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Exploring E-Commerce Big Data and Customer-Perceived Value: An Empirical Study on Chinese Online Customers

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Received: 31 August 2020; Accepted: 14 October 2020; Published: 19 October 2020

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Abstract: The purpose of this study is to make good use of the massive amount of online user comment data to explore and analyze the dimensions of customer-perceived value and the importance of each dimension, given the background of China's huge e-commerce market. We compiled a web crawler program to collect online comment data from online reviews. The crawled data were pre-processed and content analysis were performed. A customer-perceived value dictionary was constructed based on the extraction of frequent terms, literature review, and expert opinions. We re-identified the dimensions of customer-perceived value to include four key dimensions and corresponding subdivisions. Both the rationality and operability of the dimension model of customer-perceived value were validated and applied. Thereafter, the importance of various dimensions and the impacts of customer-perceived value dimensions on customer loyalty were analyzed and discussed. The empirical research results reveal that all four dimensions of customer-perceived value play an important role in customer-perceived value and that the patterns and degrees of the role of each dimension are rather different. Further, only certain parts of the dimensions of customer-perceived value have an impact on customer loyalty, and the degree of the impact differs substantially.

Keywords: e-commerce; big data; customer-perceived value; data mining; online reviews

1. Introduction

With the ongoing development of e-commerce, online shopping and the online shopping population are both rapidly expanding. The increase in the number of online transactions in China's retail market has eliminated the regional pattern of the market and changed the mode of shopping and value generation. First, the convenience of obtaining product information has greatly improved for customers, and the pattern of information asymmetry between consumers and operators is quietly changing. In the era of social connectedness, people are becoming increasingly enthusiastic about interacting, sharing, and collaborating on online collaborative media [1]. Second, the ability of consumers to evaluate their purchase experience and product use online enables information to be disseminated faster and to a much wider audience, thereby substantially increasing the importance of the word-of-mouth effect [2]. Third, consumers' quality preferences, individualized demand, and rational consumption trends are becoming more well known, thereby making it more difficult to attract customers simply by reducing product prices.

Better knowledge of customers' perceptions and needs is essential to understanding the value that consumers place on products and their loyalty to such products, which is crucial information for e-commerce platforms, enterprises, and brands. Online customer review data generated by e-commerce platforms is an important resource for understanding target customer groups. Online reviews contain valuable information that reflects the actual perceptions of users and affects the purchasing decisions of potential consumers. In a situation where an organization is interested in knowing the opinions of its customers regarding the product that it has manufactured or sold, it is rather difficult for the organization to keep track of each and every opinion [3]. How useful information can be extracted from massive semi-structured, or even unstructured, comments has become a hot research topic [4]. The development and application of big data and sentiment analysis technologies provide convenient tools for the analysis and processing of massive amounts of information. Thus, the information mining of online comments on e-commerce platforms based on big data technology is a subject that requires further exploration.

The purpose of our study is to explore the sources and results of customer-perceived value in the context of online shopping. We aim to evaluate and identify how to use online reviews to mine the source of customer-perceived value and determine which factors customers actually value in the e-commerce context. From the perspective of platforms and business, focusing on customer-perceived value is fundamental to improving competitiveness, and it is hoped that customer loyalty can be enhanced by better understanding the source of perceived value.

This research is based on large-scale, first-hand data from the online reviews of the top 10 mobile phone brands on the online shopping site Jindong from 2013 to 2016. We conduct content analysis using a mix of text processing and manual classification of terms using expert opinions and literature search. Customer-perceived value dimensions are redefined specifically into three levels. Sources of customer-perceived value and customer loyalty in the context of e-commerce are explored. On the basis of previous studies, this research innovatively indicates that the dimensions of customer-perceived value cannot be simply divided into perceived gains and perceived losses. In fact, each dimension and subdividing factor must include the two aspects of perceived gain and perceived loss. Another highlight of this study is that, unlike previous studies on customer-perceived value in the context of online shopping, this study uses a large sample of first-hand data to conduct empirical research. In this article, the dimensions of perceived value are extracted from a unique perspective and the important concept of customer loyalty—which is related to customer value—is innovatively introduced. Exploring the causes and consequences of customer-perceived value in the context of online shopping and customer loyalty based on first-hand data is an interesting exploration of customer value and customer loyalty.

The main part of the article is arranged as follows: We first review the literature of related works. We use the Python programming language to compile a web crawler program to gather online comment data from the online reviews. After obtaining the original data, the crawled data are pre-processed and content analysis and feature extraction are performed. To ensure the representativeness and accuracy of feature extraction, we invite industry experts and people with rich experience in purchasing and reviewing to guide and manually revise keywords. A customer-perceived value dictionary is constructed after several adjustments. Next, combined with literature research, we summarize and classify the keywords in the customer-perceived value dictionary, conclude the dimensions of customer-perceived value of online customers, and construct the dimension model of customer-perceived value. Finally, the rationality and operability of the dimension model of customer-perceived value are validated and applied, and the impact of various dimensions of customer-perceived value on customer-perceived value and customer loyalty is analyzed.

2. Related Works

Online customer reviews can be defined as peer-generated product evaluations posted on company or third-party websites [5]. These reviews usually consist of comments posted by customers on the shopping website based on their own purchases and usage and include feedback on their purchase process, purchase experience, evaluation of products, and opinions. Online reviews have an important impact on customers' purchasing decisions. Online comments are one of the most important forms of online word-of-mouth [2]. Online customers tend to share their shopping experience, thereby creating online word-of-mouth, and tend to take into consideration other customers' online reviews before making their own shopping decisions [3]. Online consumer reviews and comments have been found to significantly influence consumer decision-making [6] and the business bottom line [7,8]. The online commentary of customers is not only an intuitive expression of the feelings, experiences, evaluations, and emotions of people who have already purchased the products but also an important reference for potential consumers to judge the value of products [9,10]. In other words, all online reviewers have a dual identity as information providers and recommenders; moreover, the product quality, presale service, logistics, and other issues mentioned in online reviews are the important antecedents of customer-perceived value.

Online review data contains a lot of information as well as indicates the emotional tendency of customers [11]. It is of great significance to analyze the attitude of customer comments and to understand the emotional tendency distribution of online reviews. The development and application of big data technologies provide convenient tools for the analysis and processing of massive amounts of information. Big data technologies have a strong impact on different industries, and text mining is being used in various fields [12]. One such analysis approach is that of sentiment analysis, which has proved popular over the years [1,13]. For sentiment analysis, massive data such as product reviews, movie reviews, restaurant reviews, or social media data on the Internet are all treasures to be explored [13]. Research on sentiment analysis in the English language has undergone major developments in recent years. An increasing number of publications is tackling the multilinguality issue [14]. However, Chinese sentiment analysis research has not evolved significantly [15]. With the exponential growth of Chinese e-business and e-markets, sentiment analysis will continue to be a hot research topic in the field of data mining and information processing in the future.

Customer-perceived value is an important concept in marketing. It is a key feature used to define the attraction of goods or services to customers, which is the main reason that customers are interested in certain products [16]. Customer-perceived value can exert great influence on customers' attitudes [17], satisfaction [18], loyalty [19], and purchase intentions [20]. Customers play the role of co-producers in the process of value creation, especially in a context of digital transformation [21,22]; they are not merely value-receivers. We are in an era that attaches great importance to user experience and individual psychological feelings. As customers become increasingly demanding and value-conscious [23], capturing the essence of customer-perceived value has become important for companies. Brands and products that are more willing to pursue customer value are more likely to take the lead in the fierce market competition [24]. Analyzing and understanding the components of customer-perceived value, clarifying the causes and consequences of customer-perceived value, and improving customer-perceived value are key to gaining a sustained competitive edge.

The traditional means to obtain relevant information regarding customer-perceived value is to design questionnaires for target customer groups. The questionnaire survey is a well-developed method with numerous advantages, but it also has a few disadvantages, such as high cost, long processing time, and inconvenient sample acquisition. This research is based on first-hand data from the online reviews of the top 10 mobile phone brands on Jingdong, from 2013 to 2016. The time span is wide, and the amount of data is relatively large. We can obtain a giant convenience sample with less time and cost. To a certain extent, this can make up for the shortcomings of traditional methods. In the context of current big data technology applications, the technology of big data collection and big data analysis can be used to improve the existing customer-perceived value model so it can inspire product improvement and brand promotion.

3. Materials and Methods

In this study, we employed the Python programming language to compile a web crawler program to collect online comment data from the online reviews of 10 mobile phone brands sold on Jingdong from 2013 to 2016. Our data included 2,922,355 online comments. After obtaining the original data, we pre-processed the crawled data and performed content analysis and feature extraction. In order to ensure the accuracy and representativeness of feature extraction, we invited industry experts and people with rich experience in purchasing and reviewing to guide and manually revise the keywords. Finally, a customer-perceived value dictionary was constructed. Thereafter, combined with the literature review, we summarize and classify the keywords in the customer-perceived value dictionary, conclude the dimensions of customer-perceived value of online customers, and construct the dimension model of customer-perceived value. Finally, we validate and apply the rationality and operability of the dimension model of customer-perceived value. Thereafter, in this section, we analyze the importance of various dimensions and the impacts of customer-perceived value dimensions on customer loyalty.

3.1. Data Source and Basic Information

Jingdong (jd.com) is the largest business-to-customer (B2C) e-commerce platform in China and one of the largest e-commerce platforms in the world [25]. A lot has been done to ensure that online customer reviews on Jingdong are reliable and of a high quality. According to Jingdong's review creation guidelines, by providing references for other consumers regarding shopping decisions and business decision-making, consumers can make a fair, objective, and true evaluation of the order after the transaction is completed. Reviews are constituted of text and a rating on a scale from one to five stars, with five being the top rating. All reviews are dated according to the time at which they are first posted, which makes it possible to track consumer opinions over time. These reviews do not regard only the product itself but also everything about the seller, including the shipping and delivery experience, as well as anything that reflects a customer's impression of the brand that may affect investor decisions. In addition, Jingdong is the largest self-operated e-commerce platform in China, which implies that Jingdong sells most products on the platform itself; thus, there is no conflict of interest, no paid reviews or sellers posting positive reviews for their own products, or negative reviews of competing products [26]. In addition, sophisticated technical tricks like captcha are also employed to prevent possible bots and spam [27]. Therefore, we selected Jingdong as the research platform, and we chose the most representative and mature mobile phone products on Jingdong as the research samples. Our study synthetically refers to the brand ranking information published by CNPP Brand Data Research Institute (Asia), China Brand Network (Chinapp), and other websites, as well as the sales rankings on Jingdong; we selected over 300 models of 10 mobile phone brands as samples. These 10 brands are basically in line with the popular perception of the mainstream mobile phone brands in the current Chinese market and include Huawei, ZTE, MI, Meizu, Nubia, LeEco, Lenovo, VIVO, OPPO, and APPLE.

We used API to crawl the commentary data of mobile phones on the Jingdong website. The attributes included in this study are comment id, score, content, and product information (reference name), where comment id is an integer, score is an integer between 1 and 5, content is the text content of the comment created by the commentator, and reference name is the title (including brand, model number, etc.) that is used when a product is displayed for sale.

3.2. Construction of the Customer-Perceived Value Dictionary

We constructed a customer-perceived value dictionary based on actual online customer reviews, combined with existing research results and expert opinions. First, the most frequently used words in the reviews were mined. Specifically, we took each comment as a document and used unigram, which corresponds to term frequency (TF), to count the frequency of words. According to frequent word patterns, we identified a set of keywords consisting of a large number of words related to customer-perceived value. Second, word frequency simply counts the number of times that each word appears in a text. The keywords or phrases extracted only on the basis of this method have great uncertainty and often contain noise, particularly for longer texts; therefore, we needed to introduce manual means for further processing. In this case, we artificially decomposed and classified candidate keyword sets on the basis of word frequency. We combined automatic word frequency extraction with manual sorting to ensure the accuracy and unity of user needs' recognition results. Finally, because of the large number of product feature words in the keyword set, which are rather subdivided and overlapping, on the one hand, we referred to the existing research results through literature research, and on the other hand, under the guidance of product experts in the industry, we established a mobile phone-specific product evaluation system to artificially correct frequent words. Please refer to Appendix A for expert background information and the consultation process. Based on the modified frequent word results, we established a unified and scientific dictionary system of customer-perceived value. The process logic is presented in Figure 1.

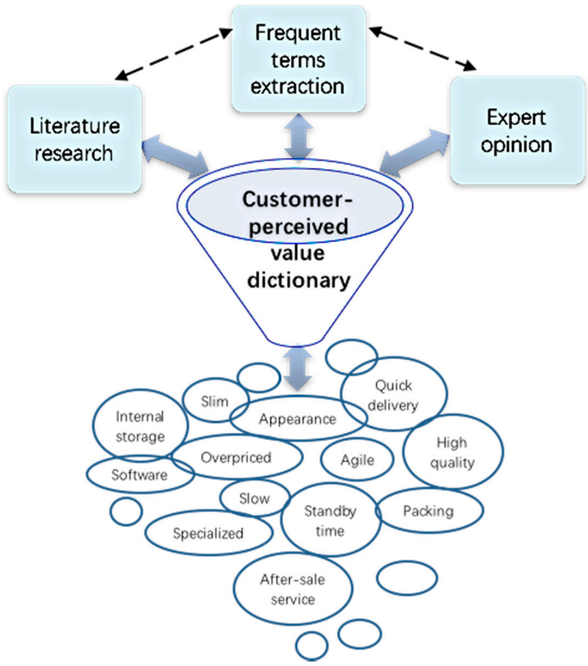

Figure 1. Construction of the customer-perceived value dictionary.

The customer-perceived value dictionary is based on literature research, extraction of frequent terms, and expert opinions. Due to the great difference in semantics between Chinese and English words, only a few high-frequency words are selected for the illustration. The entire construction process of the customer-perceived value dictionary is depicted in Figure 2.

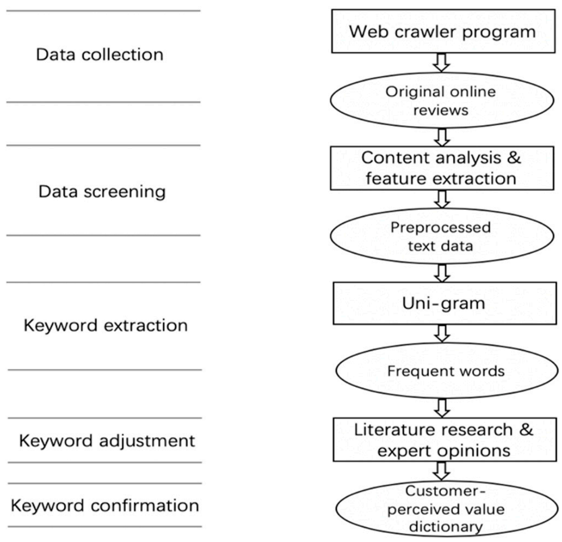

Figure 2. Flow chart of the construction of the customer-perceived value dictionary.

3.3. The Customer-Perceived Value Dimension Model

The concept of customer-perceived value has become one of the most popular approaches of business managers and marketing researchers [28,29]. From the perspective of consumers, it is the maximization of value that is most important, which is measured as the difference between the income and cost [30]. Consumers form value expectations and act accordingly. They are concerned with regard to whether the value of the product they need is in line with the expected value. If the actual value of the product is higher than the expected value, consumer satisfaction and repurchasing could happen. On the contrary, if the actual value of the product is lower than the expected value, consumers will not be satisfied and will not repurchase.

Customer-perceived value is a subjective feeling that a consumer undergoes while purchasing products or services; it represents a trade-off between benefits and costs. Customer-perceived value is a perceived utility of products or services relative to the purchase price [31], a perceived product quality relative to the cost of products [32], a dynamic rather than static concept [6], and an interactive and preferential experience [33]. Further, customer-perceived value is a customers' assessment of the value of products, services, service contacts, information, and other elements that the customer purchased [34]. The relationship between enterprises and consumers develops over time, thereby implying that customer-perceived value is reflected better in the long term. When selecting a product, consumers make their purchase decisions based on the comparative relationship between the benefits they expect from the product and the cost they pay for it. Customer-perceived value is not only the starting point but also the result of relationship marketing. It is generally believed that the driving factors of customer-perceived value and the sources of customer-perceived value are the dimensions of customer-perceived value [35]. However, the factors that affect customer-perceived value and the sources that constitute customer-perceived value are still being researched.

A majority of early studies considered that customer-perceived value consists of two aspects: quality and price. For example, the study entitled "Profit Impact of Market Strategies" [36] proposed that customer-perceived value is determined by product quality and relative price. In order to analyze different consumption situations and product types, subsequent research has proposed several multidimensional models of customer-perceived value [6,29]. One of the most important developments in the research of customer-perceived value dimensions is the emergence of the relational marketing perspective [26,37,38]. Customer-perceived value not only originates from core products and ancillary services but also includes efforts to maintain relationships, which can create value by developing valuable and sustainable customer relationships. Further, online shopping is based on the Internet, which is rather different from the traditional mode of shopping. In addition to the monetary cost, customers' shopping costs include time cost, energy, and exertion of physical strength. Moreover, the content of service quality in the network environment has changed greatly compared with the traditional mode. Research on customer-perceived value in the network environment is relatively inadequate. Most researchers have applied former models to extend the research to online business in recent years [39–41].

Various definitions of customer-perceived value suggest that it has anywhere from one to eight dimensions [42,43]. Summarizing the existing definitions, they have the following outstanding common characteristics: Most scholars agree that the core of customer-perceived value is the trade-off between perceived gains and perceived losses, whereas a few scholars believe that perceived value is merely perceived gains. More importantly, with the continuous evolution and improvement of the definition, the connotation of perceived gain and perceived loss is becoming more comprehensive. The gains do not include only the quality of products or services, and the losses do not include only the price of products or services. Customer-perceived value is closely related to the use of products or services, which is generated in a specific use situation. Customer-perceived value is subjective because it is determined by customers rather than enterprises. This study summarizes the key points of the concept of customer-perceived value on the basis of existing definitions: (1) It is based on a customer's subjective judgment; (2) it is affected by numerous factors, with individual, temporal, and spatial differences; and (3) it is a comprehensive measurement of perceived gains and perceived losses.

From the description of the dimensions of customer-perceived value, it is evident that the divisions of the perceived value dimensions lack clear criteria and the degree of research is not systematic nor adequately in-depth. Moreover, most of these dimensions are general high-level descriptions. However, in the investigation and application of customer-perceived value, we usually need to refine these high-level dimension concepts into concrete, quantifiable, and practical indicators. In the present study, we attempt to redefine the dimension of customer-perceived value. This research synthesizes the existing research results and considers the difference between the online shopping and traditional shopping modes. After an in-depth analysis of the content of customer online reviews and the existing research, we combined the customer-perceived value dictionary constructed previously to perform a comparative analysis and redefine the dimensions of customer-perceived value in an e-commerce environment. The first dimension contains four indicators: product quality, process perception, risk perception, and emotional value. Each indicator is subdivided into two levels according to the actual situation.

4. Results

The customer-perceived value dictionary is based on frequent terms extraction, literature research, and expert opinions. Literature research established the scope of the first level dimensions for us. High frequency words were extracted automatically and irrelevant noise was eliminated manually. Then the relevant high frequency words were artificially expressed, generalized, and classified into a more standardized and understandable third level dimensions one by one. Similarly, in order to move closer to the first level dimensions, the third level dimensions were further generalized and classified into the more generalized dimensions of the second level. Finally, we tried to fill our second level dimensions into the dimensions that had ever appeared in the literature. We ended up with four matches, which are our four first level dimensions (Table 1).

Table 1. Dimensions of customer-perceived value.

<table>
<tr><th></th><th>First Level</th><th>Second Level</th><th>Third Level</th></tr>
<tr><td rowspan="15">Customer-Perceived Value</td><td rowspan="5">product quality</td><td>appearance</td><td>attraction, size, weight, completeness</td></tr>
<tr><td>components and functions</td><td>screen, battery, camera, internal storage, system, software, unlock menu, headset, charger, keypad, receiver (sound quality), communication (signal), network connection</td></tr>
<tr><td>accessories</td><td>quality, types, fees</td></tr>
<tr><td>price</td><td>price</td></tr>
<tr><td>overall evaluation</td><td>overall evaluation</td></tr>
<tr><td rowspan="3">process perception</td><td>customer service</td><td>pre-sale service, after-sales service</td></tr>
<tr><td>logistics</td><td>delivery, personnel, professionalism</td></tr>
<tr><td>transaction</td><td>information acquisition, personalized recommendation, order placement, return policy, maintenance and disposal</td></tr>
<tr><td rowspan="4">emotional value</td><td>marketing empathy</td><td>advertising, sales promotion, giveaway</td></tr>
<tr><td>brand impression</td><td>major brands, domestic brand, time-honored brand, professional</td></tr>
<tr><td>emotional atmosphere</td><td>reputation, corporate values</td></tr>
<tr><td>social value</td><td>public welfare and charity, social responsibility, positive energy propagation</td></tr>
<tr><td rowspan="3">risk perception</td><td>economy</td><td>customer cost</td></tr>
<tr><td>security</td><td>transaction security, safety in use</td></tr>
<tr><td>privacy</td><td>privacy</td></tr>
</table>

Due to the great difference in semantics between Chinese and English words, we did not list all the extracted high-frequency words in this table. Moreover, we placed the "overall evaluation" under the category of product quality rather than other categories, because a few general and fuzzy descriptions of product quality such as "high quality" and "satisfactory quality" are often mentioned in customers' online reviews and such a general evaluation is not outstanding in other categories. In contrast with previous studies, this research indicates that the dimensions of customer-perceived value cannot be simply divided into perceived gains and perceived losses. In fact, each dimension and subdividing factor must have two aspects of perceived gain and perceived loss. For example, risk perception may produce perceived gain (risk perception is lower than expected) or perceived loss (risk perception is higher than expected) as well as other dimensions and factors.

According to the evaluation criteria of online customer reviews, each product has a score that ranges from 1 to 5 given by customers, thereby indicating their evaluation of the product. The higher the score, the higher the level of customer-perceived value.

4.1. Corroborating Our Findings with Those of Existing Studies

On the one hand, we verify a few classical conclusions of customer-perceived value and prove the validity of this research method. For example, in this study, the first dimension of customer-perceived value includes four factors: product quality, process perception, risk perception, and emotional value. When analyzing the first dimension, all four factors have an impact on customer-perceived value, and product quality is always the most important factor. With an increase in the score, there was an increase in the proportion of keywords related to product quality, whereas the proportion of other keywords decreased or remained basically unchanged. This indicates that the factor of product quality has a significant and positive impact on customer-perceived value. The higher the quality evaluation, the higher the customer-perceived value.

The data analysis also reveals that product quality is the main factor of the low-score and high-score sections, which indicates that the impact of product quality on customer-perceived value is not only significant for perceived gains but also for perceived losses. This is consistent with existing research [29,44,45] and our previous knowledge. Consumers pay more attention to product quality. From the first-level dimension, it is evident that product quality is the most important factor affecting customer-perceived value; it is a fundamental factor in satisfying consumers and improving customer-perceived value (Figure 3).

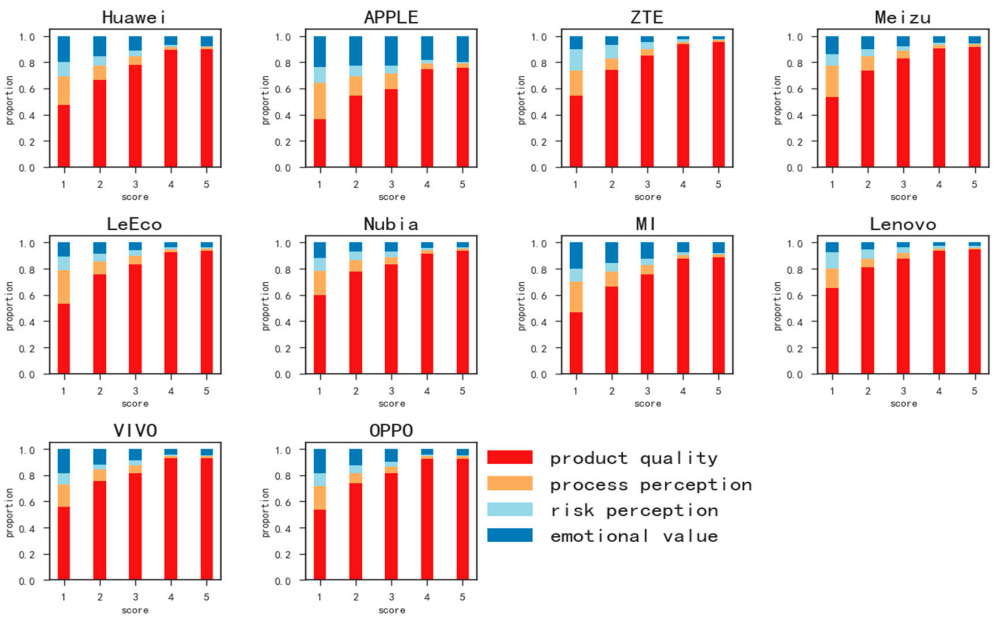

Figure 3. Importance of the first-level dimensions for 10 brands.

Another example is that, when we analyzed how the second-level factors (appearance, components and functions, accessories, prices, and overall evaluation) related to product quality, we found that 10 brands have a few common characteristics. With an increase in the score, the proportion of keywords related to the overall evaluation increases, the proportion of keywords related to functions and components decreases, and the proportion of keywords related to appearance first increases and then decreases. The proportion of price-related keywords is on the low side and it is basically stable or slightly increased with an increase in the score (Figure 4). The analysis of the second-level indicators of product quality reveals that product quality is more of an evaluation of overall quality in the minds of customers. Dissatisfaction with specific functions or components can easily lead to perceived losses—that is, customers will give negative reviews because they are dissatisfied with a function or component of the product, but satisfaction must be due to the satisfaction with the overall product quality rather than with specific components or functions. Thus, pricing strategy is not an important factor affecting perceived value for customers who have already indulged in purchasing behavior (purchasing implies that the price is within the scope of psychological acceptance). Satisfaction and dissatisfaction are mainly affected by subsequent feelings.

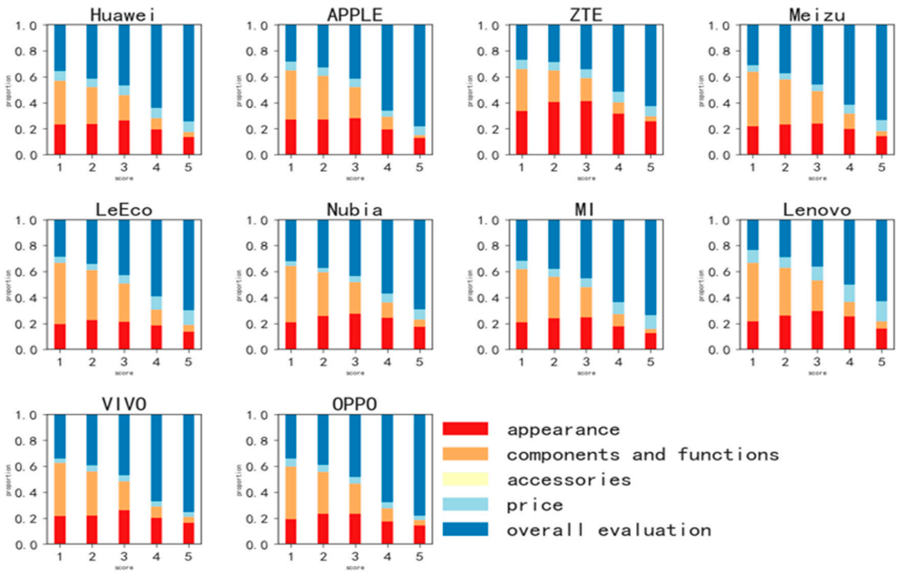

Figure 4. Importance of the second-level factors of product quality for 10 brands.

On the other hand, because our study data are relatively sufficient, and the division of perceived value dimension is more detailed and comprehensive, it is possible to identify additional subtle features in our study that differ from previous studies. Our study provides certain meaningful new discoveries.

4.2. A Few Enlightening Findings

4.2.1. The First Level of Process Perception and Risk Perception

Online review data indicate that a large proportion of online reviews that represent poor reviews reflect the problems of process perception, such as presale service, after-sales service, and logistics (Figure 3). This indicates that the impact of process perception on customer-perceived value is more embodied in the perception of losses. In other words, good process perception can only lead to an absence of dissatisfaction and does not have much effect on improving customer-perceived value. However, poor process perception will directly lead to customer dissatisfaction and poor perceived value experience. Risk perception is similar to process perception. It mainly concentrates on the low score section, thereby indicating that security and privacy are the basic needs of online customers when they are shopping online. If these basic needs are not met, customers will be dissatisfied and have a low perceived value, but if these basic needs are met, it only implies an absence of dissatisfaction among consumers. For customer-perceived value, process perception and risk perception are both hygiene factors.

4.2.2. The First Level of Emotional Value

The influence of emotional value is more obvious in the low-score section; in the high-score section, this influence tends to be stable and increases slightly (Figure 3). This indicates that, in the low-score section, low emotional value causes customer dissatisfaction, whereas high emotional value does not have a significant or positive impact on perceived value. In the high score section, emotional value has a stable and positive impact on perceived value. The role of emotional value factors in products or brands with high customer-perceived value cannot be ignored. Emotional value is a higher-level factor. When products and brands are weak in foundation and lack practical experience, they can first strive to achieve an absence of negative emotional value output and temporarily focus on the improvement and promotion of basic factors, such as product quality, process optimization, and risk control. However, to a certain extent, if products and brands have the objective of becoming bigger, better, and stronger, they must begin to pay attention to the construct of emotional value. In the course of marketing activities and other social activities, such brands must focus on developing a good brand image, assuming social responsibility, and embodying social value.

4.2.3. The Second Level of Emotional Value

The second-level factors in the dimension of emotional value include marketing empathy, brand impression, emotional atmosphere, and social value. Secondary indicators in the dimension of emotional value have few commonalities and large brand differences (Figure 5). First, the proportion of keywords related to brand image in Chinese mobile phone brands, such as Lenovo, Nubia, Huawei, and ZTE, is relatively high and mainly concentrated in the high score sections. Perhaps because these four brands have relatively domestic presence, numerous consumers who support domestic products have repeatedly mentioned relevant terms in their comments. Second, Apple, MI, and Meizu mobile phones accounted for a particularly high proportion of words related to the emotional atmosphere, and the proportion increased gradually with an increase in the score. In fact, all three brands have loyal fans and are more praised in corporate culture, word-of-mouth, reputation, and other aspects, which also proves the high proportion of words that indicate the emotional atmosphere.

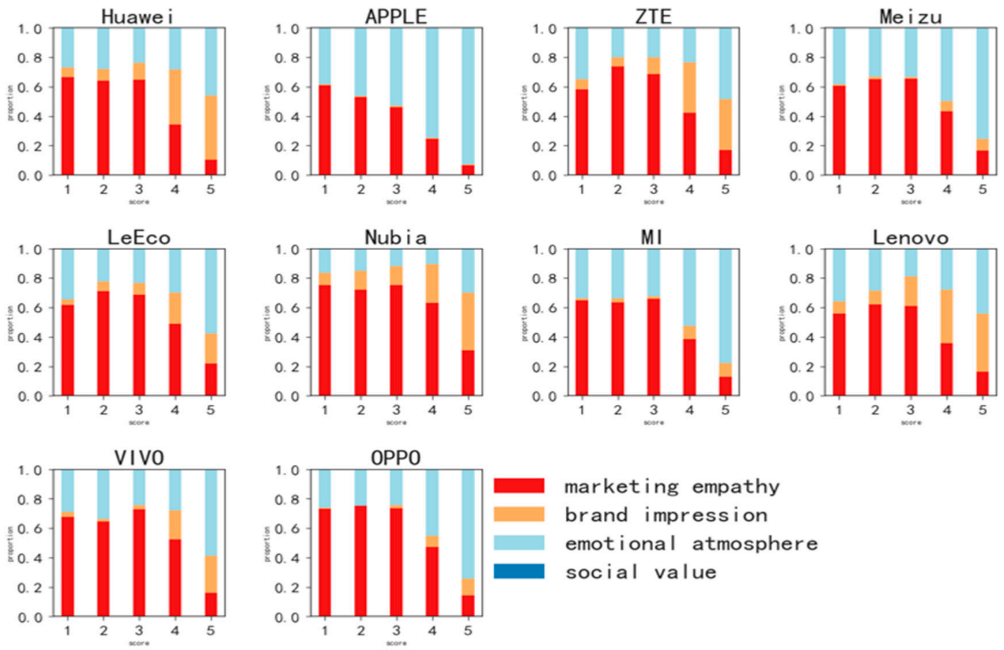

Figure 5. Importance of the second-level dimensions of emotional value for 10 brands.

4.2.4. The Second Level of Process Perception

The secondary indicators in the process perception dimension are customer service, logistics, and transaction. Through the analysis of online review data, in all scoring sections, the customer service index accounts for the largest proportion of online reviews, followed by transactions, and then logistics (Figure 6). This indicates that customers' perceptions and experience of customer service is the most important part of the process perception dimension, followed by the perception of the transaction and then the perception of logistics. The value of customer process perception is mainly indicated by the perception of the interaction with and relationship maintenance by relevant personnel.

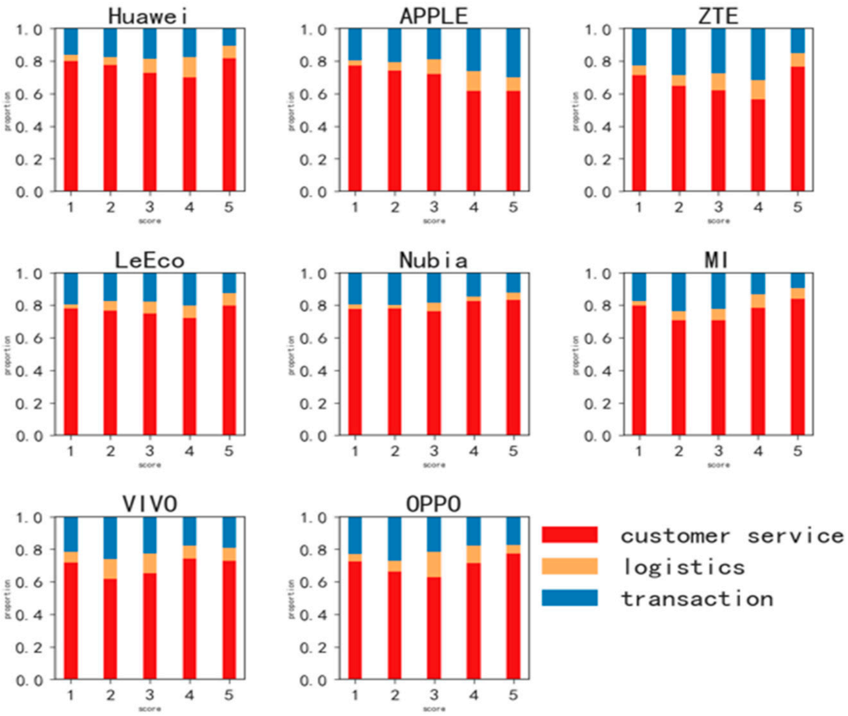

Figure 6. Importance of the second-level factors of process perception for 10 brands.

The second-level factors of risk perception include three indicators: economy, security, and privacy. Through the analysis of online review data, we find that privacy-related content accounts for the majority of the comments, followed by economy and security. First, this indicates that the security of online shopping (transaction security and use security) is basically guaranteed; thus, customers rarely mention this aspect in their comments. Second, in terms of the economy indicator, the proportion of Meizu, MI, and OPPO brands are significantly higher than that of other brands, which indicates that the economic performance of these three brands is of greater concern for consumers. Each sample brand has a high proportion of privacy-related content, and there is no obvious trend across scores. This indicates that customers of each brand are almost equally concerned about privacy. Judging from the sections with a score of 1 and 5, all 10 brands appear to have one thing in common—that is, the proportion of privacy-related reviews in the 5-score section is lower than that in the 1-score section. In other words, relatively speaking, the proportion of privacy-related content mentioned in bad reviews is greater than that mentioned in good reviews.

As a supplement, we performed correlation analysis and principal component analysis to further explore and verify the role of each factor. The first dimension only has one principal component—product quality. In the second-level dimension, the main factors are overall evaluation and appearance. Further, the results of the principal component analysis are consistent with the conclusions of the preceding analysis. In addition, the value of customer service in process perception, emotional atmosphere and marketing empathy in emotional value, and privacy in risk perception must also be considered.

5. Extension and Application

The dimensions and evaluation methods of customer-perceived value constructed in this study have strong operability. Therefore, we have made a useful expansion and found that these methods can also help to describe customer loyalty. Due to the dictionary and division of dimensions based on users' big data information, we can draw relevant conclusions regarding the effect of customer-perceived value dimensions on customer loyalty.

Customer loyalty refers to the extent to which customers regularly repeat purchases based on their preference for enterprises or brands. Customer satisfaction measures the degree to which customers' original expectations are met in past transactions, whereas customer loyalty measures customers' willingness to buy again and participate in activities [34]. According to previous studies, there are two widely accepted measures of customer loyalty: repeated purchase intention and recommendation intention. Our study extracted a set of keywords (e.g., repurchase, regular customer, recommendation) from online reviews and obtained the level of customer loyalty for each brand. The specific calculation method depends on the frequency of pre-set keywords/number of comments. Analogously, the computational method of recommendation intention for each dimension is the number of occurrences of keywords in the dimension/the number of all comments in the dimension. Therefore, the scatter diagram is linearly regressed and Pearson's correlation coefficient and *p*-value are calculated. The criteria are a Pearson's correlation coefficient that is greater than 0.3 and a *p*-value less than 0.05. The red solid line is the result of linear regression fitting. Please refer to Appendix B for the results of the full sample. The red line in Figure 7 is the one that passes the criterion. We can intuitively determine the correlation between perceived value dimensions and customer loyalty. For example, take the first-level dimensions—we randomly select the 2017 data for emotional value and the 2014 data for process perception (Figure 7). It is evident that emotional value and process perception are closely related to customer loyalty.

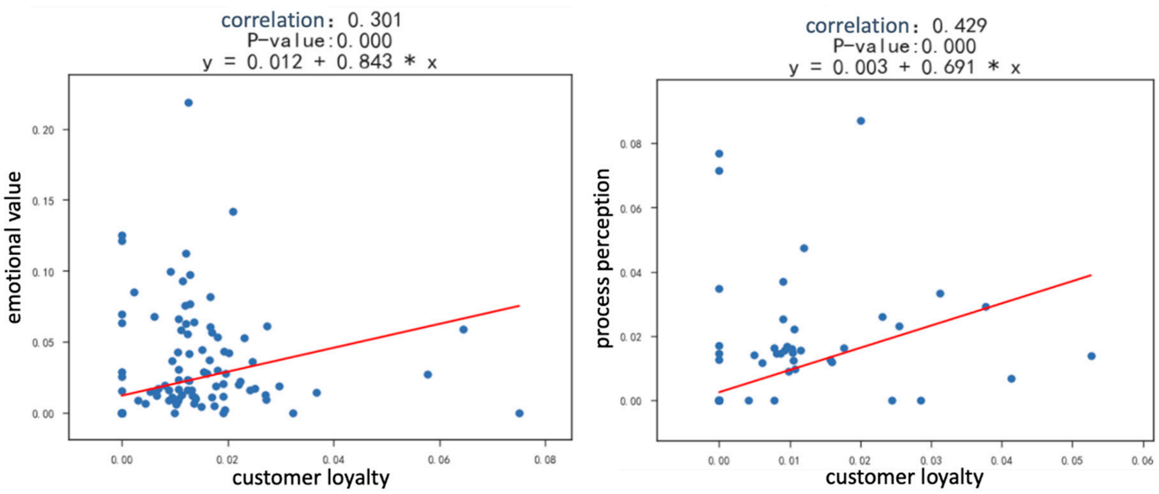

Figure 7. First-level dimensions and customer loyalty.

The analysis of randomly selected data reveals that emotional value and process perception are closely related to customer loyalty. Similarly, a more detailed and comprehensive analysis of second-level dimensions can be achieved. Specifically, in a more detailed dimension, we also obtain novel discoveries regarding the sources of customer loyalty. We randomly selected the 2017 data to demonstrate the results. There are five sub-indicators (appearance, components and functions, accessories, price, overall evaluation) under the first-level dimension product quality. Further analysis reveals that four of the five sub-indicators satisfy the criteria (Figure 8). Appearance, components and functions, price, and overall evaluation are closely related to customer loyalty, while accessories is not. From this, we can further analyze the specific sources of the high correlation between product quality and customer loyalty and determine which factors are relatively unimportant. Similarly, in the emotional value dimension, three of the second-level factors (marketing empathy, brand impression, emotional atmosphere) have satisfied the criteria, whereas social value did not (Figure 9). This indicates that, in the relationship between emotional value and customer loyalty, social value has the smallest impact.

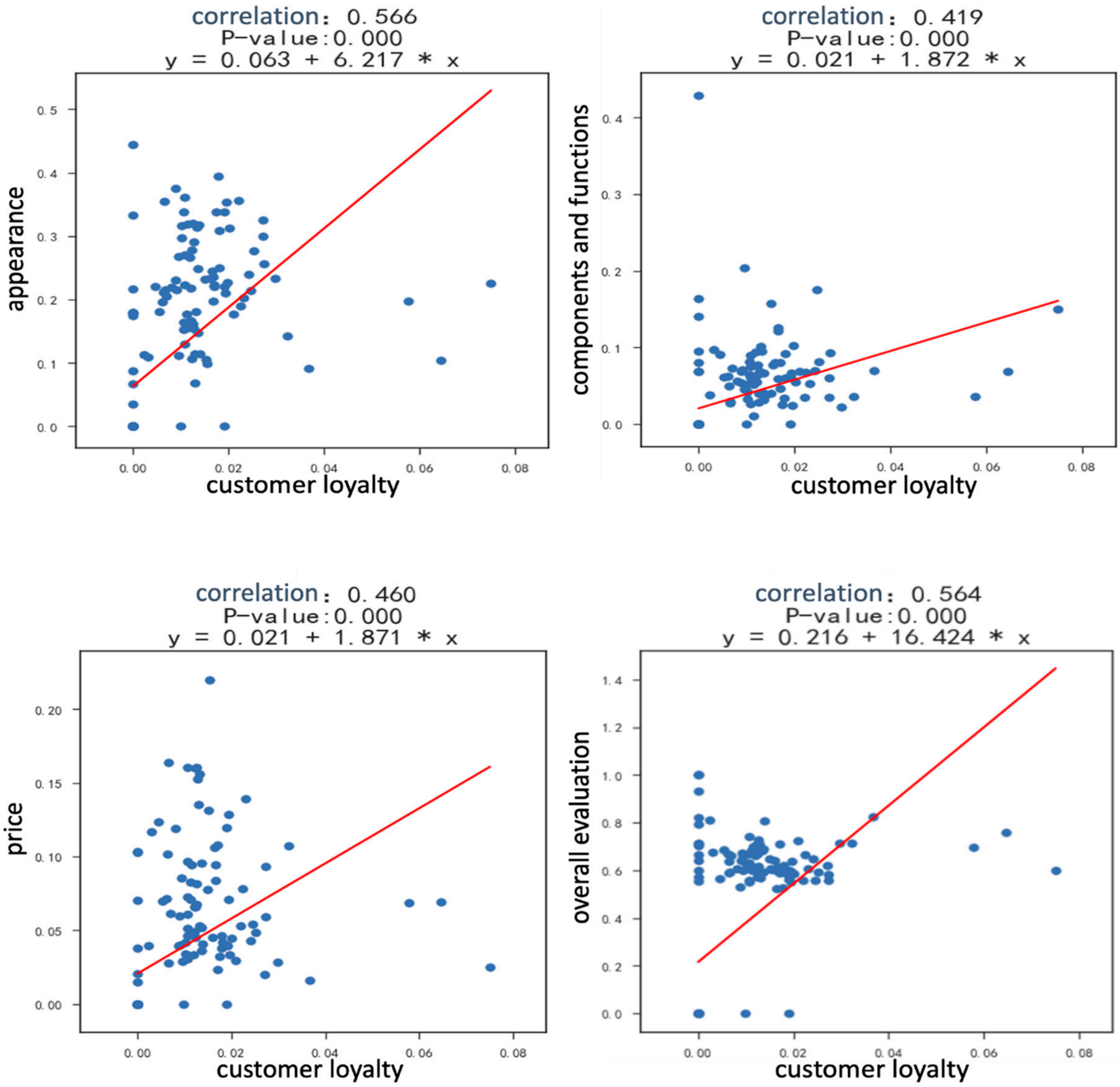

Figure 8. Subdivided second-level dimensions of product quality and customer loyalty.

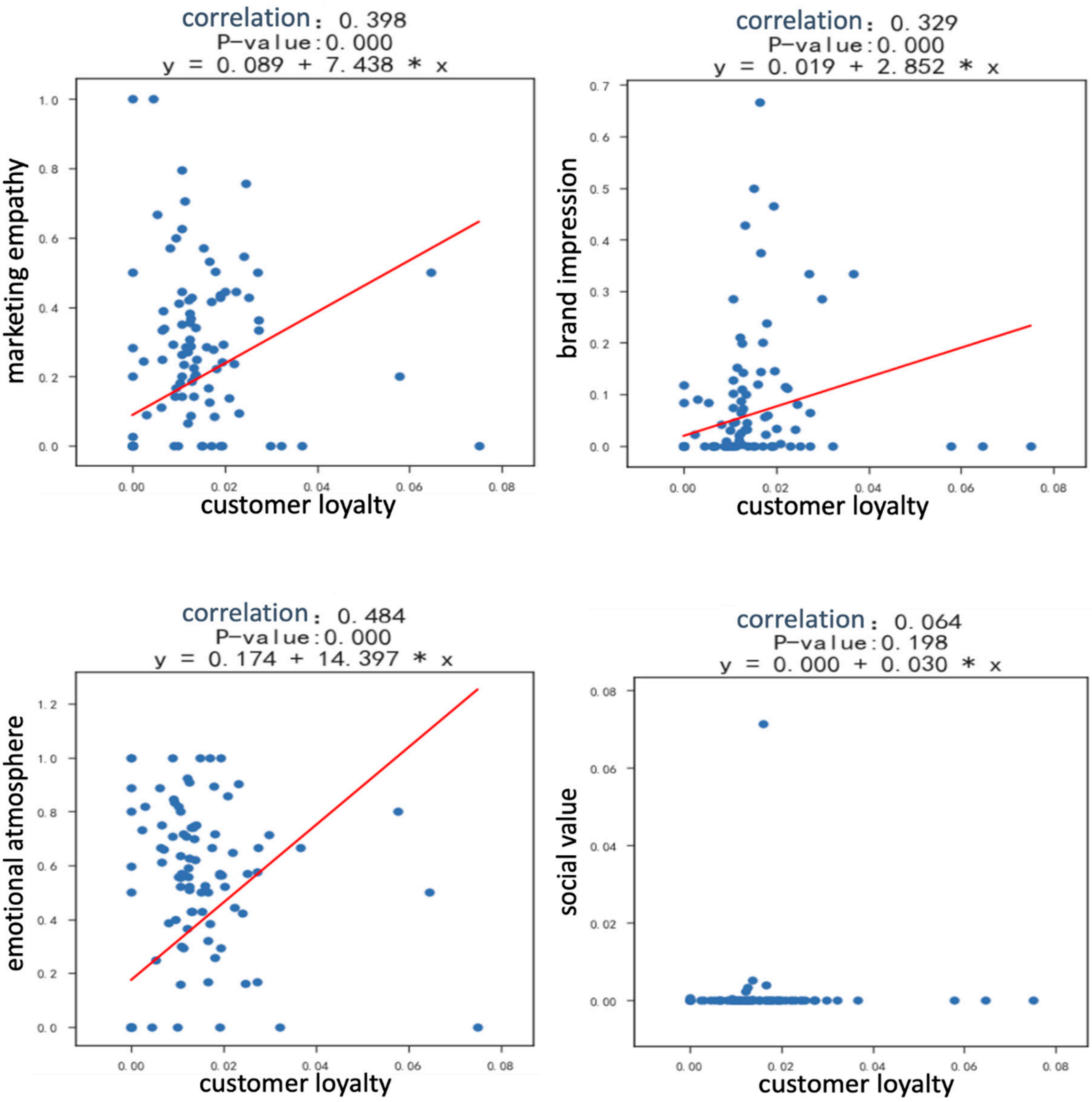

Figure 9. Subdivided second-level dimensions of emotional value and customer loyalty.

The importance of process perception, risk perception, and their subdivision can also be obtained by the same method, which is not repeated here. Product quality remains the most important factor affecting customer loyalty, but among the other dimensions of customer-perceived value and its subdivided elements, only a few portions of the elements affect customer loyalty. Compared with customer-perceived value, the customer loyalty of online shoppers does not have a strong logical relationship and correlation between the influencing factors. Customers are more likely to be loyal to a product or brand because of a specific trait that the product or brand possesses.

6. Conclusions

In this study, we extracted the dimensions of customer-perceived value from the text analysis of online customer reviews, literature study, and expert opinion. The results of the data analysis prove that our dictionary construction, dimension definition, and methodological thinking are effective and feasible. Each of the four dimensions of customer-perceived value have an impact on the customer-perceived value of online shopping, but the patterns and degrees of the impact on each dimension and its subdividing elements on perceived value are rather different. Not all dimensions have a significant or positive impact on customer-perceived value, and owing to the quantity and quality of our data, we further observed and summarized these detailed differences. In terms of the degree of impact on customer-perceived value, product quality is the most important of the four factors of the first dimension, followed by process perception and emotional value, with risk perception having the least impact. Further, with regard to impact, product quality has a significant and positive impact on perceived value. Product quality factors are not only important perceived gains but also important perceived losses, whereas process perception, emotional value, and risk perception play more important roles in perceived losses than in perceived gains. The main source of high customer-perceived value is product quality, whereas process perception and risk perception are health factors. In other words, if these perceptions are not good, it will surely reduce customer-perceived value, whereas, if they are good, it will not contribute much to improving customer-perceived value. Last, but not least, emotional value is a special dimension. It has two sides. It is similar to process perception and risk perception in the low-score section but similar to product quality in the high-score section. Emotional value is a health factor that must be handled carefully for young brands or new products. For relatively mature brands and products, emotional value can become an important source of competitive advantage after product quality. This is easily underestimated in practice. In contrast to perceived value, each dimension of customer-perceived value and its subdividing factors do not always have an impact on customer loyalty, and there is no obvious causal relationship between the higher dimension and the lower subdividing dimension—that is, each factor produces relatively independent influence. Specific to the analysis results of top-down subdivision elements, the analysis of detailed dimensions and factors is conducive to improving the products and services of enterprises and brands and enhancing customer-perceived value and customer loyalty.

Customer value and customer loyalty have always been the core aspects of marketing and guarantees for sustainable enterprise profits. Finding a means to accurately cater to customer needs, highlight differentiation, and build core competitiveness are common problems faced by e-commerce websites and retail enterprises [19,34]. Therefore, systematically studying the formation and motivation of customer value and customer loyalty in online shopping environments will provide information to enterprises that may help them better allocate resources and maintain customer relationships. This research identifies the driving factors of customer-perceived value and customer loyalty in e-commerce. Through the analysis of online consumer reviews, in this study, we defined the dimensions (and their subdivisions) of customer-perceived value and explored their effects on customer-perceived value and customer loyalty in the online shopping environment. The research results can specifically reveal what is of significance to online customers and provide directions to e-commerce enterprises and product brands to better understand their target customers.

Online customer reviews contain rich information on customer opinions and expectations. These dimensions are strongly related to customer-perceived value. We proposed a new framework for customer-perceived value and investigated the multiple dimensions of customer-perceived value in the context of e-commerce. More accurately, we identified the dimensions and corresponding subdivisions of customer-perceived value. Then we clarified and evaluated the varying importance of the value dimensions. We attempt to properly address the determination of the importance of customer-perceived value dimensions based on online reviews to help better understand such questions as "What roles do product quality, process perception, emotional value, and risk perception play in customer-perceived value?" and "Do these roles make a difference?" In this work, we take online customers as the target group and customers' online reviews as the breakthrough point. We defined the dimensions and subdivisions of customer-perceived value in the electronic commerce environment. Through the analysis of first-hand data, we have made some interesting discoveries about the impact of each dimension on customer-perceived value and customer loyalty. This study is a useful exploration of the theory and practice of customer value. We believe its main highlights are as follows:

This study is based on large-scale first-hand data collected over roughly two years. In this study, the redefinition of customer-perceived value dimensions is specific to three levels, so detailed and specific division is not yet common, and it is highly operable. This study explored the specific sources of customer-perceived value and customer loyalty in an e-commerce environment, which has practical guiding significance for the industry. Some interesting new discoveries have been made thanks to more detailed dimension division. There are great differences in the magnitude and manner of the impact of each dimension and its subdivisions.

Further, numerous achievements have been made on the dimensions of customer-perceived value, perceived value, and customer loyalty in the traditional shopping mode [8]. However, these relationships have changed in the online shopping environment. This study is a meaningful exploration and provides a new perspective to construct dimensions of customer-perceived value under a specific shopping mode. Moreover, benefiting from large-scale, first-hand data, our division of perceived value dimensions is more detailed and comprehensive. The elicitation of the results can be traced to specific indicators, which is more operable in practice. Considering that customers' interests, behaviors, and values will change over time and that customers in different regions or environments may have different requirements, it is worth noting that the dictionary constructed in this study can be updated over time and for different scenarios. Thus, our research methodology has promising continuity and expansibility.

7. Limitations and Future Research

Because of the anonymity of online consumer reviews, we cannot obtain detailed user information; therefore, this study does not subdivide the target customers. Future research could conduct in-depth analysis from the perspective of customer subdivision to obtain more accurate conclusions. Although our study sample and data size are sufficiently large and the method is practicable, it only refers to mobile phone products. Future research could extend the sample and usage scenarios of this method by investigating more diverse products and industries. In addition, this research was conducted with the background of the Chinese market, and the samples of online reviews were also taken from mainstream e-commerce in China. Follow-up research could expand the regional scope and sample diversity, which may lead to more representative results.

Another issue worthy of further study is how to identify the sources of customer-perceived losses. The factors of perceived gains of different brands have certain commonalities, but the factors of perceived losses are often different. Determining how to bridge the gap between the views of customers and managers on factors other than product quality—such as services, processes, values, and other issues—would be helpful for improving customer-perceived value and customer loyalty.

Our exploration in this study puts forward an efficient and practical way to mine value from big data, but it has to be noted that big data is just raw material, and it is not a solution. We need to find a way to efficiently use big data, as it is a wealth of important information. Although we use cell phones as a research object, our methodology was developed with a general purpose in mind and could be extended to other industries (e.g., other digital products). The proposed framework and methodology may not be perfect, but it is still instructive with good expectations. On one hand, the methodology and results achieved can be considered exploratory and used to define new research questions and hypotheses. On the other hand, the proposed procedure, like any other novel approach, should be carried out in different contexts and industries to refine it, as well as to check its validity and applicability, as indicated. We also improved the limitations and future research part. It would be great if this study can provide product managers and later researchers some inspirations or trigger more exploration in this important and interesting field. We will continue to reflect and improve the research methods on this issue from a broader perspective.

Author Contributions: Conceptualization, C.L. and G.J.; methodology, C.L. and S.W.; software, S.W.; validation, C.L., S.W., and G.J.; formal analysis, C.L.; investigation, C.L.; data curation, S.W.; writing—original draft preparation, C.L.; writing—review and editing, C.L. and S.W.; visualization, S.W.; supervision, G.J.; funding acquisition, G.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 71772010.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

We invited eight experts, including four professors and four mobile phone industry/e-commerce practitioners, and communicated with them through face-to-face interviews, email, WeChat, and telephone. The experts involved in this research have an average working experience of over 11 years in their field. The details are provided in the table below.

Table A1. Experts' background and survy details.

Experts	Title	Working Experience	Research Method	Survey Time
Expert A	Professor of Information Systems	7 years	E-mail and face-to-face interview	22/Nov/2018
Expert B	Professor of Computer Science and Engineering	12 years	E-mail and face-to-face interview	3/Mar/2019
Expert C	Professor of Business management (Marketing)	9 years	E-mail and face-to-face interview	5/Mar/2019
Expert D	Professor of Industrial Engineering	20 years	E-mail and face-to-face interview	18/Mar/2019
Expert E	Mobile phone industry practitioner (product manager)	10 years	E-mail and WeChat consultation	29/Nov/2018
Expert F	Mobile phone industry practitioner (Marketing Director)	14 years	WeChat consultation	30/Nov/2018
Expert G	E-commerce practitioner (Director of operations)	8 years	E-mail and telephone consultation	6/Apr/2019
Expert H	E-commerce practitioner (Customer Manager)	10 years	E-mail and telephone consultation	13/Apr/2019

Appendix B. Results for the Full Sample in Section 5

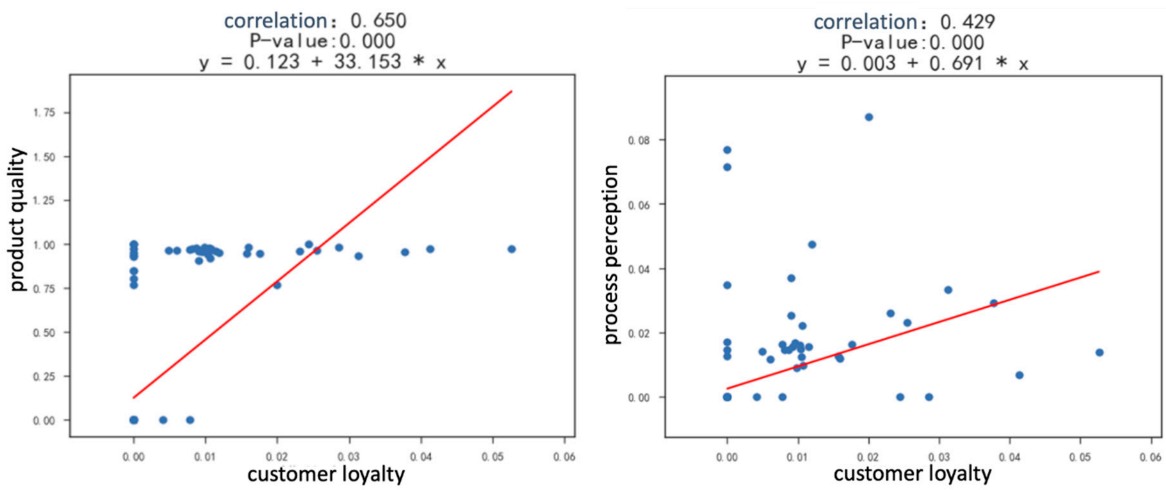

Figure A1. *Cont.*

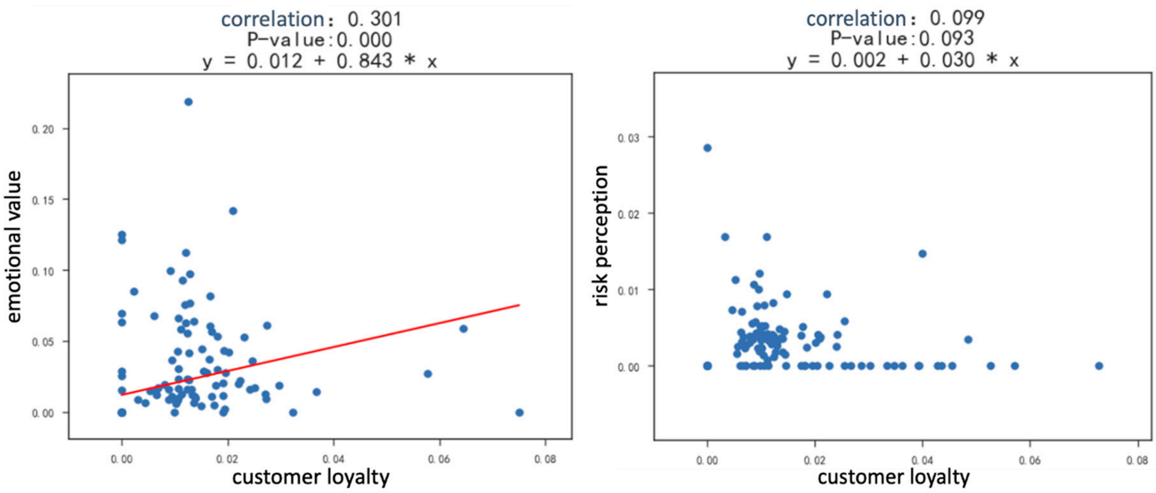

Figure A1. First-level dimensions and customer loyalty.

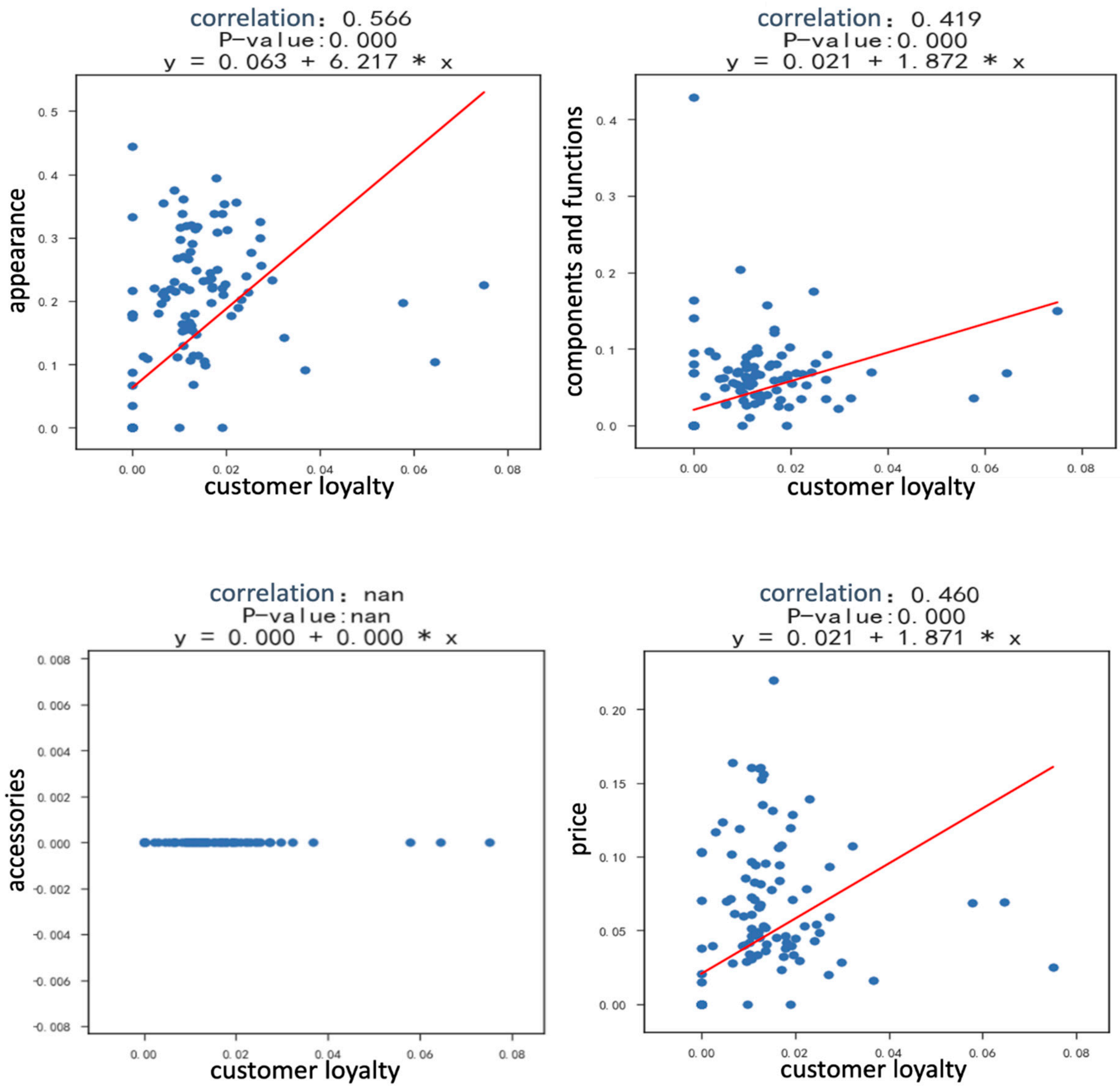

Figure A2. *Cont.*

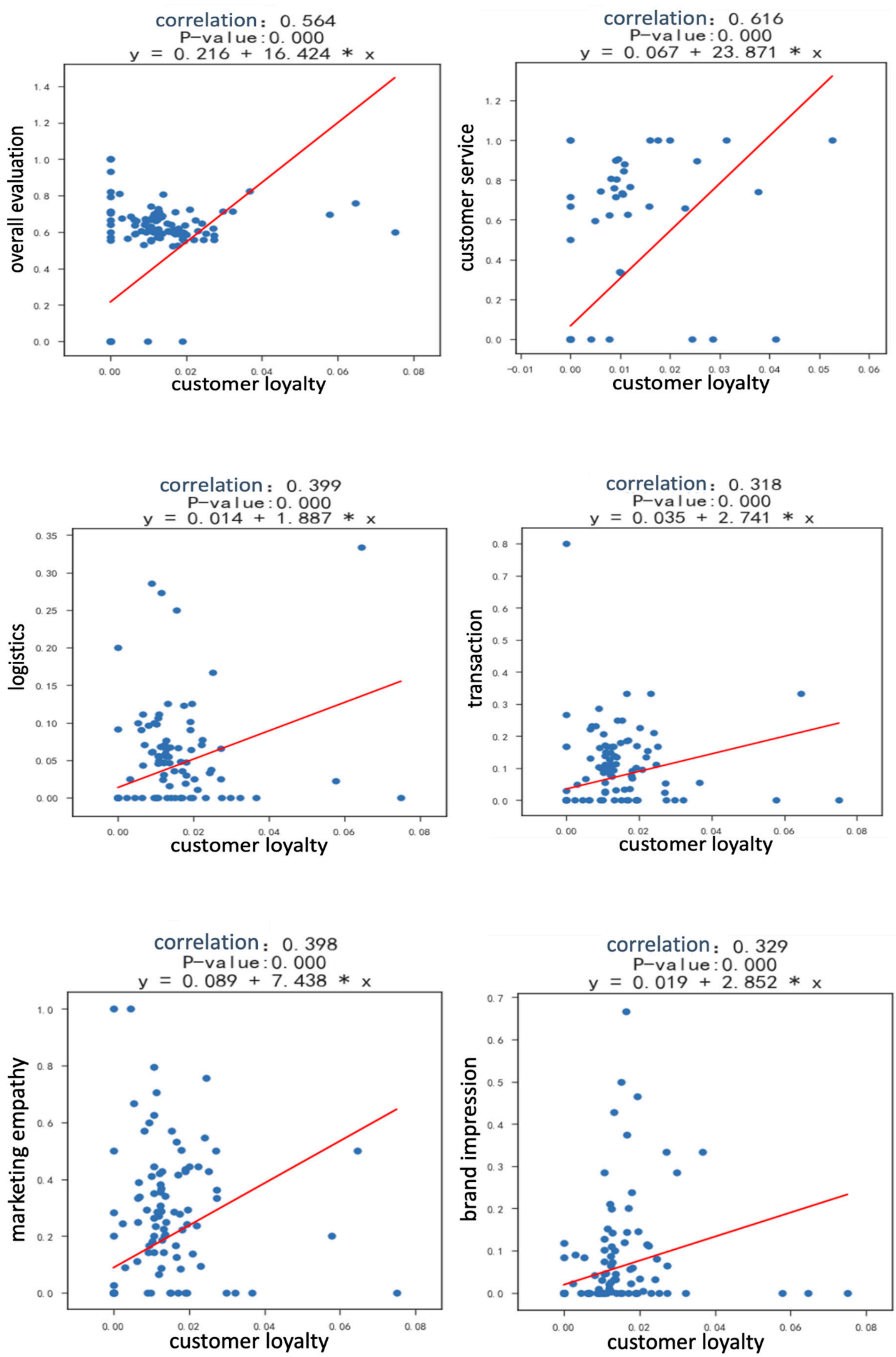

Figure A2. *Cont.*

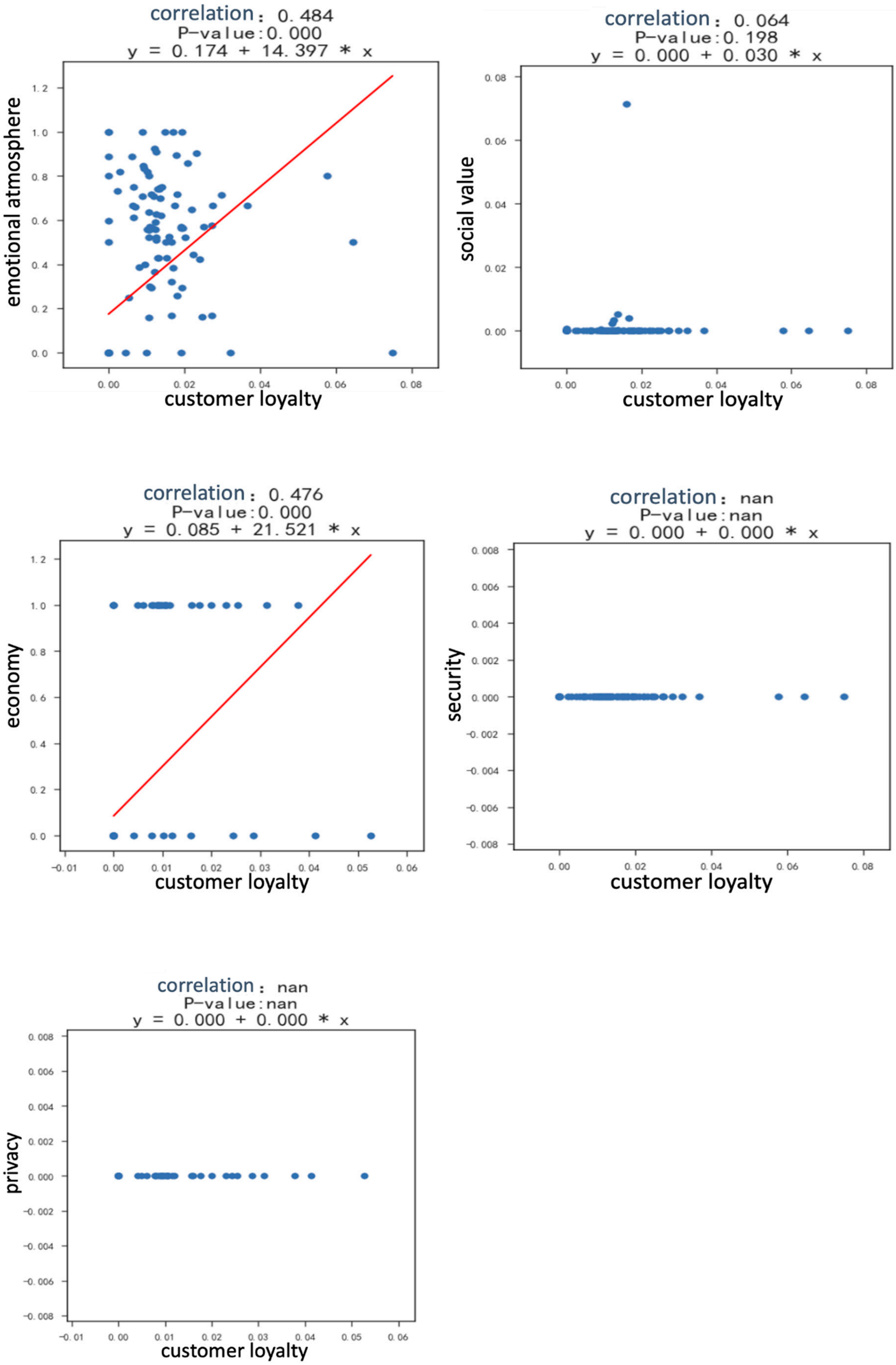

Figure A2. Second-level dimensions and customer loyalty.

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