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Product innovation based on online review data mining: a case study of Huawei phones

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Abstract Online reviews contain a plethora of useful information that plays a vital role in consumer choices and provides a dominant reference for enterprises to adopt strategies for product development and improvement. The paper examines the www.zol.com.cn website as a source of information and Huawei Mate phones as a research target, processes the data of consumers' online reviews on three types of Huawei Mate phones, discusses the correlations between online reviews and phone improvement, and proposes some suggestions for future product improvement. This empirical study shows that the correlation between the change in the degree of feature satisfaction and phone improvement is strong; the correlation between the change in the degree of feature satisfaction and product improvement is stronger than that between the change in the degree of feature attention and product improvement. Enterprises can determine the direction and contents of phone improvement based on information from reviews on its preceding phone model. This study can help enterprises master market requirements, understand consumers' behaviour and improve the quality and efficiency of product innovation.

Keywords Online review · Product innovation · Data mining · Feature extraction · Sentiment analysis

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1 Introduction

Most e-commerce websites, community websites, and third-party review websites can provide users with star ratings and comment functions. Examining online reviews before shopping online has become a habit of many consumers in China. Online reviews provide consumers with more product information, which reduces consumers' purchase risk and helps them make more informed purchasing decisions. Enterprises can also obtain information from online reviews that is more profound and extensively relates to the market and consumers, which can help enterprises understand the demands of consumers, master the market and the dynamic state of technology, exploit commercial opportunities and promote product innovation [1–4]. Therefore, online reviews have attracted the attention of researchers in recent years and have led to the accumulation of a wealth of research findings. Taking Huawei phone as an example, this paper will investigate the correlation between online reviews and product innovation, and provide suggestions for the future improvement of the product based on online reviews.

Previous studies related to online reviews are mainly focused on the following aspects: (1) the influence of online reviews on enterprises' sales performance, mainly focused on whether online reviews have an influence on sales, what factors affect sales, and the effects of sales [5–8]; (2) the influence of online reviews on market strategies, mainly focused on product strategy, price strategy, communication strategy, service strategy and competition strategy [9–13]; (3) the behavioural study of consumer participation in online reviews, which examine why consumers publish online reviews, how to use online reviews, and what features of the reviews can affect consumers' behaviour and attitudes [11, 14–16]; (4) methods of online review data mining, given that the main information to be mined is the product features and consumers' sentimental tendencies [17–20]; and (5) the usefulness of online reviews, which includes how to extract useful reviews and the impact factors of useful reviews [21, 22]. Existing studies have recognized the importance of online reviews, and the number of studies related to online reviews is increasing each year. However, these studies mostly discuss issues from the angle of consumers instead of manufacturers or product design. In addition, although many studies have mentioned the importance of online reviews for the success of a new product and product innovation [2–4, 23, 24], most of these studies are theory studies. The empirical research of Qi et al. [24] is from the perspective of product design; however, because its main focus is on the extraction of online reviews, it is a study on the extraction of useful online reviews based on product innovation instead of addressing product innovation or improvement based on online reviews. From the manufacturers' perspective, it is critical to select and learn from useful online reviews for product innovation. Big data, namely, the large quantity, high speed and diversity of data, has provided opportunities for manufacturers to use online reviews to design products. Online reviews could be the source of innovative idea and provide support for the design and improvement of new products [24]. This co-creation process, in which customers participate actively in the development of new products and services, has been confirmed to be a reliable contribution to competitive advantage [25]. For manufacturers, especially those who need to continuously update their products in an intensively competitive market, online reviews could be a source of attracting customer demand [26]. Through online reviews, manufacturers can listen to the voices of customers from the target market [27] and absorb knowledge of the market structure and competitive environment to support their market decisions [28].

As early as 1976, Von Hippel proposed the importance of users in innovation [29], which was subsequently extensively studied and disseminated into market sectors. Mostly, traditional contact modes with consumers are used to obtain user experience information for user-based innovations, and relevant studies have utilized user simulation, visual product experiences for users, and questionnaires [30]. However, these methods are limited by factors such as user group, time and area, and the innovation process is tedious as well. By contrast, online reviews can aid the process of mining information on customers' sentimental tendencies, demands and other preferences related to products. So far, the studies on online review-assisted product innovation decisions and their continuous improvement have yielded little fruit, and the number of empirical studies aimed at product improvement using consumers' online reviews are even fewer. Empirical studies can not only verify the feasibility of online review-assisted product innovation but also help enterprises master practical operation methods and improve innovation efficiency. Are online reviews related to product innovation? How do online reviews provide help for product innovation? This paper will explore the correlation between online reviews and product innovation by mining the information from reviews by Huawei phone users on the website www.zol.com.cn. The structure of this paper is as follows: the second section presents a literature review and the problems to be studied; the third and the fourth sections describe the data processing and empirical analysis; and the fifth section discusses the main conclusion and the limitations of this study.

2 Literature review and the problems to be studied

2.1 Online reviews and product innovation

Online reviews are posted on the company's website or a third-party website and provide consumer evaluations of products or services [9, 21, 31]. Online reviews supplement the information that consumers obtain through other channels. These reviews express consumers' true feelings about goods after purchasing, and customers' experiences and suggestions are objective supplements for the description of the online goods [32]. Liu et al. [33] noted that it has been a key challenge for manufacturers in the design of market-driven products to effectively and accurately recognize and analyse useful online reviews to meet the requirements of potential clients. This research introduced, from a designer's perspective, how to automatically assess the usefulness of an online review based on its content. The study of Xu et al. [23] noted that the fusion of knowledge between traditional market analysis and big data analysis can raise the success rate of new products. The study by Qi et al. [24] supported the viewpoint of Xu et al. [23]. They proposed a knowledge-based method of obtaining value through big data. Although scholars have realized the importance of online reviews for the success of new products in the big data environment, they have mainly focused on how to extract valuable reviews rather than on the relationship between the two. The concept of innovation was earliest proposed by Schumpeter [34], who believes that innovation is intended to combine essential productive factors in a new way and introduce this novel idea into the production system, that is, to build new productive relations, and product innovation is meant to introduce a new product or a new product feature. This paper uses the generalized concept of product innovation, which means that enterprises redesign or improve their products or services, including product improvement (improvement of product quality or effectiveness), new product modification (having unprecedented product attributes), and productive cost reduction [35]. The product innovation of Huawei phones studied in this paper mainly concerns the improvement of Huawei phones, including adding a new attributive character or improving an existing attributive character of the phone.

2.2 Online review data mining

As a popular topic in data mining, online review mining includes the following steps: first, obtaining the sentimental text content referring to the product and its attributes; second, preprocessing this information and segmenting words; third, classifying this content; and last, drawing conclusions. According to the research contents, online review data mining mainly includes two modules: features extraction and sentiment analysis.

2.2.1 Feature extraction for online reviews

The term ‘feature’ refers to the attribute of the product (also called entity or subject), product subassembly or product parts that are reviewed by users online. For example, a mobile phone can be regarded as an entity that includes a subassembly (such as a screen, different phone sizes, and keys). In addition, the subassembly has its own attributes, such as the battery life and size. Feature extraction is an important part of review mining. According to the difficulty level of extraction, features can be divided into explicit features and implicit features [36]. The explicit features are those directly mentioned by users in their reviews of products, whereas implicit features are those that are not directly mentioned but be inferred from the reviews [36]. This paper mentions only the explicit feature extraction for Chinese online reviews, which mainly concerns three methods. The first method is extracting with language rules, which means to extract features via sentence and word grammar in reviews. This method involves analysing the syntactic relation, or dependence relation, among feature and opinion words or other words [37]. The second method is extracting using the sequence model. The sequence model has been widely used in the information extraction field, and it can be utilized in feature extraction as well. Since the product features and users’ opinions are connected through grammatical relations in a sentence, the feature extraction can be taken as a sequence tag task [38, 39]. The third method is extracting according to frequent pattern or frequent word extraction. Frequent pattern, also called frequent feature, is a pattern whose degree of support and confidence is higher than the threshold. By contrast, features appearing in only a minority of reviews are called non-frequent features [36]. Hu and Liu [36] were the first to recognize nouns and noun groups using the Apriori algorithm and part-of-speech (POS) labelling tool, and by calculating their occurrence frequency, they kept the words whose frequencies were larger than the threshold. The validity of this method is that when people launch many evaluations on a product, evaluation objects usually converge to the product features that users truly value. Thus, in this paper, the product features are extracted according to the frequent pattern or frequent words method.

2.2.2 Sentiment analysis for online reviews

Faced with numerous online reviews on products, sentiment analysis technology was designed to mine valuable information. The sentiment polarity of online reviews reflects consumers' attitudes towards products. Thus, the sentiment polarity of reviews is divided into positive and negative [40, 41]. The reviews of positive polarity will increase consumers' loyalty to brands and stimulate their purchase desire, thus raising the possibility of consumption. In contrast, the reviews of negative polarity will lower consumers' loyalty to brands and suppress their purchase desire, thus decreasing the possibility of consumption [16, 42]. There are three primary methods in the existing literature for analysing sentiment polarity of online reviews: text-level sentiment analysis, sentence-level sentiment analysis and word-level sentiment analysis. Text-level sentiment analysis first pretreats the files (including word segmentation and part-of-speech tagging), selects text sentiment features, filters feature items and weighs them, and finally inputs the weighted text features into a classifier to obtain the sentiment polarity of the text [43, 44]. Sentence-level sentiment analysis is used to judge the sentiment polarity of the entire review according to the sentiment polarity of sentences [45–47]. In addition, word-level sentiment analysis is used to first judge the polarity of words and then sum the polarity of words or classify sentiments using syntactic analysis [48, 49]. This paper uses the online review data of Huawei phones sold on the www.zol.com.cn website. The website has sorted consumers' reviews on Huawei phones into three parts: merits (positive reviews), demerits (negative reviews) and summaries, which are all included in each review from the consumers. Thus, the website has directly classified the reviews according to consumers' sentiments, which is convenient for the data analysis in this paper. Based on the online reviews of Huawei Mate phones on this website, this paper will analyse the influence of online reviews on the product innovation of Huawei Mate phones.

2.3 Problems to be studied and the steps

Traditionally, enterprises rely on market surveys to better understand consumers' demands. Compared to offline surveys or questionnaires, online reviews can provide richer information with less time and lower costs [50, 51]. The issue to be examined in this paper is how to use online reviews to investigate their relationship with product innovation and note a direction for the future improvement of product innovation. The questions are as follows:

Question 1 How does one extract product features from online reviews?
Question 2 What is the correlation between online reviews and product innovation?
Question 3 How does one improve future products based on online reviews?

To answer these questions, the steps of conducting the analysis of online review data were as follows. First, we selected an appropriate review website; second, we extracted review information from the website utilizing the Octopus Collector, a professional data collecting software. Third, we used Institute of Computing Technology, Chinese Lexical Analysis System (ICTCLAS) and ROST content mining system (ROST CM) for text processing and statistics. Fourth, we conducted empirical analysis on Huawei Mate phones; and last, we provided conclusions from data analysis.

3 Data processing for online reviews of Huawei phones

3.1 Selection of data source

The professional phone reviewing website www.zol.com.cn was used as the data source for this paper. Most of the reviews on this website come from product opinion leaders whose reviews are long and of great reference value for other consumers and for enterprises, particularly in terms of providing more information on product improvement. In addition, the online reviews on the www.zol.com.cn website are featured by distinctions between the merits and demerits of phone attributes, which built a foundation for the consumers' sentiment analysis in this paper. Three types of phones of the Huawei Mate series were selected as analytic targets: the Huawei Mate 7, the Huawei Mate 8 and the Huawei Mate 9. Of these phones, the Mate 8 is the updated version of the Mate 7, and the Mate 9 is the updated version of the Mate 8. The reasons for selecting these three types were as follows: (1) the Huawei Mate series is very popular with consumers; (2) there are more online reviews for these three types of phones; and (3) these three types of phones all belong to the Huawei Mate series, which is useful for comparative analysis. Thus, the online reviews of consumers on the three types of Huawei Mate phones were selected as the basic data for analysis. The data collected from the reviews included the reviewer's name, the review time, the review scores, the merit review, the demerit review, and the reviewer's summary. Figure 1 illustrates a typical online review posted on www.zol.com.cn. In Fig. 1, Part A is the registered name of the reviewer. Part B is the evaluation score of the reviewer for the mobile phone. Part C is the review content of reviewer, which includes a merit review, a demerit review, and the reviewer’s summary.

3.2 Data collection and processing

The collection steps and results for the online reviews on Huawei Mate phones are as follows.

First, we used the Octopus Collector to abstract review information. A total of 2058 reviews were collected, including 1241 reviews on the Huawei Mate 7, 604 reviews on the Mate 8, and 213 on the Mate 9.

Second, we used ICTCLAS to segment Chinese words and stored the obtained data into new text. ICTCLAS is the most typical Chinese word segmentation system and has the functions of Chinese word segmentation and part-of-speech tagging. The accuracy of word segmentation can reach 98.45% [52, 53].

Then, we used ROST CM to calculate the word frequency statistic in the text that stores word segmentation data, and we selected the top 300 high-frequency words to be stored in specified text. ROST CM is a Chinese content mining software developed by Chinese scholars and is suitable for a wide range of applications.

Next, we cleaned the data of the top 300 high-frequency words using the following methods: (1) we deleted the words that did not have phone attributes; (2) we merged synonyms and summarized their corresponding word frequency; (3) we analysed repeated words and selected those that best represented the phone attributes to be recorded in the total word frequency; and (4) we deleted indistinguishable words and artificially recognized the words that were difficult to classify; if they could not be classified artificially, we deleted them.

After cleaning the top 300 high-frequency words, the 11 indicators that were of most concern to consumers and their frequency in the online reviews for Huawei Mate phones were summarized, which served as the data for the reviews on Huawei Mate phones. The extraction of the 11 attributive features of Huawei phones required comprehensive consideration of the score ranking of phone attributes by consumers on the www.zol.com.cn website, as well as the parameters of Huawei Mate phones and related studies conducted domestically and abroad. The definitions of the 11 phone attributive features and their references are shown in Table 1. Similarly, we processed the information of the three types of Huawei Mate phones separately and abstracted relevant attributive feature indicators. The results are shown in Table 2. The feature attention number is the frequency with which a type

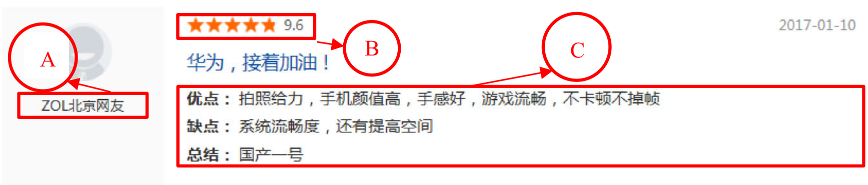

Fig. 1 Consumer online reviews

Table 1 Phone attributive features

Feature	Defining features	References
Price	The price of a phone. The mentioned words include price, cheap, expensive, pricing, and costs	Haverila [54], Balakrishnan and Raj [55], Kim and Park [56]
Battery	The battery capacity of a phone, including battery working hours, battery service life. The mentioned words include battery, electric quantity, milliampere, charging, fully charged, and continuous working time	Economides and Grousopoulou [57], Okudan et al. [58], Vanden Abeele [59], Suominen et al. [60]
Appearance	The size and colour of a phone. The mentioned words include appearance, beautiful, design, mobile phone shell, and shape	Kim and Park [56], Suominen et al. [60], Petruzzellis [61], Singh and Goyal [62]
Photograph	The photograph function of a phone, including photograph quality, flash lamp, format of video, auto-focusing. The mentioned words include taking pictures, camera, and photographs	Economides and Grousopoulou [57], Vanden Abeele [59], Suominen et al. [60], Kimiloglu et al. [63]
Screen	The precision degree of screen pictures on a phone, which involves the pixel displayed by the screen including the screen definition. The mentioned words include screen, distinct, clear, resolution, fineness, picture, and clarity	Haverila [54], Okudan et al. [58], Vanden Abeele [59], Suominen et al. [60]
Performance	The fluency of phone operation, including the CPU, internal storage, and operation stability of a phone. The mentioned words include CPU, processor, storage, internal storage, capacity, storing, main board, speed, response, running, and fluent	Economides and Grousopoulou [57]
Quality	The workmanship, texture and heat dissipation of a phone, including durability, anti-dropping, waterproof, and heat dissipation. The mentioned words include quality, durability, workmanship, metal, texture, and heat dissipation	Haverila [54]
System	The build-in UI interface of a phone, including fingerprint recognition and Android system. The mentioned words include system, software, program, interface, fingerprint recognition, and Android	Petruzzellis [61]
Audio and video	The audio and video effect of a phone. The mentioned words include games, films, tone quality, volume, music, and audio and video	Economides and Grousopoulou [57]
After-sales services	Phone producers repair the phones bought by consumers. The mentioned words include after-sale service, return goods, service, and repair	Zhang et al. [30]

Table 1 continued

Feature	Defining features	References
User experience	Consumers' feeling of using the phone. The mentioned words include convenient, satisfied, perfect, rubbish, practical, high-end, and comfortable	Haverila [54], Balakrishnan and Raj [55], Suominen et al. [60]

Table 2 The 11 indicators of greatest concern to customers regarding Huawei Mate phones

Name of feature	Feature attention number			Total feature attention number
	Mate 7	Mate 8	Mate 9	
Performance	1159	664	229	2052
Appearance	1130	394	156	1680
Battery	770	595	153	1518
System	1029	382	88	1499
Screen	727	499	110	1336
User experience	566	276	60	902
Photograph	356	239	119	714
Price	449	139	70	658
Quality	445	150	51	646
Audio and video	281	257	67	605
After-sale service	44	31	15	90

of phone was mentioned, and the total feature attention number is the sum of the feature attention numbers for each attributive feature of the three types of phones.

4 Product innovation and empirical analysis based on online reviews of Huawei phones

Based on relevant studies of the feature extraction and sentiment analysis for online reviews, this study selected two online review indicators, degree of feature attention and degree of feature satisfaction, to discuss their correlation with product innovation. Feature extraction for online reviews is usually based on the indicators of greatest consumer concern, so the degree of feature attention indicates consumers' degree of attention towards product attributive features. When reviewing a product, consumers will have positive or negative sentimental tendencies, so the degree of feature satisfaction represents consumers' degree of approval for product attributive features. With these two indicators, it is easier for enterprises to judge whether an attributive feature needs improvement.

4.1 Degree of feature attention of Huawei Mate phones

In this paper, the ratio of the number of reviews mentioning a certain feature to the total number of reviews is termed the degree of feature attention of this product: degree of attention of product feature A = the number of reviews mentioning feature A/total number of reviews. For example, the degree of performance attention of the Huawei Mate 7 = 1159/1241 = 93.39%. Through statistical analysis of the text of all online reviews of the three types of phones, we obtained the degree of feature attention of the three types of Huawei Mate phones, as specified in Table 3.

4.2 Degree of feature satisfaction of Huawei Mate phones

In this paper, positive reviews for a product feature were used to show the consumers' degree of satisfaction for the product feature: the degree of satisfaction of product feature A = the number of positive reviews on product feature A/degree of attention of feature A. For example, the degree of performance satisfaction of the Huawei Mate 7 = 360/1159 = 31.06%. Through statistical analysis of the text of all online reviews of the three types of phones, we obtained the degree of feature satisfaction of the three types of Huawei Mate phones, as specified in Table 4. Table 4 indicates that consumers' degree of satisfaction for some attributive features did not increase with the upgrades of phones. For example, the degrees of user experience satisfaction of the three phones were 40.11, 37.68, and 36.67%, which shows a decreasing trend. There are two reasons for this finding: (1) this attributive feature was not upgraded or improved, thus causing a decrease in consumers' degree of satisfaction or (2) this attributive feature had been upgraded and improved, but consumers' expectations had also increased. Thus, the attributive

Table 3 Degree of feature attention of Huawei Mate phones

Name of feature	Number of feature attention			Total number of reviews			Degree of feature attention		
	Mate 7	Mate 8	Mate 9	Mate 7	Mate 8	Mate 9	Mate 7 (%)	Mate 8 (%)	Mate 9 (%)
Performance	1159	593	203	1241	604	213	93.39	98.18	95.31
Appearance	1130	394	156	1241	604	213	91.06	65.23	73.24
Battery	770	595	153	1241	604	213	62.05	98.51	71.83
System	1029	382	88	1241	604	213	82.92	63.25	41.31
Screen	727	499	110	1241	604	213	58.58	82.62	51.64
User experience	566	276	60	1241	604	213	45.61	45.70	28.17
Photograph	356	239	119	1241	604	213	28.69	39.57	55.87
Price	449	139	70	1241	604	213	36.18	23.01	32.86
Quality	445	150	51	1241	604	213	35.86	24.83	23.94
Audio and video	281	257	67	1241	604	213	22.64	42.55	31.46
After-sale service	44	31	15	1241	604	213	3.55	5.13	7.04

Table 4 Degree of feature satisfaction of Huawei Mate phones

Name of feature	Number of positive reviews			Degree of feature attention			Degree of feature satisfaction		
	Mate 7	Mate 8	Mate 9	Mate 7	Mate 8	Mate 9	Mate 7 (%)	Mate 8 (%)	Mate 9 (%)
Performance	360	349	156	1159	664	229	31.06	52.56	68.12
Appearance	502	164	75	1130	394	156	44.42	41.62	48.08
Battery	311	408	109	770	595	153	40.39	68.57	71.24
System	257	147	31	1029	382	88	24.98	38.48	35.23
Screen	285	168	54	727	499	110	39.20	33.67	49.09
User experience	227	104	22	566	276	60	40.11	37.68	36.67
Photograph	51	98	70	356	239	119	14.33	41.00	58.82
Price	19	30	9	449	139	70	4.23	21.58	12.86
Quality	196	68	27	445	150	51	44.04	45.33	52.94
Audio and video	82	96	36	281	257	67	29.18	37.35	53.73
After-sale service	20	22	3	44	31	15	45.45	70.97	20.00

feature still failed to meet consumers' expectations, which led to a reduction in consumers' degree of satisfaction.

4.3 Comparative analysis on Huawei Mate phones

4.3.1 Comparative analysis on the Huawei Mate 8 and the Huawei Mate 7

To study whether the improvement of Huawei Mate phones was related to the degree of feature attention and the degree of feature satisfaction of online reviews, we first compared the information on the attributive features of the three Huawei Mate phones, which is stated in detail on the www.zol.com.cn website. By comparing the information of the 11 phone attributive features of the Mate 8 and the Mate 7, we determined the level of improvement of the Mate 8 based on the degree of improvement in these features. In the same way, we determined the level of improvement of the Mate 9 in subsequent analysis. Then, we compared the level of improvement to the results calculated for the changes in user reviews and judged the correlation between the two. We set three levels for the improvement of Huawei Mate phones and seven levels for degree of feature attention, degree of feature satisfaction and correlation. The detailed partition criterion and demarcation are shown in Table 5.

The statistical results of the correlation between the product improvement and the change in the degree of feature attention within the online reviews of the Huawei Mate 8 are shown in Table 6, which shows that the correlations of six features from the 11 phone attributive features are between 6 and 7, the correlation of one feature is between 4 and 5, and the correlations of four features are between 1 and 3.

The statistical results of the correlation between product improvement and the change in the degree of feature satisfaction of the online reviews of the Huawei

Table 5 Level partition criterion

Name of levels	Rank	Partition criterion
Improvement levels	1	No improvement
	2	A little improvement
	3	Noteworthy improvement
Change levels of degree of feature attention	3	Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $\geq$ 10.0%
	2	5.0% $<$ Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $\leq$ 10.0%
	1	0 $<$ Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $\leq$ 5.0%
	0	Degree of feature attention of Mate 8-degree of feature attention of Mate 7 = 0%
	− 1	− 5.0% $<$ Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $<$ 0%
	− 2	− 10.0% $<$ Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $\leq$ − 5.0%
	− 3	Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $\leq$ − 10.0%
Change levels of degree of feature satisfaction	3	Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $\geq$ 10.0%
	2	5.0% $<$ Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $\leq$ 10.0%
	1	0 $<$ Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $\leq$ 5.0%
	0	Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 = 0%
	− 1	− 5.0% $<$ Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $<$ 0%
	− 2	− 10.0% $<$ Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $\leq$ − 5.0%
	− 3	Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $\leq$ − 10.0%
Feature development direction	Increase	Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $>$ 0
	Decrease	Degree of feature attention of Mate 8-degree of feature attention of Mate 7 $<$ 0
	Increase	Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $>$ 0
	Decrease	Degree of feature satisfaction of Mate 8-degree of feature satisfaction of Mate 7 $<$ 0
Correlation (the larger the number, the stronger the correlation)	7	Improvement level-change level = 0
	6	|Improvement level-change level| = 1
	5	|Improvement level-change level| = 2
	4	Improvement level-change level = 3
	3	Improvement level-change level = 4
	2	Improvement level-change level = 5
	1	Improvement level-change level = 6

Table 6 Correlation between product improvement and the change in the degree of feature attention of the Huawei Mate 8

Name of feature	Attention degree change (%)	Improvement level	Attention degree change level	Correlation
Performance	4.79	3	1, increase	5
Appearance	− 25.82	1	− 3, decrease	3
Battery	36.46	3	3, increase	7
System	− 19.67	3	− 3, decrease	1
Screen	24.03	2	3, increase	6
User experience	0.09	2	1, increase	6
Photograph	10.88	3	3, increase	7
Price	− 13.17	1	− 3, decrease	3
Quality	− 11.02	2	− 3, decrease	2
Audio and video	19.91	2	3, increase	6
After-sale service	1.59	1	1, increase	7

Mate 8 are shown in Table 7, which demonstrates that among the 11 correlations of phone attributive features, the correlations of nine features are between 5 and 7, and the correlations of two features are between 3 and 4.

4.3.2 *Comparative analysis of the Huawei Mate 9 and the Huawei Mate 8*

In the same way, through further investigation of the improvement levels of the Huawei Mate 9 and the Huawei Mate 8, we obtained the statistical results of the correlation between level of improvement and change in the degree of feature attention and feature satisfaction, as shown in Tables 8 and 9, respectively, in online reviews for the Huawei Mate 9.

4.4 Result of the correlation between online reviews and product improvement of the Huawei Mate series

Figure 2 is the comparative analysis chart of the correlation between product improvement and change in the degree of both feature attention and satisfaction for the Huawei Mate 8. Figure 3 is the comparative analysis chart of the correlation between product improvement and change in the degree of feature attention and satisfaction for Huawei Mate 9. The two figures show that the correlation between the change in the degree of feature satisfaction and Huawei phone improvement are notably higher than that between the change in the degree of feature attention and Huawei phone improvement. Additionally, the correlation between the improvement of Huawei Mate phones and the change of consumer's degree of feature satisfaction is also quite strong (in Fig. 2, the correlations of 10 indicators are no less than 4, and in Fig. 3, the correlations of 9 indicators are less than 4). Therefore, the future improvement of Huawei Mate phones can be guided by the change of consumers' degree of feature satisfaction. It can be concluded that it is feasible to

Table 7 Correlation between product improvement and change in the degree of feature satisfaction of the Huawei Mate 8

Name of feature	Satisfaction degree change (%)	Improvement level	Satisfaction degree change level	Correlation
Performance	21.50	3	3, increase	7
Appearance	− 2.80	1	− 1, decrease	5
Battery	28.18	3	3, increase	7
System	13.51	3	3, increase	7
Screen	− 5.53	2	− 2, decrease	3
User experience	− 2.42	2	− 1, decrease	4
Photograph	26.68	3	3, increase	7
Price	17.35	1	3, increase	5
Quality	1.29	2	1, increase	6
Audio and video	8.17	2	2, increase	7
After-sale service	25.51	1	3, increase	5

Table 8 Correlation between product improvement and change in the degree of feature attention of the Huawei Mate 9

Name of feature	Attention degree change (%)	Improvement level	Attention degree change level	Correlation
Performance	− 2.87	3	− 1, decrease	3
Appearance	8.01	2	2, increase	7
Battery	− 26.68	2	− 3, decrease	2
System	− 21.93	3	− 3, decrease	1
Screen	− 30.97	1	− 3, decrease	3
User experience	− 17.53	2	− 3, decrease	2
Photograph	16.30	3	3, increase	7
Price	9.85	1	2, increase	6
Quality	− 0.89	3	− 1, decrease	3
Audio and video	− 11.09	2	− 3, decrease	2
After-sale service	1.91	1	1, increase	7

utilize consumers' online reviews for product innovation, and online reviews can help manufacturers improve innovation to the level of consumers' demand.

4.5 Suggestions for the future improvement of Huawei Mate phones

According to these findings, we can determine the direction of future improvement of the Huawei Mate series. The attributive features with a decreased degree of feature satisfaction should be improved substantially, and the attributive features with an increased degree of feature satisfaction should be maintained or improved slightly (see Fig. 4). Therefore, we can classify the future improvements of Mate

Table 9 Correlation between product improvement and change in the degree of feature satisfaction of the Huawei Mate 9

Name of feature	Satisfaction degree change (%)	Improvement level	Satisfaction degree change level	Correlation
Performance	15.56	3	3, increase	7
Appearance	6.45	2	2, increase	7
Battery	2.67	2	1, increase	6
System	− 3.25	3	− 1, decrease	3
Screen	15.42	2	3, increase	6
User experience	− 1.01	2	− 1, decrease	4
Photograph	17.82	3	3, increase	7
Price	− 8.73	1	− 2, decrease	4
Quality	7.61	3	2, increase	6
Audio and video	16.38	2	3, increase	6
After-sale service	− 50.97	1	− 3, decrease	3

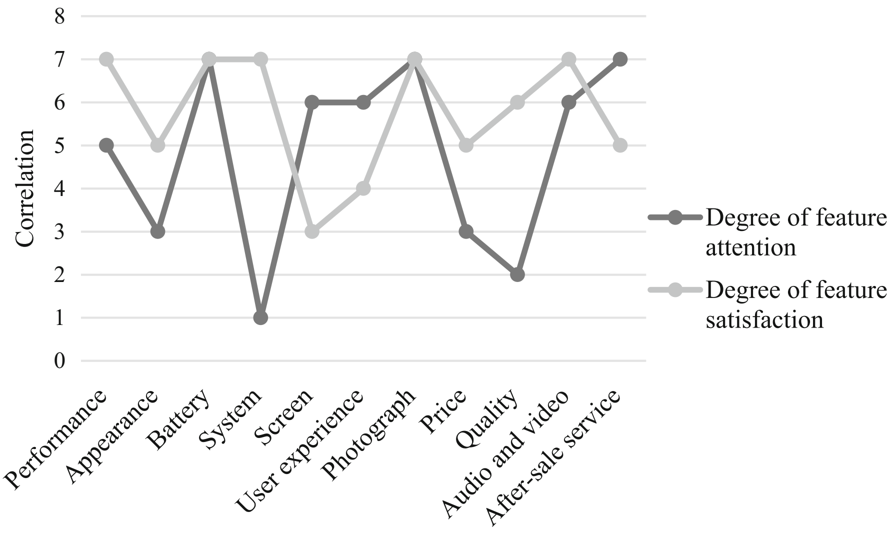

Fig. 2 The correlation between online reviews and product improvement of the Huawei Mate 8

mobile phones into three types. The first type involves maintaining or slightly improving the attributive features whose degree of feature satisfaction increased, including the following 7 features: performance, appearance, battery, resolution, photograph, quality and audio and video effects. As shown in Fig. 4, the degree of

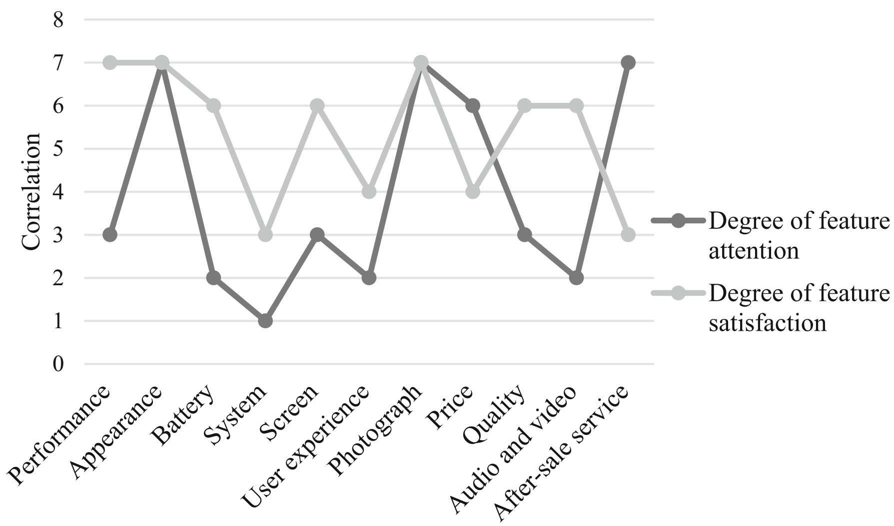

Fig. 3 The correlation between online reviews and product improvement of the Huawei Mate 9

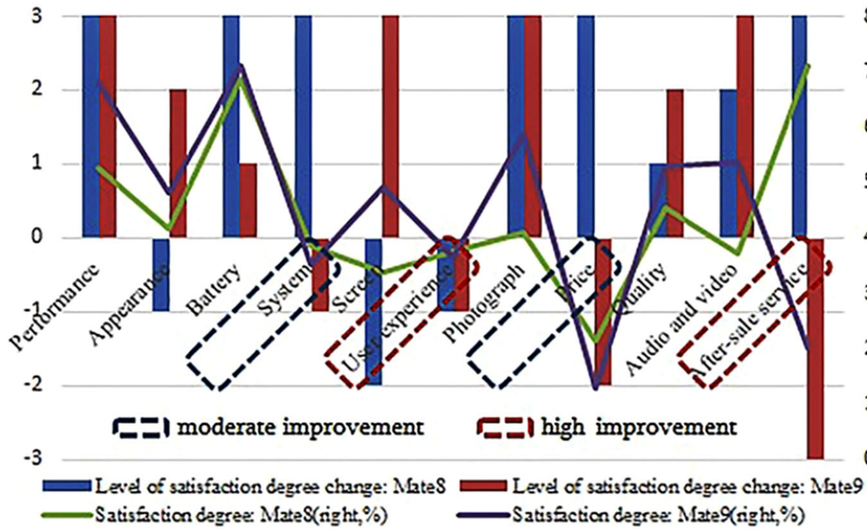

Fig. 4 Analysis results and suggestions for future improvement

satisfaction of these 7 features of the Mate 9 is rising, which can be maintained or slightly improved. The second type involves maintaining moderate improvement of the attributive features whose degree of feature satisfaction remains unchanged or is slightly decreased, including the price and system. The level of change in the degree of satisfaction with the price and system of the Mate 9 is − 2 and − 1, respectively, so both attributive features can be improved moderately. Based on online consumer reviews, price adjustment strategies can be implemented to increase the degree of price satisfaction of consumers, such as improving cost performance, adding additional functions or clearing the price positioning. For future improvement efforts, the system can be optimized in terms of the UI interface, the application program, fingerprint recognition, and system upgrades to enable greater consideration of consumers' user habits. The third type involves maintaining high levels of improvement for the attributive features with a significantly decreased degree of feature satisfaction, including after-sale services and user experiences. The level of change in the degree of satisfaction of after-sale services of the Mate 9 is -3; the level of change in the degree of satisfaction of user experiences of the Mate 8 and the Mate 9 is -1. In other words, the level of change in the degree of satisfaction of the user experience of the Mate 8 and the Mate 9 is decreasing. Therefore, the two attributive features can be improved substantially. It can be seen from online reviews that the attributive feature of user experience still fails to meet consumers' expectations; thus, it can be improved in terms of the comfort, the design and the practicability of phones. Of course, as consumers' service awareness increases, enterprises should also enhance their after-sale services.

5 Study conclusions and limitations

In examining the www.zol.com.cn website as the source of information and Huawei Mate phones as the research target, this paper processed data from consumers' online reviews on three types of Huawei Mate phones, extracted the 11 attributive features of greatest customer concern, and discussed the correlations between phone improvement and degree of feature attention and degree of feature satisfaction of the 11 attributive features. This study found a strong correlation between the change in the degree of feature satisfaction and phone improvement. When the product or its attributive features have experienced great improvement, the degree of consumer satisfaction increases, and consumers' online reviews tend to be positive. When the product is less improved or the improvement of a product is not obvious, the degree of consumer satisfaction declines, and consumers' online reviews tend to be neutral or negative. In addition, the correlation between the change in the degree of feature satisfaction and product improvement is stronger than that between the change in the degree of feature attention and product improvement. This empirical study shows that enterprises can determine the direction and contents of phone improvement according to the information in reviews on the preceding phone model. Using information from internet reviews to improve products is feasible and effective, and it is relatively simple to use internet mining tools to obtain information from internet reviews. This paper can help enterprises master market requirements, understand consumers' behaviours and improve the quality and efficiency of product innovation. In addition, enterprises can learn consumers' true preferences through their online reviews and tailor their products more closely to those preferences through product innovation and improvement.

With the development of internet technology, the cost of obtaining consumers' online reviews has steadily decreased. In addition, the existing big data analysis and Chinese text mining and analysis tools are in continuous development, which provides opportunities for enterprises' future product innovation and improvement. The Octopus Collector used in this study is an easily operated professional tool for collecting the data of online reviews. Scholars with basic knowledge of programming can also obtain online review data from the internet using programming language, which may have more complete functions. However, this study had some limitations. For example, this study examined only the online reviews of three types of phones from one website. Moreover, the classification of the merits and demerits in the phone reviews came directly from the www.zol.com.cn website, with no further analysis for sentiment polarities, which may have had an impact on the accuracy of the findings. Future research can choose other e-commerce platforms, such as tmall.com and jd.com, and further analysis sentiment polarities.

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