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Dynamic Characteristic of Consumer Attention in Online Reviews —Empirical Research Based on Mobile Store Reviews

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Dynamic Characteristic of Consumer Attention in Online Reviews

—Empirical Research Based on Mobile Store Reviews

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Abstract: Nowadays consumer online reviews are becoming more and more important for enterprise decision-making. While the existing research seldom discussed review data from a dynamic perspective, especially ignored consumers' attention change during the product life cycle. To study whether there are dynamic changes and the characteristics of changes in the attention degree of consumers in each phase of the product life cycle, this paper coded a specific node program to collect the online reviews data of the four mobile phones in the entire product life cycle and used python's Chinese automatic word segmentation tool library to segment each word and count word frequency, and then a stepwise regression method was used to analyze the dynamic changes of consumer attention. The paper finds that consumers' attention on logistics and products presented in online reviews show a downward trend, and the attention on brands shows an upward trend; There is no obvious change in the attention degree on services, prices, and promotion; On the different dimensions of products, there is a significant difference in the attention degree. The research results broad the research ideas of online reviews, provide decision-making basis for enterprises to grasp the characteristics of consumers at different stages and to formulate production and marketing strategies.

Keywords: online reviews, attention degree, dynamic, stepwise regression

1. INTRODUCTION

With the upgrade of online shopping, the massive amount of e-commerce data has provided enterprises with many structured or unstructured data related to user behavior. Evaluations made by consumers on e-commerce sites after purchasing products or services can be used by businesses. After researching consumer concerns through data analysis, the available information will be of great significance to the organization of production and marketing.

At present, data analysis has been widely used in various industries such as e-commerce, finance, and medical care. Using big data to analyze massive review data can provide useful guidance for the production and sales of enterprises. The development of natural language processing technology, especially Chinese word segmentation technology, has facilitated massive review analysis. With these technologies, it is very convenient to extract information from reviews.

Based on most of the static perspectives, the extraction of existing review opinions, sentiment analysis, and usefulness analysis methods for review data acquisition cases are improved. The research emphasizes that consumers' attention in different aspects may change regularly in the product life cycle analysis. This essay will be based on the empirical research of mobile phone store reviews to explore the changes of consumer concerns and their attention levels in the product life cycle reflected in e-commerce website reviews and consumer attention to different concerns in e-commerce website reviews. Four basic mobile phone review data were collected from two mobile phone official malls, extracting consumer concerns, and trying to find the consumer's attention to the changes in the different concerns of mobile phones and different concerns. The differences and connections between the two provide a basic idea for analyzing reviews from a dynamic perspective. The

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purpose is to analyze the dynamic characteristics of consumer attention in online reviews in order to provide guidance for the production of enterprises, provide solutions for marketing planning. Specifically, the research can not only provide guidance for enterprises to organize production, R & D and product improvement, and enhance customer value, but also guide enterprises to follow the product life cycle and scientifically formulate or adjust marketing strategies in different stages. In a nutshell, the essay will provide various and specific solutions for production of enterprises, marketing planning and provide new ideas for the whole field of e-commerce website review analysis.

2. LITERATURE REVIEW

2.1. Research on Review Data Mining Methods

Analysis of data mining for review of e-commerce websites mainly involves three aspects:

First, the extraction of review opinions, that is, identifying what the review is talking about：Ji Yahui [2] improved the two-way propagation algorithm. By adding many product features, viewpoints, and interdependences between sentences, and adding verbs describing the products, the selected viewpoints and features were ranked using the HITS algorithm. Wang Hongwei[3] combined the artificial rule base and the rules generated by the class sequence to construct a hybrid rule base comparison sentence and judged the comparison entity name again to extract the comment point. Jiang Lin [4] innovatively used the word polarity algorithm, and proposed the extraction algorithm based on statistically relevant product keywords, using opinion association pairs, based on structured syntax analysis, and the word polarity algorithm to extract the Negative perspective approach. Xu Bing [5] added shallow syntactic, location, part-of-speech, and contextual features to the conditional random domain model, and proposed a method for extracting review opinions without the help of a domain dictionary.

The second is the sentiment analysis of comments, that is, to analyze whether the comments are ambiguous or derogatory texts, and the degree of derogation：Song Xiaoyong'[6] constructed a PORSC model for emotion classification by introducing a global emotion classification model and a specific type of user classification model, and Use distributed acceleration algorithms to speed up calculations. Gong An et al. [7] selected monogram features, syntactic features, and dependent word features as text features, and processed these features through machine learning methods. Each clause in the sentence was treated as a unit, and each unit was processed by the emotional rule method. Taking each small clause in the sentence as a unit, the emotion tendency calculation is performed for each unit by the emotional rule method, and the score values of all units are superimposed to obtain the emotional tendency of the entire review text. Zhang Jing et al. [8] constructed a support vector machine classifier to analyze the sentiment tendency of comments by selecting multiple features. Shi Wei et al. [9] segmented comments, marked product features, emotional polarity, and intensity based on fuzzy emotional ontology, and completed the sentiment calculation from the dimension of the word to the dimension of the entire document in turn, improving the semantic processing ability of sentiment analysis .

The third is the research on the identification and usefulness of false reviews, that is, to study the characteristics of fake reviews and the quality of reviews, and to identify non-worthy and meaningless reviews: Guo Shunli [10] proposed an index to measure the usefulness of comments. He weighted and quantified the eight selected indexes through fuzzy analytic hierarchy process, calculated the usefulness and ranked them by weighted grey correlation analysis, and constructed a Review usefulness ranking model. Liu Junqing [11] used in-depth interview method and inductive summary method to study the characteristics, influence and identification of false comments.

2.2Research on the dynamics of reviews

Godes D, Silva JC [12] calculated the Amazon website review scores. By studying the ratings in the time dimension, it was found that the review scores showed a downward trend, explaining that people's ability to analyze previous reviews weakened over time. When previous reviewers vary widely, more reviews may lead to more lower ratings. Shao Jingbo et al. [1] found that the sentiment polarity, sentiment intensity, and subjectivity of the comment content have certain dynamic changes. It was found that the comment content tended to be objective and complex, while the sentiment polarity and sentiment intensity of the comment had a significant negative correlation with time. He thinks that this regulation is related to the ability level of consumers. Wenjing Duan [13] analyzed the positive feedback mechanism of sales volume and word of mouth. He characterizes this process through a dynamic simultaneous equations system in which the influence of online word of mouth is used as a factor for retail sales, and sales are used as dependent variables. Zhou Shuling [14] based on the review valence, by studying the initial reviews and additional reviews given by the same reviewer, attitude changes will occur, and this easily overlooked change will have an impact on consumers ’perceived usefulness and purchase intention. , To conduct more detailed and more research on the dynamics of reviews in the field of online reviews. The study takes consumers 'perceived usefulness as an intermediary variable and self-efficacy as a moderating variable, and analyzes the initial comments and additional comments of Taobao sneakers. The two types of dynamic changes have a difference on consumers' purchase intention. Combining with the product cycle, Hu Wei [15] analyzed the logistics strategies that should be adopted at each stage, and pointed out the differences in the influencing factors of logistics strategies at the stages of each product life cycle. Pan Chengyun [16] pointed out the deficiency of the traditional product life cycle theory and proposed to classify the product life cycle according to the product category. Based on this, it analyzed how to develop marketing strategies for different types of life cycle.

2.3 Application of online review data

For the usefulness analysis of online reviews, Guo Shunli [10] also built a usefulness model for O2O online reviews based on fuzzy analytic hierarchy process. Text mining techniques in online review research include Hidden Markov Mod-el (HMM) model [17], Support Vector Machine (SVM) model [18], and Condition Random Fields (Condition Random Fields, CRFs) model [19] and other typical machine learning algorithms for text feature extraction. As an effective information for scholars to analyze, online reviews provide help and support for countless researches.

By using various natural language analysis methods, user review data is used for product analysis, user analysis and marketing strategy analysis, recommendation systems, etc. Judith A. Chevalier and Dina Mayzlin [20] studied the impact of user reviews on Amazon.com and Bonnand NoBuff.com on book sales. It is found that the number and quality of user reviews have a significant impact on book sales. The more reviews and the higher the quality, the higher the book sales. Liu Jiaxue et al. [21] proposed a method for measuring consumer satisfaction based on consumer reviews, using automated text analysis software to extract review dimensions. The values of the dimensions are weighted to obtain the main factors affecting consumer satisfaction. Liping et al. [22] also conducted research on consumer satisfaction based on review data, and conducted sentiment analysis on reviews to obtain evaluation attributes and their emotional intensity weights. Then VIKOR multi-attribute decision-making method was used to measure customer satisfaction. Fan Weihao et al. [23] measured the urgency of the user's pain points from the aspects of attention and emotion in the comments, quantified the user's pain points through sentiment analysis, gave the user pain point calculation formula, and derived the user pain point model. Tu Haili [24] etc. used KANO model and LDA model to analyze reviews, researched the degree of satisfaction of product attribute requirements, built a product demand model based on reviews. Wang Yubin [25] etc. used the LDA model to analyze the distribution of user review topics, and performed user similarity analysis from multiple dimensions such as user rating similarity, preference similarity, and trust similarity to implement a recommendation algorithm. Wang et al.[26] improved the traditional filtering algorithm and added the sentiment polarity similarity to the traditional filtering algorithm. Zhang Duo [27] first analyzed the reviews syntactically, then judged and clustered them, and finally used the multi-attribute decision-making method to rank the products, recommending products with high similarity. Based on the time dimension, research on the time series of online reviews of experience products with different text lengths, with the purpose of grasping regular information such as online review behavior habits and demand preferences of e-commerce platform consumers, Wang Jun [28] and other researchers use python crawler language Tool to grab online reviews from movie review sites. First, the information in the review database is extracted, divided by the content of the review, the review time, the user rating, and the user level, and then the number of characters is counted and the type is divided (long text / short text). According to different types of comment data, perform time feature analysis to construct time interval sequences, and text content analysis, and explore comment feature segments and keyword word frequency statistics.

2.4 Summary of related research

Scholars have conducted extensive research on text analysis, online reviews, and product life cycles, and have proposed many data mining methods based on reviews. They have deeply studied product information, user information, and emotional information contained in reviews. There have also been some useful explorations in big data and marketing, focusing on the use of data analysis for precision marketing. However, the existing research still has the following deficiencies. First, it only analyzes reviews from a static perspective, and few studies focus on the dynamic changes of reviews. Although Shao Jingbo and others [1] paid attention to the dynamic characteristics of reviews, they only studied from three dimensions: emotional polarity, emotional intensity, and subjectivity, and did not reflect the changes in consumers ’concerns. Second, it is not enough to show the dynamic change characteristics in the product life cycle, and the data support for describing the dynamic change process of certain indicators in the product life cycle is not enough. the study.

3. RESEARCH MODEL AND HYPOTHESIS

3.1 The degree of consumer attention

The statistics of certain words in the comments can be used to measure the consumer's attention to a certain extent. In general, if consumers have a lot of words related to a certain aspect of the comments in a certain period of time, that is, the focus point of the focus point related words occur with the high frequency. It can be judged that consumers in this period are particularly concerned about this aspect; otherwise they are not particularly concerned. Based on this, the formula for calculating consumer attention can be obtained:

$$\text{The of consumer attentiodegree n F} = \frac{\sum_1^n pk_i}{pt} \times 100\% \quad 3.1$$

(Where n is the number of words related to a certain point of interest, which means the number of comments containing words related to the i-th point of interest in a period of time, and pt is the total number of comments in the same period.)

3.2 Dynamic changes in the degree of consumer attention

According to the related research on the product life cycle by this scholar and other related scholars[29], it can be inferred that the degree of consumer attention on certain concerns may show certain characteristics of change as the product life cycle progresses.

3.3 Hypothesis presentation

This paper divides the aspects of consumer attention into six aspects includes product attention, logistics attention, price attention, promotion activities, service attention and brand attention:

(1)At the initial stage of product introduction into the market, consumers are completely unaware of the product. In addition, the product itself has limitations which will prompt consumers to be more cautious in their purchase decisions and pay more attention to product information. However, during the product growth stage, the market scale has expanded, in order to facilitate consumers to distinguish the same type of products, brand awareness has gradually emerged. At the mature stage, market demand tends to be saturated, intensifying market competition, and the market transitions from a seller's market to a buyer's market. At the same time, the quality competition of this product will also change into brand competition. Consumers who have a thorough understanding of the product will pay more attention to the brand image that represents the characteristics of the product to a certain extent and rely more on the brand's personal preferences to make purchasing decisions.

Accordingly, the following hypothesizes are proposed:

H1: The degree of consumers' attention to the product is negatively related to the time of comment

H3: The degree of consumers' attention to brands is positively correlated with review time

(2)More and more companies choose to rely on third-party logistics or self-built logistics systems in their e-commerce business. The general improvement in the efficiency of logistics services and the general decline in time costs have made consumers generally trust the speed of product logistics. Products that rely on universal third-party logistics services will gradually lose their differences in logistics factors. Therefore, the continuous improvement of the logistics network has caused the market to pay less attention to product logistics factors.

Accordingly, the following hypothesis is proposed:

H2 Consumers' attention to logistics has a negative correlation with the time of comment posting

(3)Though price and promotion also promote consumers to make purchases behavior within the time pass, the following hypothesizes are proposed:

H4 Consumers' attention to price is positively related to the time of comment

H5 Consumers' Attention to Promotions Is Negatively Relevant to the Time of Comment Posting

(4)The growth of the service industry has deepened consumer attention to merchant services. Merchant services as a by-product of products are also closely linked to consumers' overall experience. With the passage of time, consumers who have sufficient knowledge of the product have shifted their attention to the service level that distinguishes similar products. The quality of the service provided by the product has become the key to competition. Excellent service improves the consumer's shopping experience, while also promote its brand loyalty.

Based on this, this study makes the following assumptions:

H6 Consumers' attention to merchant services is positively related to the time of comment posting

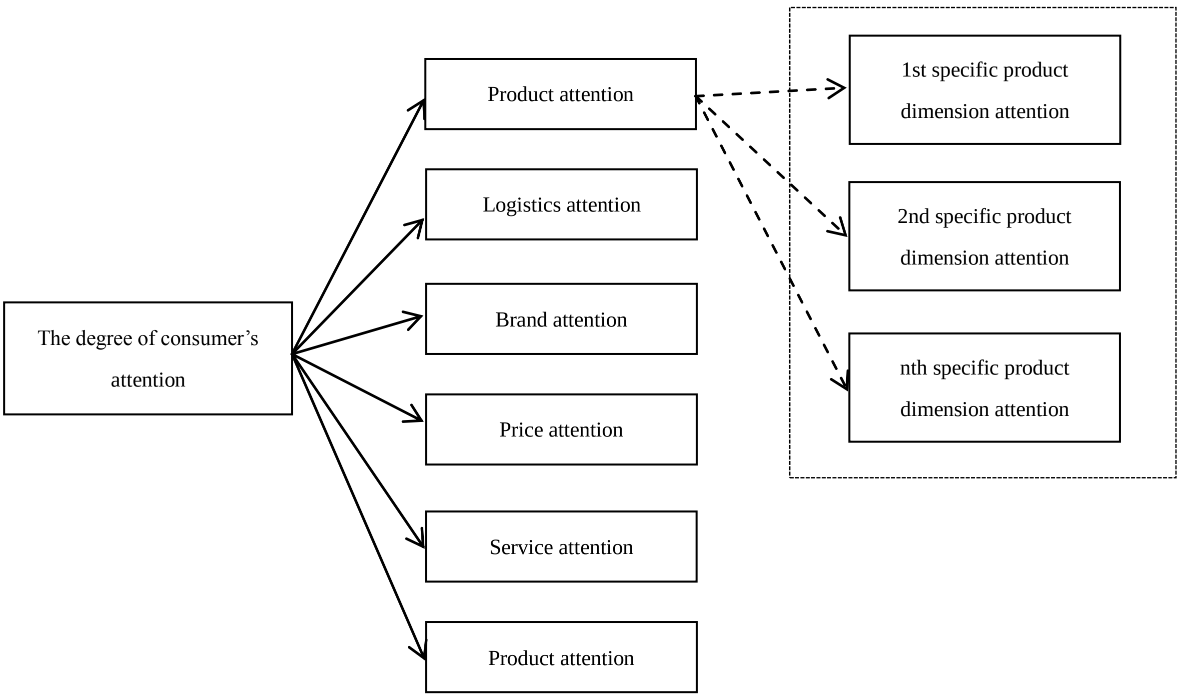

Figure. Research model

4. DATA COLLECTION AND ANALYSIS

4.1 Data collection

This essay uses the web crawler to selectively crawls pages related to a predefined topic. By visiting several mobile phone brand online malls to be researched, we got 23754 comments were collected for Huawei P10, 17350 comments for Huawei Enjoy 7plus, 17340 comments for vivox9, 12386 comments for vivox9s, and 70380 data in total, generating four xlsx format files.The collected data period can basically be considered to cover the entire life cycle of the product.

4.2 Taxonomy construction

4.2.1 Keyword extraction in comments

The python file system open method and the csv file processing class library csv are used to read the four collected data sets. Read the comment content line by line from the csv file, first use snownlp to segment the comment, then traverse the clause, use snlp to segment each clause. Finally, the dictionary traversal is written to a csv file and a word cloud is generated using the word_ cloud library. After the above processing, 21,825 unique words were obtained from the four data sets, and a noun word cloud was generated.

4.2.2 Focus point extraction and focus point related word thesaurus construction

Sort the extracted words according to their frequency of occurrence, and select all words that appear more frequently and may be meaningful to the analysis. There are 13 points of focus this time, namely appearance, price, promotion, logistics, brand, screen, running speed, memory, sound effects, camera, battery, games, and services. Among them, appearance, screen, running speed, memory, sound effects, photos, batteries, and games are the concerns that describe the attributes of the product itself. Consumers' concerns can be divided into six aspects: products, services, prices, promotions, brands and logistics.

4.3 Consumer attention calculation analysis

4.3.1 Frequency of focus points

Process the four review data sets separately, read the review data set line by line, use the snownlp clause to segment each clause, find the word in the thesaurus where the focus is concerned, and find all the thesaurus if it is not found. Record the number of focus point in the comments statistics.

4.3.2 Summary of attention frequency and calculation of attention

The specific method is to divide the life cycle of the four mobile phones into 25 phases, summarize the data of the first phase of the four mobile phones as the first data, and summarize the data of the second phase of the four mobile phones as the second data. By analogy, the statistical results are written to a csv file. Finally, the statistical results of word frequency summary of four data sets are obtained.

4.3.3 Stepwise regression analysis

This study uses stepwise regression to find several points of interest that have the most stable changes in attention over time. Based on the positive and negative coefficients, we can determine whether the degree of interest in the point of interest is rising or falling.

Table 4.2. Definition of variables

variable name	Variable identification
Natural logarithm of the cycle number	lnt
Screen attention	X1
Running speed attention	X2
Internal storage attention	X3
Sound effect attention	X4
Photograph attention	X5

variable name	Variable identification
Battery attention	X6
Game attention	X7
Appearance attention	X8
Price attention	X9
Promotion attention	X10
Logistic attention	X11
Brand attention	X12
Service attention	X13
Product attention	X14

The regression results are shown in Tables 4.4 and 4.5. Table 4.4 reflects the degree of fitting of each regression model. The deterministic coefficient R2 is a statistic that measures the goodness of fit of the regression model. The closer the value is to 1, the better the model's fitting effect.

The regularity of the attention of consumers at different points of concern over time can be described by (4.1):

$$\ln t = -0.092X14 - 0.146X11 + 0.073X12 + 6.448 \quad (4.1)$$

Consumers pay attention to the product in many ways. The resulting regression equation is shown in (4.2).：

$$\ln t = -0.126X8 - 0.371X3 - 0.150X5 + 0.224X6 + 3.834 \quad (4.2)$$

Table4.3. Summary of stepwise regression results

Model	R	R	R^2	Deviation. Error
1	.864a	.746	.735	.429471376676
2	.918b	.843	.829	.345473499171
3	.930c	.865	.846	.327895410177

Note: a. Predictors: (constant), product attention X14; b. Predictors: (constant), product attention X14, logistics concern X11; c. Predictors: (constant), product concern X14, logistics Attention X11, Brand Attention X12

Table 4.4. Variables that ultimately enter the model

Model		Non-standardized coefficient		Standardized coefficient	t	Sig.Value
		B	Error	ß		
1	（Constant）	5.569	.404	--	13.769	.000
	Product attention X14	-.094	.011	-.864	-8.220	.000
2	（Constant）	7.612	.643	--	11.831	.000
	Product attention X14	-.092	.009	-.853	-10.084	.000
	Logistic attention X11	-.155	.042	-.311	-3.680	.001
3	（Constant）	6.448	.876	--	7.357	.000
	Product attention X14	-.092	.009	-.850	-10.591	.000
	Logistic attention X11	-.146	.040	-.293	-3.627	.002
	Brand attention X12	.073	.039	.150	1.850	.078

4.4 Result analysis

(1) Analysis of the first regression results

Through the first regression, it was found that the product attention coefficient is -0.092, and the Sig. Value is 0.000, which is less than the significance level of 0.1. Assuming H1 is established, that is, consumers' attention to the product information (X14), logistics (X11), and brand Degree (X12) shows a steady downward trend with the time of product launch.

It shows that consumers in the early stages of product listing pay more attention to some characteristics of the product itself, while the latter pay less. This may be related to the cyclical changes in consumer maturity. Consumer maturity is a dynamic evolution process. As the product life cycle advances and consumer experience and knowledge increase, the consumer's level of cognition of the product tends to mature[25]. As consumers become more aware of the product, their attention to the product itself has declined.

Table4.5. Summary of stepwise regression results

Model	R	R^2	Adjusted R^2	Deviation. Error
1	.895a	.800	.792	.380914757840
2	.909b	.827	.811	.362413178809
3	.922c	.850	.828	.345853536468
4	.939d	.881	.857	.314968283357

Table4.6. Variables that eventually enter the model

Model		Non-standardized coefficient		Standardized coefficient	t	Sig.Value
		B	S.E.	Beta		
1	（constant）	4.659	.255	--	18.250	.000
	Appearance attention X8	-.225	.023	-.895	-9.598	.000
2	（constant）	4.949	.289	--	17.104	.000
	Appearance attention X8	-.215	.023	-.854	-9.360	.000
	Internal storage attention X3	-.433	.234	-.169	-1.846	.078
3	（constant）	4.830	.284	--	16.995	.000
	Appearance attention X8	-.162	.037	-.646	-4.422	.000
	Internal storage Attention X3	-.411	.224	-.160	-1.834	.081
	Photography attention X5	-.107	.060	-.259	-1.777	.090
4	（constant）	3.834	.503	--	7.615	.000
	Appearance attention X8	-.126	.037	-.500	-3.394	.003
	Internal storage attention X3	-.371	.205	-.145	-1.813	.085
	Photography attention X5	-.150	.058	-.362	-2.588	.018
	Battery attention X6	.224	.097	.199	2.307	.032

The coefficient of logistics attention is -0.146, and the value of Sig. Is 0.002, which is less than 0.1. Assuming H2 is established, it indicates that logistics attention has a significant negative correlation with time, that is, consumers' attention to logistics will decrease with time. In the early stages of product introduction, consumers have high levels of desire for higher logistics speeds, and vice versa in later stages.

The coefficient of brand attention is 0.073, and the value of Sig. Is 0.078, which is less than 0.1. Assuming that H3 is established, it indicates that brand attention is positively correlated with time, that is, consumers are paying more and more attention to brand comparison. Brand attention here mainly refers to the situation where consumers compare multiple brands in reviews. The results show that consumers have fewer choices in the early stages of product launch, high loyalty to a certain brand, fierce competition among brands in the later stages, and consumers tend to compare multiple brands.

The variables X9 (price attention), X10 (promotional attention), and X13 (service attention) are not included in the model. It is assumed that H4, H5, and H6 do not hold, that is, consumers' attention to these concerns has a certain randomness. Possibly due to the difference in price sensitivity between consumers who buy at different times; the time of the merchant's promotional activities may not show regularity; consumers see services as additional attributes of the product.

(2) Analysis of the results of the second regression

The coefficients of appearance attention, memory attention, and photo attention are all less than 0, and the Sig. Values are all less than 0.1. The results are significant, indicating that the attention of these three attention points has a significant negative correlation with time, indicating that consumers are looking at mobile phones. Attention to features such as memory, memory, and photography has declined over time. The battery attention coefficient is positive, and the Sig. Value is 0.032, which is less than 0.1. It shows that battery attention has a significant positive correlation with time. The above proves that consumers ’attention to products is generally on the decline, but their attention to different product dimensions is different. The attention on some product dimensions is decreasing, and the attention on some product dimensions is increasing. Attention to other dimensions shows some randomness.

5. CONCLUSIONS AND RECOMMENDATIONS

The research results show that the consumer's focus on some concerns or attention reflected in e-commerce website reviews has obvious dynamic changes, and some do not. This conclusion provides new ideas for researching the product life cycle, online reviews, and e-commerce, and will also provide a useful reference for the organization of production and marketing strategies. This paper takes the research of mobile phone reviews as an example to find that consumers’ attention to logistics and products itself is declining, and brand attention is on the rise. Based on this, the companies can cooperate with more efficient logistics partner in early sales and choose a cheaper and less efficient logistics partner in the later period. The research finds that although consumers’ attention to the product itself is on the decline, there is still a difference in attention in different product dimensions. For example, this research finds that consumers’ attention to mobile phones’ appearance, memory, and photography is declining, but attention to batteries is increasing. Therefore, enterprises should focus on analyzing the changes in consumers’ attention to different dimensions of the product in order to formulate marketing strategies based on the characteristics of changes in consumers' attention to different dimensions of the product.

Of course, there are still some limitations in this research: The first is that this essay only uses mobile phones as an example, whether other products have this rule needs further research. The second is that the classification of keywords has a certain subjectivity when constructing the thesaurus of attention. In subsequent studies, different products can be researched to check whether this rule is universal; the correctness of the constructed thesaurus can also be tested through investigation methods to reduce subjective impact.

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