Research on Emotional Needs of AR Product Users Based on Online Review Mining

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Abstract. This paper will provide a reference for the development and design of augmented reality devices in the metaverse era by analyzing users' emotional needs for existing AR products from the perspective of user-product interaction experience. This research mainly uses the method of text mining to obtain the user reviews of the top 100 augmented reality products from the Jingdong platform, and obtains 12,450 review information through de-duplication screening, and combines the LDA topic modeling method with the sentiment classification method to obtain The user's product perception attribute, which analyzes the user's perception and emotional preference characteristics of AR products. Based on this analysis, user emotional preferences and application design directions of augmented reality devices under the background of the metaverse are analyzed, providing reference for the development and design of future metaverse technology equipment.

Keywords: Augmented Reality; LDA topic model; user emotional preference

1 Introduction

Augmented reality technology (“AR” for short) is currently at a stage of technological perfection, and related products are entering the consumer market on a large scale [1]. AR technology is a technology based on real-time computing and multi-sensor fusion. Research on AR technology in the world mainly has two directions. One is the technical basic research of augmented reality technology, such as image display, battery life, wearable AR product design, etc. On the other hand, it mainly focuses on the application research of AR technology, such as applications in military, office, medical, education, entertainment, etc [2].

Online user comment mining is a research method that uses text mining methods to obtain, filter, and cluster analysis of user comments on network platforms [3]. Current research on online review information mining mainly focuses on related implementation technologies of online review information extraction, sentiment analysis, text classification and their corresponding commercial applications [4]. Some scholars can use LDA method for topic clustering analysis of user perception dimensions in text mining [5]. Some scholars have also used the BERT sentiment model to process text mining demerits and obtain users' emotional experiences and evaluations [6],[7].

This study hopes to obtain user reviews of AR products on domestic e-commerce platforms through user review mining, and analyze consumers' perceived current status and emotional needs for AR products. Combined with relevant literature, we provide suggestions for the

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development path of AR products to promote the realization of Metaverse technology. Through the combination of LDA topic clustering and BERT sentiment analysis methods, we can fill the research gap in the interaction between users and technology in the metaverse field.

2 Methods

This study will use text mining methods to obtain user review data, and use the LDA topic clustering model to analyze users' perceived dimensions of AR products; and then use BERT sentiment analysis to analyze the emotional tendencies of user reviews. Finally, it summarizes users' concerns and emotional tendencies towards AR products, providing references and suggestions for future AR product development and design directions.

This study uses the JD.com shopping platform as the data source. By retrieving the target AR products of this study, we obtained the top 50 product information recommended by the platform, and used the "Octopus" text mining tool to obtain user comments as the analysis data for this survey. By analyzing the characteristics of user comments, the number of user perception dimensions is determined, and then the LDA topic modeling method and BERT emotional tendency analysis method are used to process the data.

2.1 LDA Topic Modeling Analysis

After the comment data is obtained, the data is preprocessed first, combined with the stop word list of Harbin Institute of Technology, and the " Jieba " word segmentation tool is used for word segmentation. Next, LDA topic clustering analysis is performed on the results after word segmentation, and the perception attributes and corresponding keywords of the products involved in user reviews are extracted, which are used as the measurement dimensions for analyzing users' product perception.

2.2 BERT Sentiment Analysis

First, build an AR product sentiment dictionary by analyzing the main user emotional experience of AR products, then import the word-segmented user comment data, use the BERT sentiment classification model to mark the polarity of the emotional experience in each perception measurement dimension, and obtain the user's perception of each perception attribute Dimensional emotional preference, extracting the user's emotional perception and emotional needs during the experience of AR products.

3 Result

Obtain user reviews of AR products by filtering product reviews under "Electronic Equipment > Smart Products > XR Equipment > AR Glasses Category" on the JD.com shopping website. Use the "Bazhuayu" text mining tool to obtain review information. The conditions are that the product price is within 1,000-10,000 yuan, and the review data length is greater than 10 characters. After removing non-target products and duplicate data, a total of 12,450 user review information was obtained, including review content, user ID, review time, and corresponding product information. Some results are shown in Table 1.

Table 1. Some AR Product User Review Information.

User ID	Product	Time	Subhead
u***1	ROKID Max	2023-06-18 18:50	The first moment I opened the package, I was attracted by the appearance, which is as high as a promotional advertisement…
c***h	EPSON AR Glass	2022-10-31 11:20	The logistics is fast, the effect is clear, and it is quite light. It is very convenient to carry when going out, and the battery is also durable. It frees your hands. The charm of technology!
x***x	Leiniao Air Plus	2023-06-04 10:29	I think it's ok, some chucks, nose pads are better than last time, try again for a few days
a***y	ROKID Max	2023-07-04 13:17	Just arrived, open it and experience it, it feels good, the picture quality is clear, and the quality of workmanship: I like it very much...

After After obtaining user comments, it is necessary to extract key words in the comments. First, use JIEBA word segmentation software to extract key words such as adjectives, nouns, and verbs in the comments. Then use the Harbin Institute of Technology stop word list to eliminate words that have no actual meaning in the sentences such as "and, or, between". Sort out words with the same or close meanings, and finally obtain the main keywords and corresponding word frequencies of user reviews of AR products.

The obtained user evaluation information is analyzed through the LDA topic cluster analysis method. Therefore, this study divides users' cognitive evaluation dimensions of AR products into three dimensions: application, experience, and appearance. Then use the LDA topic model with a topic number of 3 to analyze the data and obtain the user's multi-dimensional cognitive model of AR products. Finally, there were 2209 comments on the application dimension, including 83 keywords; 998 comments on the experience dimension, including 85 keywords; and 981 comments on the appearance dimension, including 66 keywords. The statistical chart of the proportion of evaluation words and shared words in each dimension is obtained, as shown in Figure 1.

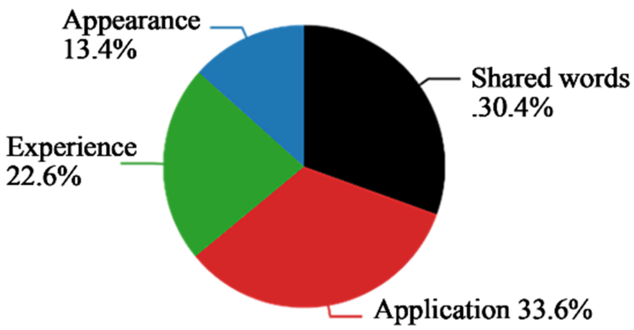

Fig. 1. Proportion chart of vocabulary and shared words in each dimension.

Based on the results obtained by LDA topic cluster analysis, word frequency analysis was performed on the data. After removing the shared words in these three dimensions, the user's main evaluation perceptual words in these three perceptual dimensions and the corresponding word frequencies were obtained, and the results are shown in Table 2.

Table 2. Main vocabulary and frequency table of each topic.

Dimensions	Words	Frequency	Number of comments
Application	glasses	2076	1416
	Screen	544	452
	picture	539	429
	Video	432	360
Experience	Experience	904	733
	product	589	487
	Function	379	315
	customer service	372	311
Appearance	Effect	1754	1423
	Feeling	838	693
	Quality	553	516
	comfort	538	508

After LDA topic cluster analysis, emotional preference analysis is performed on the user evaluation text information in each dimension. By creating an emotional dictionary corresponding to electronic products, setting the emotional word preference value range to -3~3 (a score less than 0 represents negative emotion, and greater than 0 represents positive emotion), then analyzes the user's emotional preference value in three dimensions. as shown in Table 3.

Table 3. Distribution table of vocabulary of emotional tendencies in various dimensions.

Dimensions	positive emotion	neutral emotion	Negative emotion
application	1175	511	541
experience	751	122	125
appearance	744	160	77

4 Disscussion

After completing the user review data acquisition, LDA topic cluster analysis and BERT emotional preference analysis, all results need to be sorted and further analyzed. By processing the LDA topic cluster analysis results, you can obtain user evaluation word clouds, topic word distribution frequency diagrams, topic word relationship diagrams, etc. in each dimension. Afterwards, by sorting out the BERT sentiment analysis results, you can export user evaluation sentiment word clouds, sentiment word distribution maps of various dimensions, product review sentiment score statistics, etc.

4.1 LDA topic model analysis

By sorting out the vocabulary distribution under each dimension in the LDA topic analysis results, the dimensional distribution statistical diagram of AR product user evaluation data can be obtained (Figure 2). As can be seen from the figure, there are more user evaluation words under the application dimension, indicating that users' evaluation of AR products focuses more on the functions and effects of the products. However, relatively little attention is paid to product experience value and appearance value.

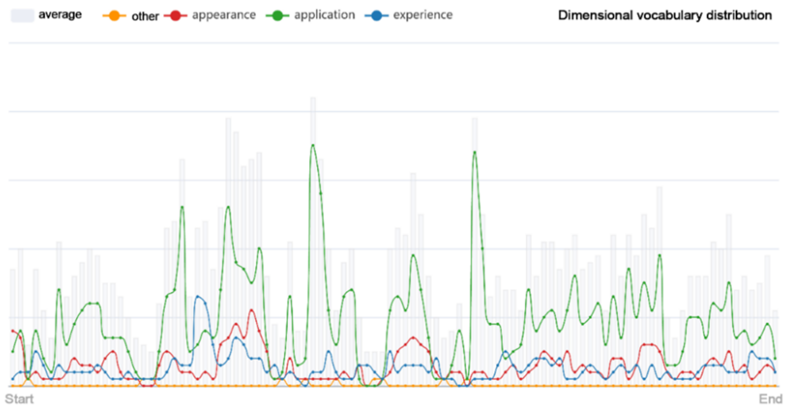

Fig. 2. Distribution chart of user comments in each dimension

Afterwards, the LDA topic modeling method can also analyze the relationship between review words and obtain the user evaluation word relationship diagram of AR products (Figure 3). It can be seen from the figure that the evaluation vocabulary of the two dimensions of application and experience is more closely related to other vocabulary. The evaluation vocabulary of the appearance dimension has a weak correlation with other vocabulary.

Fig. 3. User evaluation vocabulary connection diagram

4.2 User emotional preference data analysis

Through BERT user emotional preference score analysis, the emotional preference scores of all users are obtained. Then, the user comment sentiment score distribution map can be obtained based on the score of each user comment (Figure 4). It can be seen from the figure that most users' evaluation emotions are in a relatively satisfactory state, and users in the application dimension have the highest emotional satisfaction scores.

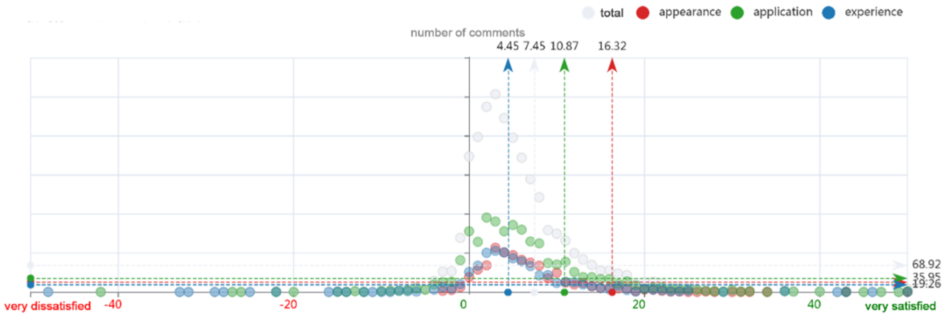

Fig. 4. Sentiment distribution map of user comments in various dimensions.

5 Conclusions

The following conclusions can be drawn from this study: First of all, from the user's cognitive dimension, users will pay more attention to the application value of AR products, so the design and development of AR products should focus on expanding functions and improving application value. In addition, from the perspective of users' emotional preferences, the current AR products on the market can basically meet the basic needs of users, but there is still room to further improve user satisfaction in terms of experience and product appearance. Finally, the BERT sentiment analysis algorithm used in this article reduces the difficulty of obtaining analysis data by combining it with user comment mining. By independently building an emotional vocabulary, the accuracy of the analysis results can also be improved.

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