empirical results show that topic diversity is a reliable measure for gauging information amount of reviews.

Keywords: Online Consumer Review, Topic Distribution, Deceptive Review, Topic Modeling

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Ⅰ. Introduction

With the widespread use of mobile devices and growth of the logistics industry, e-commerce has correspondingly changed retail business (Dong et al., 2018). Advances in web technology have resulted in the radical growth of customer review websites, such as Yelp and Amazon, where consumers leave reviews about their experiences with product/service quality (Lee and Lee, 2016; Luca, 2016). On Amazon.com, five percent of 244 million users write reviews on their purchases (Zhang et al., 2018). In public surveys, 90% of online shoppers agree that they are influenced by online reviews when making a purchase decision and 88% of them agree that online reviews are equivalent to personal recommendations (Zhang et al., 2018).

On the other hand, online review platforms pose a high risk for fraud since online customers are less likely to discern visible deceptions over audible deceptions (Yoo and Gretzel, 2009). Customers may find it difficult to detect deceptive reviews because of reduced cues to deception (Chernyaeva et al., 2021). The research questions of the studies on review manipulation are broad: prevalence of review manipulation, impact of manipulation, review spam detection, fake and genuine review characteristics, and strategies to deal with manipulation (Ansari and Gupta, 2021). The studies that investigated consumer perception of truthful and deceptive reviews found that the important cues are based on review content (Filieri, 2016). Sentiment (Martinez-Torres and Toral, 2019), readability (Lappas, 2012), length (Pan and Zhang, 2011), subjectivity (Shan et al., 2021), and sentence structures (Ong et al., 2014) showed the importance to distinguish between them. Context data of reviews regarding authors' personal and social information, review activity, and trust features are also used to detect fake reviews (Barbado et al., 2019).

In previous studies, information in online reviews was measured through the number of words or characters in a review (Liu and Park, 2015; Pan and Zhang, 2011). Review length was an indicator of information quantity and effort exerted in writing about a product evaluation (Mudambi and Schuff, 2010; Yoo and Gretzel, 2009). However, simple counting of words may not thoroughly evaluate the quantity of information present in a review (Son et al., 2019). In this study, we propose topic diversity as an additional variable to better measure the quantity of information contained in an online review. Several text mining studies have measured topic diversity in online reviews to show how heterogenous a text review is (Azarbonyad et al., 2017). The usual approach in these studies is to extract the topics by means of a topic modeling algorithm and then estimate topic diversity (Li et al., 2022). This study uses Shannon's information entropy of topic distribution to measure the topic diversity in a review. By qualifying topic diversity, we consider topic diversity as the information value of a review.

Thus, the aims of this study are (1) to measure the amount of information contained in a review using topic diversity and (2) to investigate how the amount of information affects the truthfulness of the review. This study uses datasets extracted from Yelp.com containing Filtered (deceptive) and Unfiltered (genuine) reviews to examine the effect of topic diversity on truthfulness in an online review.

This study adopted the Information Manipulation Theory (IMT) as an overarching theory to test the hypotheses. We found that topic diversity has an inverted U-shape relationship with review truthfulness (whether it is genuine or deceptive reviews) and the effect was moderated by review ratings. This study provided a way to measure the information amount of a review with topic diversity and showed that topic diversity is a valuable factor in predicting review truthfulness.

The remainder of this study is structured as follows; a review of the extant literature including deception theory and the development of the paper's research hypotheses are explained. The researchers then discuss data, variables, and results. Finally, we present our findings and directions for future research.

Ⅱ. Literature Review

2.1. Online Customer Reviews and Consumer Behavior

Online customer reviews are an extremely popular information source providing recommendations or opinions to other customers (Filieri et al., 2018). An online customer review is defined as any comment and rating with valence (i.e., positive, negative, or neutral evaluation) made online by a former customer regarding a product or service and shared with other customers through a social media blog, a consumer review website, an e-commerce website, and/or a corporate website (Filieri, 2016). Customers most commonly use review websites to make better and easier purchase decisions (Dabholkar, 2006). Online reviews provide potential buyers with an indirect experience – ultimately influencing customer behaviors (Choi et al., 2019).

The five stages of the buying decision process start with (1) problem recognition, (2) passing through information search, (3) evaluating alternatives, (4) purchasing decisions, and (5) post-purchase behavior (Comegys et al., 2006; Kotler, 2000). After identifying possible alternatives, consumers use online reviews to search for information in order to choose the best option (Aprilia, 2018; Mudambi and Schuff, 2010). The information search stage helps customers make better decisions and improve consumer satisfaction through shared experiences (Kohli et al., 2014). This means that online reviews provide customers with better potential value (Mudambi and Schuff, 2010; Zhong et al., 2018). Studies to examine the role of online review focus on the reviewers' characteristics such as real name, geographical location, expertise (Forman et al., 2008; Huang et al., 2015) and review characteristics (Jiang and Benbasat, 2004; Mudambi and Schuff, 2010).

Perceived diagnosticity is related to product understanding and positively influences customers' satisfaction (Jiang and Benbasat, 2004). Online reviews positively affect sales (Wu et al., 2015) while rating (Clemons et al., 2006; Liu et al., 2019) and review quality positively affect sales growth (Chen et al., 2008). A 1-star increase in Yelp can affect the revenue of independent restaurant sales by 5-9% (Luca, 2016).

2.2. Deceptive Review

Deception is defined as a message deliberately conveyed for the purpose of fostering false information to the receiver (Buller and Burgoon, 1996; Sarkadi, 2018). Deceptive review is defined as an opinion-based-false review posted online with the intention to mislead (Kumar et al., 2018; Yoo and Gretzel, 2009) and can be equated with untrustworthy, fake, sponsored reviews (Filieri, 2016). Deceptive review has three types: one is untruthful opinion or commonly known as fake reviews (Type 1), another is reviews on brands only (Type 2), the last is non-reviews (Type 3) (Jindal and Liu, 2008). This paper focuses on fake or bogus reviews (Type 1) because Type 2 and Type 3 reviews are easily detected using content analysis (Vidanagama et al., 2020). The definition of Type 1 is equivalent to that of deceptive reviews-giving undeserving positive reviews for promotion (hyper spam) and/or providing malicious negative reviews for reputation damage (defaming spam) (Harris, 2012; Jindal and Liu, 2008). Studies in tourism have investigated textual analysis to identify the properties of deceptive reviews (Ott et al., 2012).

2.3. Information Manipulation Theory

Information Manipulation Theory presents multidimensional approaches to deceptive message design by combining the theory of conversational implicature and deceptive research to information control. IMT suggests that deceptive messages perform as such because they intentionally and discretely violate the rules of conversational exchanges (McCornack, 1992). This theory utilizes the Cooperative Principle (Grice, 1989) and its maxims as a framework to represent various deceptive message forms. Deception is comprehensible by conducting the opposite of cooperative communication based on Gricean principles. The Gricean maxims of cooperative communication offer four maxims; 1) *the maxim of quantity* purports to the expected amount of information delivered within a message as required by the situation; 2) *the maxim of quality* asserts the veracity and validity of messages. The expectation is that participants should not provide false claims or express messages that lack ample evidence; 3) *the maxim of relation* pertains to the participant's required relevant contribution to the conversation; and lastly 4) *the maxim of manner* suggests "how" messages are delivered briefly and clearly without ambiguity and obscurity (McCornack, 1992). McCornack (1992) presents a robust insight that a deception attempt always occurs when a speaker violates one or more of these maxims or diverges from them significantly. Specifically, Quantity violations involve no notable distortion or fabrication but disclose none or only some sensitive information (Ekman, 2011; Metts, 2016; Turner et al., 1975). The deceptiveness derived from manipulating quantity occurs when individuals fail to disclose a critical piece of sensitive information to mislead their reader (McCornack, 1992).

2.4. Interpersonal Deception Theory

General theoretical concepts of deception refer to everyday deceptions in interpersonal conversations (Boush et al., 2015). Interpersonal deception theory (IDT) is regarded as a combination of interpersonal communication and deception principles. Deception occurs when participants attempt to control the information included within messages. As a result, their messages convey a meaning that diverges from the truth (Buller and Burgoon, 1996). The deceiver will strategically change his or her behavior in response to the suspicion of the receiver and will display non-strategic leakage cues or indicators of deception (L. Zhou et al., 2003). For example, IDT analyzes verbal behavior by examining pre-interactional and interactional factors that influence language choices during deception (Buller et al., 1996). In this case, language is a critical point of deceptive behavior. Specifically, the most relevant factor related to language choice during deception is information management. Deceivers strategically manipulate their language to reduce the number of specific content details given by withholding truthful information or opting for vagueness such as equivocation. In addition, deceivers opt for non-immediacy reducing the degree of directness and interaction intensity. The self-presentational perspective illustrates cues for nonverbal communication (DePaulo et al., 2003). This perspective identifies five "cue-types" on differentiating lies from the truth: it anticipates that liars will be less forthcoming, tell less compelling tales, be less optimistic and pleasant, and be tenser than true tellers; liars will incorporate fewer ordinary imperfections and less unique contents (Boush et al., 2015). Furthermore, (DePaulo et al., 2003) introduced 105 cues to deception, of which over 30 cues, a smaller subset, are called linguistic cues or text-based cues used in automated text classification methods. These methods can efficiently read deception cues to identify untruthful messages.

An eight-construct framework was built by (Burgoon and Qin, 2006; Lina Zhou et al., 2004; L. Zhou et al., 2003) using the self-presentational perspective, and interpersonal deception theory, among others (Fuller et al., 2013). Studies that used this framework have successfully classified texts as truthful and deceptive and have discriminated between genuine and misleading language.

Ⅲ. Hypothesis Development

3.1. The effect of topic diversity on its truthfulness

Deceptive speakers intentionally offer too little or too much information and present false, incorrect, and/or inadequately valid information (McCornack, 1992). The Information Manipulation Theory (IMT) asserts that deceptive messages violate at least one of the four Gricean maxims (McCornack, 1992). Furthermore, IDT reveals that deceivers generally have fewer words and sentences to intentionally convey the least amount of detail in their messages (Buller and Burgoon, 1996). According to the self-presentation perspective, deceptive messengers offer fewer details such that their messages are less forthcoming, less compelling, and less positive and pleasant than truth tellers (DePaulo et al., 2003).

We propose to utilize topic diversity in a review to assist producers and consumers in discerning whether reviews are deceptive or not. Deceivers provide less mixed messages than truth-tellers (Lina Zhou et al., 2004). A longer review tends to include more detailed information about product experiences (e.g., when and where the product was purchased) and may be perceived as more truthful (Filieri, 2016). IMT explains that deceptiveness from quantity violations occurs when one fails to provide critical information. In hotel reviews, short dishonest reviews provide no further details such as information about the room, the amenities, the breakfast offered, and focus on sensational titles. Reviews providing two-sided information can be perceived as more truthful because they include good and bad characteristics of the product (Filieri, 2016). Therefore, we hypothesize that a review's topic diversity positively influences the extent of the review's truthfulness.

H1: Topic diversity in a review is positively associated with its truthfulness.

Existing studies regard the "length of a message" as an indicator of information quantity, with longer messages anticipated to offer higher-quality information (Mudambi and Schuff, 2010). Longer messages cause greater certainty than shorter ones because individuals perceive longer messages as more complete (Rucker et al., 2014).

The maxim of quantity (Grice, 1989) is that the expected amount of information delivered within a message should be much as required by the situation. Deceivers tend not to disclose important information to mislead the readers. According to IDT, deceivers try to control the information included within messages and strategically manipulate their language to reduce the required amount of information (Buller and Burgoon, 1996). In addition, deceivers initiate new topics with the potential goal of eliciting deception and conveying contextually irrelevant information to deviate from the original topics (McCornack, 1992). IMT suggests that deceptive messages perform as such because they intentionally and discretely violate the rules of conversational exchanges (McCornack, 1992).

Based on IMT, omitting the required information and adding too much information than the required level can be signals of deception. Thus, the positive effect of topic diversity will be maximized at a certain point, and if a threshold is exceeded, the effect will decrease. Since this paper uses topic diversity to measure information quantity, it will likely be a deceptive review if too diverse or few topics are provided. Therefore, we expect a nonlinear relationship between topic diversity and truthfulness.

H2: Topic diversity in a review has an inverted U-shaped relationship with truthfulness.

3.2. The moderating role of a review's ratings

There have been many studies on the relationship between review ratings and customer behavior (Chevalier and Mayzlin, 2006; Ghasemaghaei et al., 2018; Mudambi and Schuff, 2010; Shin et al., 2021). Though the direction of effect is ambiguous, ratings influence review helpfulness. Moderate reviews are more helpful than extreme reviews for experienced goods (Mudambi and Schuff, 2010), and extreme ratings are more helpful for hotels than moderate ratings (Filieri et al., 2018). Ratings moderate the effect of service attributes and review length on review helpfulness (Shin et al., 2021). Reviews tend to be perceived as more helpful when the review text is longer, and the significance of length was increased when the review rating was low.

Usually, reviews with lower ratings provide more details about a product or service (Ghasemaghaei et al., 2018). Reviews with negative ratings (i.e., 1-star) have significantly longer reviews than reviews with positive ratings (i.e., 5-star). Also, Chevalier and Mayzlin (2006) showed that the average review length of four or higher star ratings is shorter than the average length of less than four-star ratings.

The longer reviews are likely to have more information and cover diverse topics (Chevalier and Mayzlin, 2006). The longer text in a review positively influences the usefulness or helpfulness of reviews (Liu and Park, 2015). They are perceived as more helpful than short reviews because a reviewer posting a long review may spend more effort writing than one posting a short review about staying at a hotel (Filieri et al., 2018).

Deceivers give extreme ratings either to intentionally promote a particular product or service or to defame competitors for bad reputation (Kumar et al., 2018; Vidanagama et al., 2020). This study assumes that the effect of topic diversity in a review is different according to its ratings. Reviews with lower ratings tend to have a longer length, and the impact of information amount on review truthfulness may differ from reviews with higher ratings. Thus, we posit an interaction effect between a review's ratings and topic diversity.

H3: The impact of topic diversity on review truthfulness is moderated by a review's ratings.

Ⅳ. Data and Variables

4.1. Data description

This paper uses two real-world datasets with near-ground-truth extracted from Yelp.com containing filtered (spam, deceptive) and recommended (non-spam, genuine) reviews (Rayana and Akoglu, 2016). The first dataset, named YelpNYC, contains restaurants' reviews in the NY state and the second dataset, named YelpZip, contains restaurants' reviews in NY, NJ, VT, CT, and PA.

Both the YelpNYC dataset and YelpZip dataset have review content and metadata. Review content includes the reviewer's user id, the product reviewed (prod_id), and the date of posting (date). The metadata includes ratings and labels. The YelpNYC dataset has 160,225 reviewers and 923 restaurants while the YelpZip dataset has 260,277 reviewers and 5,044 restaurants. There are 358,280 reviews in YelpNYC and 607,575 reviews in YelpZIP as used for the analysis. The summary statistics of two datasets are given in <Table 1>.

4.2. Variables

4.2.1. Topic diversity

Topic modeling is a powerful computational technique that obtains latent topic discovery and semantic meaning from unlabeled data (Jelodar et al., 2019). The underlying idea of probabilistic topic modeling is based on the distributional hypothesis of linguistics (Harris, 1954): words that occur in similar contexts tend to have similar meanings (Turney and Pantel, 2010). For example, co-occurrence words such as "Ramen", "Chicken", "Noodle", "Sandwich", "Soup" in restaurant reviews can be interpreted as a topic or category (namely "food menu").

<Table 1> Descriptive Statistics: Two Datasets

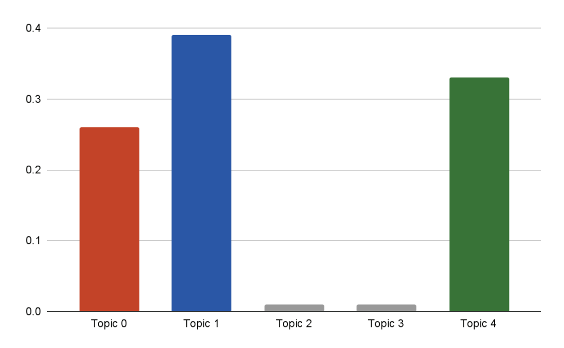
Column Name	YelpNYC	YelpZip
user_id (reviewer)	160,225	260,277
prod_id(restaurant)	923	5,044
reviewContent (reviews)	**358,280**	**607,575**

Researchers apply distributional methods to unsupervised text categorization on large volumes of data, of which the most frequently used approach is Latent Dirichlet Allocation (LDA). The assumption is that each document is a probability distribution of topics and each topic is represented by a probability distribution of terms (Dong et al., 2018). Researchers can exploit the estimated probability distributions as predictors in regression or classification models. Topic modeling with LDA is extensively used in academic research with the use of free and open-source LDA software libraries (including R, Python, Java). It is validated by existing empirical studies such as semantically meaningful topics' extraction from texts and assigning topics to texts (Debortoli et al., 2016). Topic modeling with LDA (Latent Dirichlet Allocation) is used a lot in analyzing customer reviews in diverse fields (Cho et al., 2022); (1) Service quality between full and low-cost carriers was compared by applying LDA to a vast number of passenger's online reviews (Lim and Lee, 2020). (2) Guest satisfaction dimensions were identified by utilizing 104,161 online reviews of accommodations (Sutherland et al., 2020). (3) Topic modeling was applied to social media analysis to understand the interactions among people who participated in online communities, such as valuable features extraction and hidden structure finding (Jelodar et al., 2019).

<Figure 1> shows the topic distribution of the dataset used in this study. The example below covers three topics, and their distribution is 39% (topic 1),

Document
I came at 8:45pm on a Tuesday, and they were sadly out of shawarma, so I had a chicken hero. It was good but it seemed like it relied a little heavily on the added sauces for flavor. From past experiences with shawarma cuisine, I think you want the meat itself to provide the flavor. The guys were nice and gave me a free falafal before the hero was ready.

Topic Distribution



Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
good	pizza	wait	great	good
place	just	come	food	order
pork	place	table	good	fry
raman	say	order	place	sauce
food	make	place	service	burger
chicken	eat	food	restaurant	dish
noodle	know	good	love	flavor
try	good	time	wine	chicken
sauce	time	friend	delicious	taste
really	want	service	nice	cheese
sandwich	review	just	menu	bread
soup	food	seat	amazing	come
order	restaurant	hour	friendly	just
rice	way	really	really	sweet
spicy	think	drink	dinner	salad

<Figure 1> Illustrative Example of LDA

33% (topic 4), 26% (topic 0), and others are not present (0.01%). Topic 1, including "want" and "think", covers the menu's evaluation. Topic 4, including "good" and "nice", covers menu quality and taste. Finally, topic 0's most probable words are "chicken" and "source", which indicate the food offered by the restaurant. Right table of <Figure 1> shows frequent words in each topic after we performed LDA using 5 topics. Topic 0 contains several words related to menu and place, Topic 1 is about the general experience of the customers in the restaurants, Topic 2 is about the experience of services, Topic 3 has words for the evaluation of food and place. Finally, Topic 4 is about the food menu and order.

The concept of information entropy was introduced by Claude Shannon (Shannon, 1948). Shannon's entropy can measure the extent to which the information contained for classification in machine learning. In this paper, we propose information entropy of topic distribution to measure the topic diversity in a review. Equation 1 is Shannon's information entropy formula. In Equation 1, where p_i represents the probability associated i^{th}topic in a review.

$$H = -\sum_{i=0}^{n} p_i \log p_i \qquad (1)$$

<Equation 1> Shannon's information entropy

We model the entropy H of a given topic distribution of a review while n refers to the number of topics. Maximum entropy occurs when all the probabilities have equal value, i.e., 1/n. Minimum entropy occurs when one of the probabilities is 1 and the rest is 0. Thus, we can measure whether a review has diverse topics or not in terms of topic diversity measured by Equation 1. In <Table 2>,

<Table 2> Examples of Computing Topic Diversity

Review Case No.	Topic 0	Topic 1	Topic 2	Topic 3	Topic 4	Topic diversity (Information entropy)
1	1.0	0.0	0.0	0.0	0.0	0.000
2	0.0	0.5	0.3	0.2	0.0	0.447
3	0.2	0.2	0.2	0.2	0.2	0.699

the entropy score of review 1 is 0, 0.447 and 0.699 for review 2 and review 3 respectively. This paper uses information entropy of a review's topic distribution as the measure for topic diversity in the review.

4.2.2. Control Variables

We controlled the following variables to further examine the impact of topic diversity on review truthfulness: (1) Rating, (2) Length, (3) Sentiment, and (4) Readability. The introduction and explanation of the control variables are as follows;.

Rating. The review rating represents a 1-star to a 5-star scale where a 1-star is equivalent to least satisfied, and a 5-star is equivalent to most satisfied (Hu et al., 2012). Deceptive reviewers give extreme ratings either to intentionally improve a particular restaurant's rating or to defame competitors for bad reputation, which will negatively affect the authenticity of reviews (Kumar et al., 2018; Vidanagama et al., 2020). Consumer response to a restaurant's star rating is higher when a rating contains more information, 5-star reviews logically contain more positive information than 1-star reviews (Luca, 2016). Son et al. (2019) incorporated review rating as a control variable to estimate the effect of topic diversity.

Length. Length is defined as a review text's length and is measured by counting the number of words or characters (Pan and Zhang, 2011; Shin et al., 2021). The length of a text review refers to an indicator about the amount of information contained in the review (Wang and Karimi, 2019). A long review carries more information than a short review (Mudambi and Schuff, 2010). As a review gets longer, its topic diversity also tends to increase (Son et al., 2019). Therefore, we included review length as a control variable.

Sentiment. Sentiment analysis is the study of natural language processing to analyze people's opinions, sentiments, evaluation, attitudes, and emotions contained in a text (Hutto and Gilbert, 2014). The growth of internet media such as e-commerce and online communities highlight sentiment analysis due to the subjectivity in the text found online (Kwon et al., 2021). Most sentiment analysis methods rely on the sentiment lexicon, which refers to a list of labeled lexical features as either positive or negative or as words are associated with valence score for sentiment intensity (Hutto and Gilbert, 2014). LIWC (Linguistic Inquiry and Word Count) is a widely used lexicon in the social media domain for sentiment analysis (Pennebaker et al., 2001). Deceivers use sentiments on deceptive reviews to affect an unselected large audience in areas such as public relations, law, marketing (Hu et al., 2012). Review sentiment is used to classify deceptive reviews from truthful reviews (Ong et al., 2014). Sentiment analysis can identify a reviewer's attitude about a specific topic and the effectiveness of deception (Ghasemaghaei et al., 2018; Hu et al., 2012). Because sentiment affects review truthfulness, we controlled sentiment in this study.

This study uses VADER (Valence Aware Dictionary for sEntiment Reasoning), a simple rule-based model for general sentiment analysis (Hutto and Gilbert, 2014). Five general rules embody grammatical and syntactical conventions for expressing and emphasizing sentiment intensity. VADER is more sensitive to sentiment expressions in social media contexts and presents the positivity and negativity score and the extent to which a sentiment intensity is positive or negative (Hutto and Gilbert, 2014). This paper uses a compound score of VADER as the review's sentiment. The compound score is calculated by summing the valence points of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive).

Readability. Readability can be defined as the cognitive effort required for a user to comprehend a review text's meaning and has been used to discern deceptive reviews (Ong et al., 2014). Deceptive and truthful reviews have different intentions, and their purposes are reflected in readability (Banerjee and Chua, 2014). The readability of truthful reviews can be arbitrary by reflecting variable factors (e.g., clarity of expression, ability to properly convey ideas, etc.), whereas that of deceptive reviews has the intention of trying to reach a large audience (Hu et al., 2012). Deceptive reviews generally tend to be less readable

<Table 3> Variable Description

Variables	Explanation
Independent Variables	
Topic Diversity	Information entropy of the topic distribution of review is calculated by Equation 1 above.
Dependent Variables	
Truthfulness	Review i's classification task labeled as a fake (deceptive, encoding 0) or a genuine (truthful, encoding 1) review
Control Variables	
$Rating_i$	$Review_i$'s rating ranging from 1 star to 5 star
$Length_i$	The length of $review_i$ by the number of characters
$Sentiment_i$	The sentiment of $review_i$ from VADER sentiment analysis is classified into positive, neutral, or negative classes. - Positive sentiment: compound score >=0.05 - Neural sentiment: -0.05 < compound score < 0.05 - Negative sentiment: compound score <=0.05
$Readability_i$	FRES (Flesch reading ease score) improves the comprehension and the retention of the textual material. The readability of textual data is a score generated by the readability formula. - 90-100: Very Easy, 80-89: Easy - 70-79: Fairy Easy, 60-69: Standard (Plain English) - 50-59: Fairy Difficult, 30-49: Difficult - 0-29: Very Confusing

than truthful reviews. Therefore, the readability of reviews is a critical predictive variable about review manipulation (Banerjee and Chua, 2014). Because readability affects review truthfulness, we controlled readability. In this study, the readability of a review was measured by the Flesch reading ease score implemented in the textstat library of Python. While higher scores mean an article is easier to read, lower scores indicate it is more difficult to read. The formula for the Flesch reading-ease score (FRES) test is:

$$206.835 - 1.015\left(\frac{total\,words}{total\,sentences}\right) - 84.6\left(\frac{total\,syllables}{total\,words}\right)$$

The Flesch reading ease is a widely used readability metrics and is used as a standard by the United States Department of Defense (Si and Callan, 2001). It is bundled with popular word processing programs such as Microsoft Office Word (Wang et al., 2013).

Ⅴ. Results

5.1. Descriptive Statistics

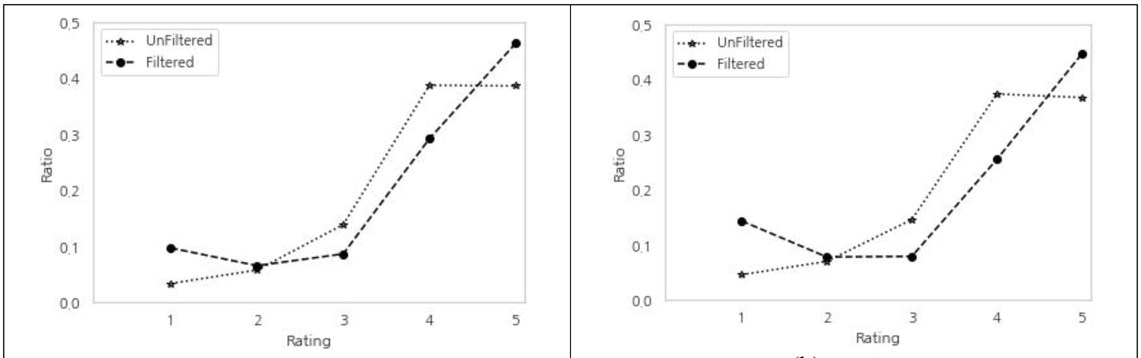
<Table 4> shows the descriptive statistics of the datasets. Filtered refers to deceptive reviews, while Unfiltered refers to truthful reviews. Around 10% of the reviews in YelpNYC and 13% of the reviews in YelpZip are filtered. The differences on the average ratings between genuine and deceptive reviews are relatively small in both datasets. However, the length of the unfiltered reviews is longer than the filtered reviews. In Sentiment, the average sentiment values of reviews are around 0.75～0.78 and there is a difference between the Filtered and Unfiltered reviews in both datasets. Filtered reviews are less positive than Unfiltered reviews. In addition, there was no significant difference between the filtered and the unfiltered in terms of Readability and the readability scores are in the standard (plain English) range with values between 60 and 69.

<Figure 2> shows the rating distribution of the reviews. Filtered reviews have more five-star and one-star than Unfiltered reviews. Therefore, it can be interpreted that deceptive reviewers try to promote or demote products they reviewed.

<Table 5> shows the distribution of dominant topics when the number of topics is five. The dominant topic in a review is defined as the topic which has the maximum percentage value out of topic percentage distributions in a review. For example, the first row shows that the percentage of reviews dominated by topic 0 is 16.84% among genuine reviews and 13.24% among deceptive reviews respectively. Both the genuine and deceptive reviews have the largest proportion of Topic 2 (experience of service)

<Table 4> Descriptive Statistics

Data	YelpNYC			YelpZip		
	All	Unfiltered	Filtered	All	Unfiltered	Filtered
Number of reviews	358,280	321,473	36,807	607,575	527,256	80,319
Average Rating	4.026	4.034	3.956	3.924	3.945	3.783
Average Length	637.391	659.541	443.931	631.177	654.812	476.029
Average Sentiment	0.775	0.786	0.685	0.752	0.769	0.640
Average Readability	65.839	65.572	68.171	65.265	65.113	66.261



(a) YelpNYC (b) YelpZip

<Figure 2> The Rating Distribution of Reviews

<Table 5> Topic Distribution between Genuine and Deceptive Reviews

Topic	Distribution of dominant topics			
	Genuine (Unfiltered)		Deceptive (Filtered)	
0	54,260	16.84%	4,883	13.24%
1	41,311	12.82%	2,527	6.85%
2	114,352	35.50%	17,388	47.17%
3	54,214	16.83%	4,180	11.34%
4	57,960	17.99%	7,882	21.38%

and the smallest proportion of Topic 1 (general experience of the restaurant). The LDA method does not show the reason why the proportion of a specific topic is higher compared to that of other topics but it can identify the proportion of each topic in a review. Since the reviews we analyzed are based on the dining experiences of the restaurants, we assume that diners have posted a lot of reviews that reflect their actual experiences (Topic 2).

Before applying logistic regression, we calculated correlation coefficients among variables and investigated whether the magnitude of coefficients is relatively small to avoid any potential problems on the performance of logistic regression models (Kumar et al., 2018). <Table 6> shows the correlation values among the variables. Both the YelpNYC and YelpZip dataset show similar correlation relationships and there are no strongly correlated variables.

The variance inflation factor (VIF) investigates the extent to which the variables in the regression models were highly correlated (Filieri et al., 2018). VIF analysis indicates that multicollinearity is not a critical concern as shown in <Table 7> since VIF values of each variable is below 10.

5.2. Data Preprocessing and Number of Topics

Before conducting topic modeling for the hypothesis test, we performed pre-processing using python libraries for the following purpose - (1) Removing new line characters and eliminating single quotes

<Table 6> Variable Correlations for 5 Topics

Data	YelpNYC				YelpZip			
Correlation	**Rating**	**Length**	**Sentiment**	**Readability**	**Rating**	**Length**	**Sentiment**	**Readability**
Rating								
Length	-0.1099				-0.1162			
Sentiment	0.4387	0.1730			0.4978	0.1503		
Readability	0.0393	-0.2364	-0.0514		0.0415	-0.2455	-0.0443	
Topic Diversity	0.0224	0.3622	0.1257	-0.1187	-0.0061	0.4104	0.1092	-0.1242

<Table 7> VIF Values

Data	YelpNYC	YelpZip
Rating	1.3	1.4
Length	1.3	1.3
Sentiment	1.3	1.4
Readability	1.1	1.1
Topic Diversity	1.2	1.2

<Table 8> Optimal k Topics by Perplexity

k (number of topic)	YelpNYC	YelpZip
2	1,278.8	1,317.2
3	**1,256.2**	**1,287.4**
4	**1,259.7**	**1,284.1**
5	**1,281.1**	**1,308.3**
6	1,315.6	1,335.7
7	1,333.3	1,348.4
8	1,335.0	1,377.3
9	1,373.7	1,402.4
10	1,368.8	1,412.3
11	1,401.4	1,432.0
12	1,415.4	1,447.3
13	1,432.7	1,474.3
14	1,447.8	1,483.3
15	1,477.7	1,503.5

(i.e. ‘’) by using re(regular expression) module, (2) splitting a review sentence and eliminating punctuation marks (i.e., !, .) with gensim library (3) lemmatizing each word into standard forms to tag each word's part-of-speech (noun, adjective, verb, adverb). One of the important procedures about LDA topic modeling is to determine the optimal number of topics(k). Perplexity is a commonly used measure to evaluate topic models. A lower perplexity represents a better topic model by generalizability (Blei et al., 2003). We generated 14 topic models for both YelpNYC and YelpZIP by differing the number of topics ranging from 2 to 15 and evaluated these models by measuring perplexity. We found the most generalized topic model (out of 14 models) whose perplexity is the lowest three topics for YelpNYC and four topics for YelpZip when the number of topics were three, four, and five. <Table 8> shows a similar tendency of perplexity when the number of topics varies from three to five in both datasets. Though the minimum perplexity scores were at three in YelpNYC and four in YelpZip, the perplexity scores at five were not significantly different from the lowest scores in both datasets. And for measuring topic diversity, rather greater number of topics are favorable to see the distributions. Thus, the optimal number of topics is chosen as five.

5.2.1. Results of Hypotheses Testing

The results of the hierarchical logistic regression

<Table 9> Analysis Results with All Reviews – The Number of Topics: 5

Data	YelpNYC				YelpZip			
Models	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Rating	0.2420***	0.1317***	0.0850***	0.2219***	0.2039***	0.0883***	0.0808***	0.1078***
Length	0.0014***	0.0010***	0.0009***	0.0009***	0.0010***	0.0006***	0.0006***	0.0006***
Sentiment	0.2037***	0.2541***	0.2800***	0.2809***	0.2947***	0.3653***	0.3712***	0.3734***
Readability	0.0048***	0.0030***	0.0021***	0.0017***	0.0045***	0.0025***	0.0024***	0.0022***
Topic Diversity		1.6263***	3.5906***	2.2822***		1.8278***	2.1476***	2.0343***
Topic Diversity^2			-2.9341***				-0.4971***	
Rating* Topic Diversity				-0.3582***				-0.0850***
Pseudo R-squared	0.0220	0.0290	0.0300	0.0300	0.0210	0.0310	0.0310	0.0310
AIC	232,077	230,452	230,163	230,031	464,400	459,692	459,675	459,638
Log-likelihood	-116,030	-115,220	-115,080	-115,010	-232,200	-229,840	-229,830	-229,810

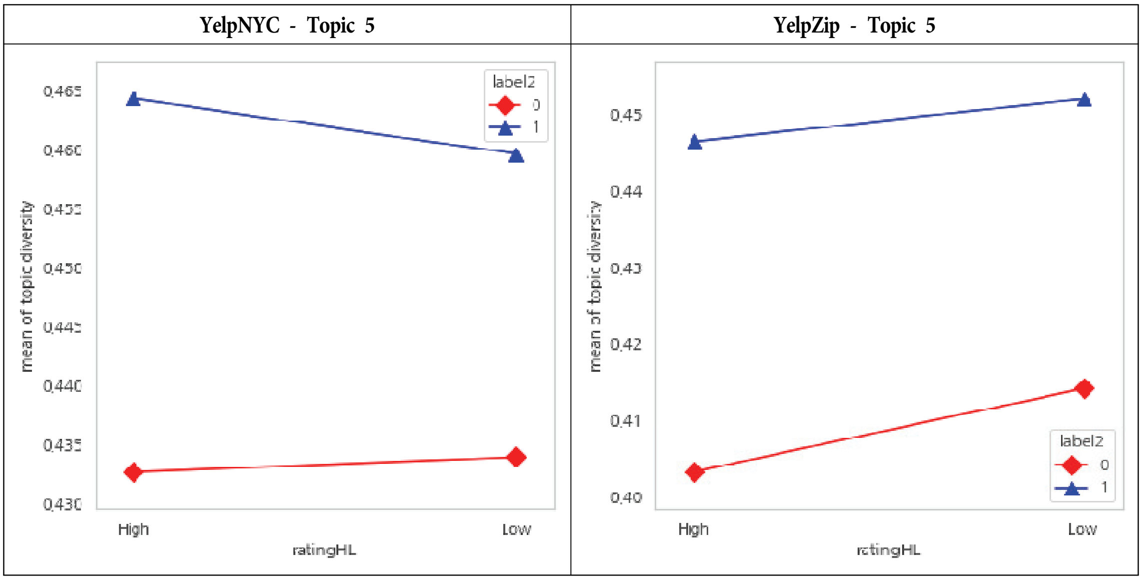
** p <0.05, ** p <0.01, *** p <0.001*

Note. YelpNYC – topic 3～ 15 all accepted, YelpZip – topic 3～15 all accepted except 10, topic diversity^2 was positive

models are summarized in <Table 9>. Model 1 is the base model that includes control variables only. Model 2 includes topic diversity to Model 1 and in Model 3 the square term of topic diversity is added to Model 2. Model 4 adds the interaction term between ratings and topic diversity results (i.e., rating × topic diversity) to Model 2.

H1 is supported, as topic diversity in a review has a significant effect on the truthfulness of the review. We also found the evidence supporting H2 that the effect of the square term of topic diversity on review truthfulness is significant but negative. As topic diversity in a review increases, the probability of truthfulness increases. However, excessive topic diversity in a review produces an inverted U-shape relationship and leads to a decrease in the probability of truthfulness while holding the other variables constant. To test Hypothesis 3, we created the interaction term by multiplying rating and topic diversity. As shown in <Table 9>, there is a significant relationship between the interaction term of rating and topic diversity and truthfulness.

<Figure 3> depicts the interaction effects by which the effects of genuine or deceptive reviews on topic diversity (i.e., y-axis) are evaluated at high and low ratings (i.e., x-axis). 4-star or more ratings are classified as high and less than 4-star ratings are classified as low. The blue and red lines show the moderating effect of rating on genuine and deceptive reviews, respectively. In the YelpNYC dataset, when rating was low, reviews, on average, had lower topic diversity compared to the topic diversity value of high ratings with the genuine reviews. However, the topic diversity value of high rating reviews is lower than the low rating reviews with the deceptive reviews. Conversely in the YelpZip dataset, when rating was low, reviews had higher topic diversity in the genuine and deceptive reviews. But the decline of topic diversity values to high rating reviews is different according to the review truthfulness. The decline of topic diver-



<Figure 3> The Interaction Effects between Rating (High, Low) and Topic Diversity

sity value for the deceptive reviews is greater than the one for the genuine reviews. Hypothesis 3, for YelpNYC, low ratings weakened the impact of topic diversity in the genuine reviews condition, but for YelpZip strengthened that of topic diversity. Namely, a review's ratings moderate the impact of topic diversity. Hypothesis 3 is supported.

Ⅵ. Discussion & Conclusions

The results of this study show that topic diversity plays a crucial role in identifying the truthfulness of online reviews. Reviews that convey more diverse topics tend to be more informative, helpful, and thus truthful to consumers. However, topic diversity has a curvilinear relationship with review truthfulness. As a review conveys more (or fewer) topics than required, it is perceived as more suspicious, and its purpose is considered a deception attempt to convey more (or fewer) topics to hide its deception. In addition, review ratings moderate the effect of topic diversity on truthfulness.

6.1. Theoretical implications

While many aspects of deception have been studied at length in the literature, this study emphasizes the information amount of review content. This study builds the connection between topic diversity in a review and its truthfulness based on IMT. Previous studies investigating the characteristics of deceptive and genuine review used Deception theory (Yoo and Gretzel, 2009) and Expectancy theory (Ong et al., 2014). Peng et al. (2016) applied IMT to test the effect of strategies to deal with deceptive reviews. Peng et al. (2016) stated that there have been no empirical investigations of IMT in the online context until then. Thus, this study expanded IMT to discern deceptive reviews. Consistent with the findings of previous studies, we reveal that topic diversity is positively associated with the review's truthfulness.

Also, we find that if too many topics are provided, the effect of topic diversity diminishes then. In addition, this study provides a topic diversity measure using information entropy. Though there have been some studies using topic diversity in their studies, they used the number of topics in a review as topic diversity (Son et al., 2019). Instead of the number of topics, this study considers the distribution of topics in a review, whether it is focused on a topic or discusses diverse topics. The empirical results of this study provide evidence that topic diversity is a reliable measure for gauging review information content.

6.2. Practical implications

This study also has beneficial implications for practitioners. First, industry practitioners (i.e., marketers, manufacturers, retailers, etc.) can apply topic modeling to identify the characteristics of products that consumers care about the most. Moreover, they can monitor the amount of information in reviews by measuring topic diversity, as suggested in this paper, and develop possible ideas to filter out deceptive reviews. Since there is an inverted U-shape relation between topic diversity and truthfulness, practitioners can empirically find the threshold level of topic diversity for filtering out positive deceptions. Second, this study will help consumers discern genuine or deceptive reviews. For reviews that contain too much information, individuals should consider further noticing the suspicious behaviors of deceptive reviewers. Lastly, platforms should adopt measures such as topic diversity in their deception detection algorithms. These algorithms should consider the moderating effects of ratings and criteria to filter out deceptive reviews should vary according to review ratings. Deceptive reviews with low ratings tend to have more information than deceptive reviews with high ratings. In addition, genuine reviews tend to have greater information amount than deceptive reviews. These trends should be confirmed in their platforms, and the threshold levels must be fine-tuned with empirical experiments.

6.3. Limitations and future research

This study acknowledges its limitations that open opportunities for future research.

First, we used topic modeling with LDA to extract the topic distribution of a review and information entropy to measure topic diversity in a review. Future research can apply other topic modeling techniques which consider different aspects of a text and devise a novel information amount measure. Second, the relationship between topic diversity and review truthfulness was tested in restaurant reviews. A comparative study on other products or services should be conducted to see if any differences in the relationship between topic diversity and truthfulness exist.

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