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The Detection of Well-known and Unknown Brands' Products with Manipulated Reviews Using Sentiment Analysis

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ABSTRACT

The detection of products with manipulated reviews has received widespread research attention, given that a truthful, informative, and useful review helps to significantly lower the search effort and cost for potential customers. This study proposes a method to recognize products with manipulated online customer reviews by examining the sequence of each review's sentiment, readability, and rating scores by product on randomness, considering the example of a Russian online retail site. Additionally, this study aims to examine the association between brand awareness and existing manipulation with products' reviews. Therefore, we investigated the difference between well-known and unknown brands' products online reviews with and without manipulated reviews based on the average star rating and the extremely positive sentiment scores. Consequently, machine learning techniques for predicting products are tested with manipulated reviews to determine a more useful one. It was found that about 20% of all product reviews are manipulated. Among the products with manipulated reviews, 44% are products of well-known brands, and 56% from unknown brands, with the highest prediction performance on deep neural network.

Keywords: Online reviews, Manipulated reviews, Manipulation detection, Brand awareness, Sentiment analysis, Readability analysis

Ⅰ. Introduction

Word-of-mouth has been one of the most influential resources of information transmission. However, the widespread use of the Internet, and advances in information technologies have significantly changed the way information is transmitted. Customers can freely and easily access information and exchange opinions about products, services or purchase experience on an unprecedented scale in real time. Currently,

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the volume of available online reviews has grown at an exponential rate. According to Eslami et al. (2018), about 85% of consumers make their final purchase decisions based on online customer reviews (OCRs) generated by previous customers. Accordingly, online reviews have become one of the most trusted sources of information for sharing personal past purchase experiences (Susan and David, 2010).

Online reviews play an important role in influencing new customers in the purchase related decision-making process (Lee et al., 2013). Based on the belief that online reviews can significantly affect customers' purchase related decisions, some companies, or sellers strategically manipulated OCRs in an effort to influence customers' purchase decisions (Dellarocas, 2003; Harmon, 2004). Review manipulation is a new and critical issue in the e-commerce service area. Hu et al. (2012) confirmed that 10.3% of products' online reviews are manipulated on online retail sites. A large number of studies have focused on identifying and estimating the impact of products with manipulated reviews (Chen and Lin, 2013; Hu et al., 2011). However, according to these studies, no one has investigated how brand awareness influences customer perceptions of product's review manipulation.

Therefore, this study aims to examine the association between brand awareness and existing manipulation with products' OCRs. Correspondingly, we utilized the Wildberries.ru online retail site, one of the largest and most popular online shopping sites in Russia. Considering that accurate, informative, and useful reviews help to significantly lower the search effort and cost for potential customers, we propose a method to determine products with manipulated OCRs by examining the sequence of each customer review polarity (sentiment scores), readability, and rating scores by product. The manipulation detection method is based on the concept that each customer comes from a diverse background, therefore, reviews written by customers will also be different and unique (Barbado et al., 2019). Specifically, each customer review's sentiments, rating, and readability scores should be mutually independent and product reviews should be random with respect to time in the case where there is no manipulation. Subsequently, we examined the difference between well-known brands and unknown brands' products OCRs with and without manipulated online reviews based on the average star rating and the extremely positive sentiment scores.

The remainder of the paper is organized as follows. Section 2 provides a literature review, including a basic concept of brand awareness, OCRs, manipulation detection of OCRs, sentiment analysis, readability analysis, and machine learning methods for the prediction of products with manipulated OCRs. Section 3 develops the research framework and proposes research questions, while Section 4 conducts laboratory experiments to examine research questions. Section 5 analyses and reports the results, and Section 6 presents the conclusion with the summary of findings, contributions and limitations of our study and provides directions for future research.

Ⅱ. Literature Review

2.1. Brand Awareness

Brand awareness refers to the ability of a customer to recognize or recall a brand. Specifically, whether a customer can or cannot identify a brand. Since brand awareness precedes brand equity (Keller, 2003), customers tend to link knowledge about the brand with the brand's logo or name that is an essential part of brand equity (Aaker and Equity, 1991). Where brand equity is the perceived worth of a brand (Ailawadi et al., 2003), and a well-known brand is a brand with which the customer is familiar with, has knowledge of, or purchase experience (Baltas and Saridakis, 2010). An unknown brand is a brand that the customer has never heard of and does not have any knowledge about (Foroudi, 2019). If the customer is already familiar with the brand, therefore, has knowledge about this brand, then the known brand has a learning advantage compared with unknown brands. Consequently, brand awareness plays a role in the purchase decision-making process and increases brand market performance (MacDonald and Sharp, 2000). Specifically, a customer will make a quicker and more willing decision to purchase a product of a well-known brand than the brand the customer is hearing about for the first time.

Many prior studies have illustrated the impact of brand awareness on the product purchase decision-making process by customers by using blind tests as an example (Dabbous and Barakat, 2020). A study of Allison and Uhl (1964) has shown that consumers in blind taste tests were unable to detect their own favorite brands. In this study, beer drinkers were first asked to rate several beer brands in a blind taste test and repeat it when the brands were identified. Consequently, it was found that the beer drinkers tended to rate the taste of the beverage of their favorite brand significantly higher when the beer brand was identified than when they did it in the blind taste test. Moreover, the beer drinkers could not distinguish their favorite brand from the others when they tasted it in the blind taste test. Based on this experiment, it can be concluded that customers make decisions based on their previous knowledge about the brand.

Meanwhile, marketers are concerned about brand promotion, so they communicate with external customers in different ways, often using a strategy involving corporate advertising (Hatch and Schultz, 1997). Advertisements help firms develop strategic positions to differentiate a company or brand and provide goodwill from customers and stakeholders (Tokajian and Irshaidat, 2020). A certain reputation of the company and the company's brand is created, and customers choose the brand with the image that best suits their self-image. Additionally, reputation aims to generate a more favorable company or brand-oriented image through social media and advertising coverage (Park et al., 2016) that causes customers to consider the company to be trustworthy and respect (Fombrun, 2012). With the expansion of online shopping and the influence of online reviews on customers in the purchase related decision-making process (Lee et al., 2013), promotion on online retail sites such as Amazon.com and WildBerries.ru through OCRs has become an important part of the marketing strategy of companies.

2.2. Manipulation of Online Customer Reviews

Online word-of-mouth or electronic word-of-mouth (eWOM) is "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al., 2004). Presently, OCRs are one of the most trusted sources for evaluating and comparing information of various alternatives (Salehan and Kim, 2016). Based on the belief that online reviews can significantly influence customers' purchase related decisions, some companies or sellers strategically manipulate OCRs in an effort to influence customers' purchase decisions (Dellarocas, 2003; Harmon, 2004). Furthermore, previous studies have investigated how marketers can strategically manipulate customers' perceptions and opinions of products or services through online communication channels such as online reviews of retail sites (Mayzlin et al., 2014). Posting an untruthful review or a review without an accounting of a real customer's experience can be considered as manipulation (Tian et al., 2020). Therefore, manipulation of online reviews can occur when online vendors or agencies hired by them produce customers' reviews by posing as real customers.

Hu et al. (2011) state that "unethical users manipulate online reviews, they can either post reviews with a high numeric rating or manipulate the textual statements posted in the review." Through the textual statement, the writing style can be identified, regarding how a customer constructs sentences together when writing online reviews. In this study, the writing style of books' reviews in English consists of sentiment analysis and readability analysis scores. For providing sentiment analysis, we extracted strong positive sentiment terms from each OCR and employed a standard term frequency measurement for determining the sentiments (Kim et al., 2019). For providing readability analysis, Automated Readability Index (ARI) is used in this study.

According to Hu et al. (2012), based on the distribution of the readability, sentiments, and star rating over time, it can be determined whether or not the product's OCRs are manipulated. Each customer's writing style is different from the other since customers often express personal opinion of the product or the service experience while writing an online review (Chirita et al., 2005). The difference in writing style reflects the heterogeneity in customers' backgrounds, cultures, and previous experiences (Shan et al., 2021; Wu et al., 2020). However, in the case of a product with manipulated reviews, when reviews are posted by manipulators, these reviews will be homogeneous (Fei et al., 2013). Peng and Zhong (2014) proposed a method that computes sentiment score from natural language text by a shallow dependency parser. Their study also established a time series combined with discriminative rules to identify the spam store and spam review efficiently and examined the relationship between sentiment score and spam reviews (Noekhah et al., 2020).

2.3. Sentiment and Readability Analysis

Sentiment analysis is used to identify and extract the positive and negative parts in the text (Hu et al., 2012). The polarity of OCRs was used for categorizing them into positive or negative reviews in the proposed approach (Kim et al., 2019). Sentiment analysis has been widely researched by text mining community researchers (Dave et al., 2003; Pang et al., 2002). For classifying text sentiments, the lexicon-based approach is widely used. A lexicon is a dictionary containing words that reflect positive, neutral, and negative sentiments. For Russian language, the vocabulary of Chetverkin et al. (2012) is well-known, and it includes a list of 5,000 rating words extracted from collections of reviews in several subject areas (films, books, games, phones, cameras).

Readability analysis generates a score and derives from a mathematical model, which evaluates the reading ease of different text parts by a number of words, sentences, syllables (Correa et al., 2020). There are many techniques and readability indexes for evaluating the readability of the text through the count of words. According to Spool et al. (1999), in our research, we used three different readability analysis techniques to evaluate WildBerries.ru readability. The first technique which was used is the ARI (Senter and Smith, 1967). It is one of the simplest and most common techniques for evaluating text readability that counts the measure of word difficulty in average letters per word and the measure of sentence difficulty in average words per sentence (Kincaid and Delionbach, 1973). The second readability analysis technique is the Coleman – Liau index (CLI) (Coleman and Liau, 1975), which, along with the ARI, can be used to determine readers' perception of text by comparing its complexity with the official USA educational level at which, if obtained, this text can be easily understood. The third technique used for analyzing text readability is the Flesch reading ease (FRE), which uses the parameters: total words, total sentences, and total syllables to analyze text readability. The concept of FRE is that the fewer words in sentences and the shorter the words, the simpler the text.

Since an average sentence in Russian is shorter than an average sentence in English, although the average number of characters in Russian words is greater compared to English, the readability gradation of text in English is not suitable for our readability analysis results of reviews in Russian (Solnyshkina et al., 2020). There are only a few studies devoted to the analysis of the readability of texts in Russian that distribute the results of an analysis of the readability into grades adapted only for the Russian language (Laposhina et al., 2018). The reason for this may be the lack of readability analysis methods of text in Russian and the complexity of the Russian language. However, there are no studies on the gradation of the readability of Russian language, so the assessment of Russian text by grades is not possible (Ivanov et al., 2018). Considering that the purpose of this study does not depend on the gradation scale and relies only on the results calculated by the formulas of readability indices, the aforementioned readability indices can be applied to text in Russian.

2.4. Machine Learning Methods

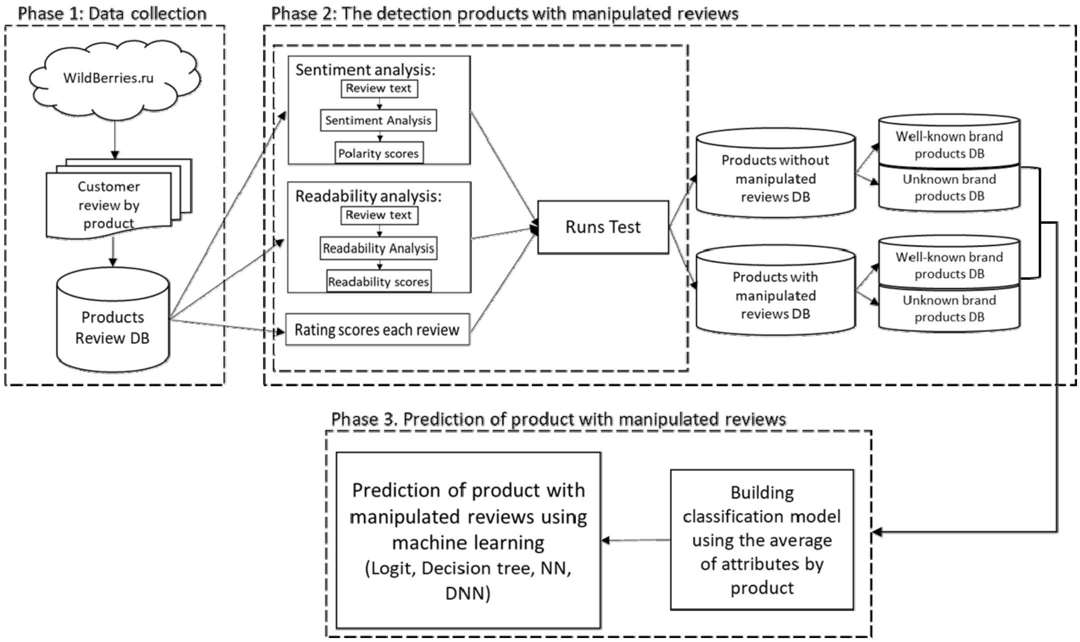
Machine Learning is a set of mathematical, statistical, and computational methods for developing algorithms that can solve the problem not in a direct way but based on the search for patterns in a variety of input data (Lei et al., 2020). Machine learning is becoming increasingly significant because it is difficult to process and analyse data that has recently surged on traditional platforms (Li et al., 2019). Logistic regression is a machine learning classification algorithm which is used for classifying problems and to assign observations to a discrete set of classes; it is a predictive analysis algorithm based on the concept of probability (Press and Wilson, 1978). Decision tree uses a set of binary rules to calculate a target value. It is used for either classification (categorical target variable) or regression (continuous target variable) (Safavian and Landgrebe, 1991).

Neural networks (NN) are one of the representative machine learning techniques (Kim et al., 2020). The main strength of NNs is their high predictive performance. NN's structure supports capturing very complex relationships between predictors and an outcome variable, which is the main strength of NNs (Shmueli et al., 2017). Deep neural network (DNN) is a class of machine learning algorithms that uses several layers of nonlinear processing units for classification, feature extraction, and transformation, so the successive layer uses the output from the previous layer as input (Tian et al., 2020). DNN is used for effective learning and improving the performance of the prediction.

Ⅲ. Research Framework

3.1. Research Framework

This study proposes a framework for the detection



<Figure 1> Research Framework

of products with manipulated reviews. This research framework is presented in <Figure 1>. The proposed method is to identify products with manipulated OCRs by examining the sequence of each review polarity (sentiment scores), readability, and rating scores by product on randomness. The study also aims to examine the association between brand awareness and existence of manipulation with product OCRs.

3.2. Research Questions

Past research investigated the different methods to identify manipulated reviews, however, the influence of product brand awareness to detection product with manipulated reviews was not counted. Accordingly, this research compares and describes the characteristics of popular and unknown brands' product reviews with or without manipulation. In view of these research gaps, this paper aims to answer the following research questions.

First, since a customer is already familiar with the brand and has knowledge about it, brand awareness offers a learning advantage to well-known brands (Du et al., 2020). Moreover, brand awareness plays a major role in the purchase decision-making process and increases brand market performance (Shamsudin et al., 2020). Specifically, a customer will make a quicker and more willing decision to purchase a product of a well-known brand than the brand a customer is hearing about for the first time. According to a study by MacDonald and Sharp (2000), initially, customers perceive more positive well-known brands' products than unknown brands' products, therefore we assume that even in the absence of manipulation, customers tend to more willingly give high ratings to well-known brands' products than unknown brands' products. To prove this issue, the study proposes the first research question:

Q1: Is there a difference between the average star rating of products of well-known brands and unknown brands without manipulated reviews?

Second, reputation aims to generate a more favorable company or brand oriented image through social media and advertising coverage and causes customers to consider the company to be trustworthy and respectful (Fombrun, 2012). Some companies or sellers strategically manipulated OCRs in an effort to influence customers' purchase decisions (Dellarocas, 2003; Harmon, 2004); such companies can be not only unknown brands but also well-known brands. According to a study by Hu et al (2011), boosting rating, as a common and feasible review manipulation strategy, implied creating a very positive rating to a product assuming the identity of a customer through review manipulation. Furthermore, based on previous studies, some hotels in review manipulation purpose post fake negative reviews for their local competitors and post fake positive reviews for themselves (Hu et al., 2011; Mayzlin et al., 2014). To identify the difference between the star rating of products of well-known brands and unknown brands without manipulated reviews, the second research question is:

Q2: Is there a difference between the average star rating of products of well-known brands and unknown brands with manipulated reviews?

Previous research has explored the relationship between review star rating and the results of review sentiment analysis (Al-Natour and Turetken, 2020). On one hand, a study by Greetha et al. (2017) states that customer sentiment polarity has a positive effect on customer rating. The study determined a relationship between reviews star ratings given by customers and actual customers' feelings across hotels. Meanwhile, Lak and Turetken (2014) state that sentiment polarity is not the same as star rating, and also that sentiment polarity cannot replace star rating, due to the limited ability of the sentiment analysis to identify extreme ratings of OCRs. Since this study's objective is to identify the features of well-known and unknown brands in case of existence and absence of review manipulation, extremely positive sentiments were selected that were higher than the average sentiment for all products. According to a study by Cao et al. (2011), reviews with extreme opinions were found more impactful to customers than reviews with moderate or neutral opinions, considering that customers tend to pay more attention to extreme opinions. OCRs with extreme opinion may also be an indicator of review manipulation by some companies, especially with the purpose of writing a very positive OCR for themselves to raise their rating (Almatarneh and Gamallo, 2018). Therefore, for comparison, the role of star rating and sentiments of products of well-known and unknown brands' with and without manipulated reviews, the study proposes a similar hypothesis with Q1 and Q2, but in the context of extreme positive sentiments:

Q3: Is there a difference between extremely positive sentiment scores of products of well-known brands and unknown brands without manipulated reviews?

Q4: Is there a difference between extremely positive sentiment scores of products of well-known brands and unknown brands with manipulated reviews?

Since, in the case of identifying products with manipulated online reviews, the main condition for carrying out supervised machine learning methods is the availability of a labelled dataset (with and without manipulation) (Lim et al., 2010), therefore, we applied machine learning techniques in the third phase after the detection of products with manipulated reviews. Supervised learning in the case of OCRs manipulation detection classifies products into two categories: with manipulated OCRs and without manipulated OCRs (Shan et al., 2021). This study tests four different machine learning techniques for the prediction of products with manipulated OCRs: logit, decision tree, neural networks, and DNN. DNN uses effective learning compared to other machine learning algorithms such as decision tree and logit (Shmueli et al., 2017). The study proposes that DNN shows the best performance through the empirical analyses of machine learning techniques for the identification of products with manipulated reviews. To test this idea, this study proposes the last research question:

Q5: Which machine learning technique is more useful for predicting products with manipulated reviews using machine learning?

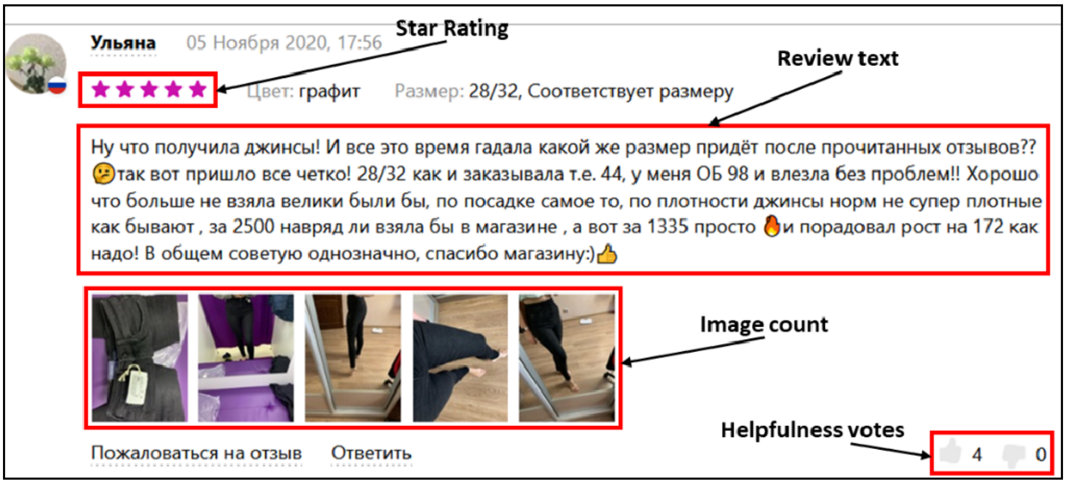
Ⅳ. Experiments

4.1. Conducting a Survey on Brand Awareness

For the reliability of the study, a survey was conducted among a group of Russians aged between 20 and 35. Fifteen respondents answered questions on 10 brands: "Do you know this brand? Or have you heard about it before?" Based on the survey results, the brands were consolidated into two categories: Well-known brands and Unknown brands. In the first category, Well-known brands, "YES" answers ranged from 14 to 15. The Well-known brand list consists of Mango, Zarina, Ostin, Oliver, and Concept Club. The second category, or Unknown brands, included brands, with the number of answers "YES" in the survey, equalling 0. The well-known brand list consists of LAFEINIER, Vittoria Vicci, Abby, Malkovich, and Violeta.

4.2. Phase 1: Data Collection Using Web Crawling

The data were collected from the Russian retail site Wildberries.ru. Sites such as Amazon.com,



<Figure 2> An Example of Online Review's Attributes from Wildberries.ru

TripAdvisor.com, and Yelp.com are known all over the world. In Russia, one of the largest and most popular online shopping sites is the WilBerries.ru online retail site. In 2017 Wildberries.ru had revenues of $1 billion. Wildberries.ru works in 5 countries: Russia, Kyrgyzstan, Kazakhstan, Belarus, and Armenia, with more than 20,000 employees. An example from Wildberries.ru of online reviews with the main online review's attributes is shown in <Figure 2>. For analysis, 101,248 products' reviews of women's clothing were collected, including outerwear, jeans, and blouses. The main criterion for selection was a product with more than 30 reviews (Hu et al., 2012). Based on a survey of well-known and unknown clothing brands, 100 products were selected for each brand. Using the Java programming language, web crawling was performed, data for each review: review text, star rating, image count, helpfulness votes.

4.3. Phase 2: Manipulation Detection of OCRs

In this phase, we performed the sentiment analysis, which was used to identify and extract the positive and negative parts in the text (Hlee et al., 2021). The sentiment analysis has been widely studied by text mining community researchers, especially lexicon-based approaches (Dave et al., 2003; Pang et al., 2002). To analyze the sentiment of the text in Russian, this study used a natural language pipeline polyglot in the Python programming language. Polyglot package supports massive multilingual applications and the scale of polarity consisted of three degrees: +1 for positive, 0 for neutral, and -1 for negative.

Since this study does not depend on the gradation scale and relies only on the results calculated by the formulas of the readability index, it applied ARI, CLI, and FRE for readability analysis of OCRs. ARI is one of the simplest and most common techniques for evaluating text readability and counts the measure of word difficulty in average letters per word and the measure of sentence difficulty in average words per sentence (Kincaid and Delionbach, 1973). The formula below illustrates the way of calculating ARI (Senter and Smith, 1967):

Coleman – Liau index (CLI) is a readability index that, along with the ARI, can be used to determine readers' perception of text by comparing its complexity with the official USA educational level at which, if obtained, this text can be easily understood. The formula below is used for calculating CLI (Coleman and Liau, 1975):

The next commonly used technique for analyzing text readability is the Flesch reading ease (FRE). The concept of FRE is that fewer the words in sentences and the shorter the words, the simpler the text. The formula below illustrates the method of calculating FRE (Kincaid et al., 1975):

Finally, for the detection of products with manipulation reviews, we conducted statistical test of the randomness of sentiment analysis scores (polarity) and readability analysis scores (ARI, CLI, FRE) of the reviews over time for each product. Each customer's writing style, consisting of sentiments of readability (Hu et al., 2011), is unique, therefore, if particular product reviews are indeed written by customers, then the polarity and readability scores and star rating over time of the reviews would be random. As a result of manipulations, the writing styles of observed OCRs will not be random.

Runs test for randomness or the Wald-Wolfowitz test is a non-parametric statistical test that is used to test the hypothesis with random series of numbers; also the interpretation of the results is independent

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<Figure 3> An Example of Runs Test

of any parameterized distributions. "A 'run' of a sequence simply refers to a segment consisting of adjacent equal elements" (Hu et al., 2012). As demonstrated in <Figure 3>, the 20-element-long sequence: consists of 7 runs, 4 of which consist of "+" and 3 "−." The run test is based on the null hypothesis (H0) that the sequence was produced in a random manner. In the opposite case H1, it means that the sequence was produced in a non-random manner. To obtain runs test for this research dataset, runs test (the median as the reference point) was conducted for a non-normal distribution. A positive run (n) has values that are higher than the median, and a negative run (m) has values that are lower than the median.

To conduct the runs test, the observed number of runs (R) was calculated first, the expected number of runs (E(R)), and the standard deviation of the number of runs (V(R)). The total number of positive and negative runs is the total number of runs or the observed number of runs. The values of expected number of runs (E(R)) and the standard deviation of the number of runs (V(R)) are computed as follows:

The large sample test statistic Z are computed as follows:

For the test statistic (Z) with absolute values less than 1.96, it means that the data are random. In this study, runs test is used as a manipulation index for each product, where the null hypothesis (H0) represents random (without manipulation) and H1 represents non-random (with manipulation). This study checked for randomness sentiment analysis results, readability analysis results, and the star rating for each product.

4.4. Phase 3: Prediction of Products with Manipulated OCRs

Based on Phase 2: Manipulation detection of OCRs, we calculated the average rating scores, the average polarity scores, and the average readability scores. Description of dataset for Phase 3 is shown in <Table 1>. Our research built a classification model using the average of attributes by product and tested these machine learning techniques for prediction of products with manipulated reviews. In order to predict products with manipulated reviews, the current study used previously described machine learning techniques: logit, decision tree, NN, DNN. All techniques were carried out using the Python programming language. Logit, decision tree, and NNs were provided using the free software machine learning library Sklearn. In the case of logit, the study used forward stepwise selection, thus the forward and backward stepwise selections' results were similar. In order to provide DNN, we used opensource machine learning framework TensorFlow.

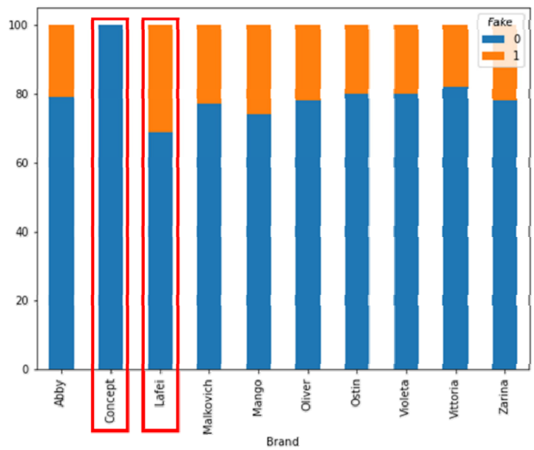
<Table 1> Description of Data

Variables	Description
AvrRaiting	Average rating scores by products
AvrPolarity	Average polarity scores by products
AvrARI	Average Readability ARI scores by products
AvrCLI	Average Readability CLI scores by products
AvrFRE	Average Readability FRE scores by products
AvrImage	Average image count by products
AvrHelp	Average number of helpful votes by products
AvrUnhelp	Average number of unhelpful votes by products
BrandDummy	1 = Well-known brand, 0 = Unknown brand
Fake	1 = manipulated, 0 = unmanipulated

Ⅴ. Analysis and Results

5.1. Manipulation Detection

Based on the manipulation detection results, the study identified 203 products with manipulated OCRs, and 797 without manipulated OCRs. Specifically, around 20% of the total products have manipulated reviews. Of the 203 products with manipulated reviews, 90 are well-known brands, and 113 are unknown brands. In the case of products without manipulated reviews, 410 were of well-known brands, and 387 of unknown brands. These results differ from the study of Hu et al. (2011), which stated that product popularity can serve as a manipulation indicator and vendors have a higher incentive to engage in online review manipulation. According to the findings, the number of products of well-known brands with manipulated reviews were lower than the number of products of unknown brands with manipulated reviews. Among the products with manipulated reviews, 44% are products of well-known brands, and 56% are products of unknown brands. As shown in <Figure 4>, all unknown brands have products with manipulated reviews, where Fake = 1 means a product with manipulated reviews, and Fake = 0 means a product without manipulated reviews. For example, one brand from the well-known brand category — Concept Club — does not have products with manipulated reviews. The largest number of products with manipulated reviews was found in the unknown brand — LAFEINIER. In the case of products of well-known brands, 18% turned out to be with manipulated reviews, while in the case of unknown brands, the percentage of products with manipulated reviews was 22.6%.



<Figure 4> Manipulation Detection by Brands

5.2. Comparison of Well-known and Unknown Brands' Products

In this research, we utilized the t-test to confirm the difference between well-known and unknown brands' products. Based on the results shown in <Table 2>, we can see the difference between the average star rating of products of well-known brands and unknown brands without manipulated reviews. The average star rating of well-known brands' products without manipulated reviews is 4.571, while in unknown brands' products without manipulated reviews, the average star rating is lower and equals 4.504, and the t-test result of these two samples is -2.16 and significant. Therefore, the answer to Q1 is that there is a difference between the average star rating of products of well-known brands and unknown brands without manipulated reviews.

Similar results can be observed in cases where there has been no manipulation (<Table 3>), the average star rating of well-known brands' products with manipulated reviews is 4.593, while in unknown brands' products with manipulated reviews, the average star rating is lower and equals 4.512, and the

<Table 2> Well-known and Unknown Brands Products without Manipulated Reviews

Without manipulation			
Brand awareness	Well-known	Unknown	t value
Number of products	410	113	
Average star rating	4.571	4.504	- 2.16**
Extreme sentiment scores	0.542***	0.533***	- 1.047

Note: *$p < 0.01$, **$p < 0.05$, *** The average of the only scores that are larger than the mean of the sentiment scores for all products.

<Table 3> Well-known and Unknown Brands Products with Manipulated Reviews

With manipulation			
Brand awareness	Well-known	Unknown	t value
Number of products	90	387	
Average star rating	4.593	4.512	- 3.017*
Extreme sentiment scores	0.565***	0.548***	-2.002**

Note: *$p < 0.01$, **$p < 0.05$, *** The average of the only scores that are larger than the mean of the sentiment scores for all products.

t-test result of these two samples is -3.017 and significant. Accordingly, we can answer Q2 that there is a difference between the average star rating of products of well-known and unknown brands with manipulated reviews. Based on these results, it can be summarized that customer perceive more positive well-known brands' products than unknown brands' products regardless of the absence or presence of manipulation.

To answer Q3 and Q4, we selected products with extremely positive sentiment scores, where average sentiment score is higher than the mean of the sentiment scores for all products. Based on <Table 2>, we can see the difference between the average of extremely positive sentiment scores of well-known brands' products and that of unknown brands' products without manipulated reviews. The average of extremely positive sentiment scores of well-known brands' products without manipulated reviews is 0.542, while in unknown brands' products without manipulated reviews, the average extremely positive sentiment scores is 0.533. However, since the t-test result of these two samples is not significant, the answer of Q3 is: there is no difference between extremely positive sentiment scores of products of well-known brands and unknown brands without manipulated reviews.

Nevertheless, as we can see from <Table 3>, in the case of manipulation presence, the t-test result of well-known brands' products with extremely positive sentiment scores and unknown brands' products with extremely positive sentiment scores is significant, therefore we can answer to Q4 that there is the difference between extremely positive sentiment scores of products of well-known brands and unknown brands with manipulated reviews. Moreover, the average of extremely positive sentiment scores of well-known brands' products with manipulated reviews is 0.565, and that of unknown brands' products with manipulated reviews is 0.548.

5.3. Prediction of Product with Manipulated OCRs

In order to predict products with manipulated reviews, we conducted machine learning techniques

<Table 4> Prediction of Product with Manipulated OCRs

Model	Prediction accuracy
Logit	58%
Decision tree	51%
Neural networks (NN)	61%
Deep neural networks (DNN)	78%

such as logit, decision tree, NN, and DNN. <Table 4> shows the results of prediction performance. The prediction accuracy of products with manipulated OCRs was the highest at 0.78 in DNN. Accordingly, the answer to Q5 is that DNN is a more useful technique for predicting products with manipulated reviews.

Ⅵ. Conclusion

6.1. Summary of Findings

This research has several findings that will be illustrated as follows. First, we proposed a method to identify products with manipulated OCRs by examining the sequence of each review polarity (sentiment scores), readability scores, and rating scores by product on randomness. This method was partially adapted from the study of Hu et al. (2012). The manipulation detection method is based on the idea that each customer has a different background, therefore, reviews written by different customers will also be different and unique (Li et al., 2020). In this research, we discovered that around 20% of total products are manipulated.

Second, we examined the association between brand awareness and the prevalence of manipulation with product OCRs. Based on previous studies, it is clear that brand awareness impacts brand perception by a customer, and brand awareness influences a customer's purchase decision-making process (Graciola et al., 2020). Consequently, we discovered that among the products with manipulated reviews, 44% belong to well-known brands, and 56% are of unknown brands.

Third, this research analyzed the differences in the nature of OCRs' extremely positive sentiments and average star rating with and without manipulation of products of well-known and unknown brands. Previous researchers proposed that manipulation of reviews is most often a generation of fake positive reviews with high (five stars) rating scores (Mayzlin et al., 2014), however, they have not counted brand awareness impact to the presents of review manipulation. In our research, we investigated a difference between the average star rating of products of well-known brands and unknown brands without and with manipulated reviews. The answers to research questions Q1 and Q2 clearly show that in both cases, without and with manipulation, there is a difference between the average star rating of products of well-known brands and unknown brands. However, after the selection of products with extremely positive sentiment scores, products without manipulation and products with manipulation showed different results. On the one hand, in the case of products without manipulated reviews, there is no difference between extremely positive sentiment scores of products of well-known brands and unknown brands. On the other hand, in the case of products with manipulated reviews, there is a difference between extremely positive sentiment scores of products of well-known brands and unknown brands. Therefore, we can assume that in the absence of manipulation, the effect of brand awareness on the extremely positive sentiments of the customer decreases, as the result, the customer does not see the difference between a popular brand and an unpopular one.

Finally, we also tested different machine learning techniques for predicting products with manipulated reviews and attempted to identify more useful one. Findings suggested that the Deep Neural Network (DNN) is a more useful technique for predicting products with manipulated reviews.

6.2. Contributions

Our study makes several interesting contributions to theory and research. First, previous researchers proved that brand awareness impacts brand perception by a customer, and brand perception influence a customer's purchase decision-making process (Huang and Sarigöllü, 2014). Since our research proved that in both cases, with and without manipulation, the average star rating of well-known products is greater than the average star rating of unknown products, our research can serve as proof that brand awareness influences customers evaluation of the product after purchase regardless of the presence or absence of manipulation. In other words, regardless of the presence or absence of manipulation, customers tend to give a higher rating to well-known products than unknown ones. However, in the case of the absence of manipulation, the effect of brand awareness on the extremely positive sentiments of the customer decreases, as the result, the customer does not see the difference between well-known brands and unknown ones. Therefore, in research settings when the effect of brand awareness on products perception is evaluated, the extremely positive sentiments and the existence of manipulation should be taken into account.

Second, previous researchers associated review star rating and reviews sentiments as variables that have a similar value with similar impact (Hu et al., 2011), however, in our research, the average star rating and the extremely positive sentiments showed different results. We, therefore, hope that, by uncovering the difference between customer-given star rating and review sentiments, our study provides an impetus for further research in the context of detection products with manipulated reviews.

Our study carries several practical contributions as follows. First, for online retail sites providers, our study provides insights that both well-known and unknown brands use manipulation of the review as an instrument to influence the customers' purchase decision-making process, but unknown brands use manipulation to a greater extent. Since manipulative actions might hurt the overall reputation of the sites, therefore, our results might help sites providers to identify brands that generate manipulated reviews and punish them.

Second, we also see practical implications that should be considered by the creators of brands and products retailers. Creators should be aware that, even though product review star rating can be a decisive factor for campaign success and an important product quality signal, regardless of the presence or absence of manipulation, customers tend to give a higher rating to well-known brand products than unknown ones. However, the presence of manipulation can increase the influence of brand awareness in the perception and evaluation of the product by customers.

6.3. Limitations and Further Research

This research provides important insights for both research and practice. However, we acknowledge certain limitations that have to be considered in further research. First, in this study, we examined only the sequence of each review sentiments scores, readability scores, and rating scores by product on randomness to identify products with manipulated OCRs. Further researchers can explore other methods of detecting manipulation, such as other non-machine learning methods or unsupervised learning methods. Also, there may be new factors that have a potential effect on the detection of manipulation, which future researchers can explore deeper.

Second, in our research, we examined products with and without manipulated reviews by brand awareness, however, future researchers might examine products with and without manipulated reviews by other factors such as location (international or domestic brands). Finally, we used only women's clothing brands' product reviews from Russian retail site, therefore future researchers might explore different types of products, not just women's clothing from other sites.

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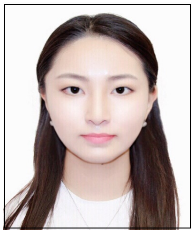

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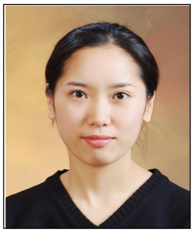

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