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Application of Sentiment Analysis and Data-Driven User Profiling in Product Iteration Design

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Abstract. Our study employs sentiment analysis and data-driven methodologies to construct precise user profiles and apply them to product iteration design, aiming to enhance marketing effectiveness and user satisfaction. The research data comprises 178,563 user comments and 42,786 social media posts. Sentiment features are extracted using advanced sentiment analysis algorithms such as BERT and Transformer. These features are combined with user behavior data and classified into five primary groups using the K-means clustering algorithm, each representing distinct user needs and sentiment tendencies. Based on the user profiles, three product iteration schemes were designed and implemented. The effectiveness of these iterations was validated through A/B testing, resulting in significant improvements in user satisfaction and usage rates. Regression analysis reveals that both sentiment scores and user behavior features have a significant positive impact on user satisfaction. The findings demonstrate that combining sentiment analysis with data-driven user profiling plays a crucial role in product design and marketing, offering new insights for optimizing products and enhancing competitiveness.

Keywords: Sentiment Analysis, Data-Driven, User Profiling, Product Iteration, Marketing.

1. Introduction

In recent years, the proliferation of the internet and social media has provided a wealth of user-generated data, offering valuable resources for marketing and product design. Sentiment analysis, an important natural language processing technique, extracts sentiment features from user comments and social media posts, significantly supporting the construction of user profiles. According to Birjali et al. (2021), sentiment analysis enables companies to quickly identify user sentiment trends from a vast amount of user comments, providing a solid foundation for product improvement and marketing strategies. Rust (1993) and Yao (2024) found that sentiment analysis not only enhances user satisfaction but also significantly boosts market sales and user retention rates. Mostafa (2013) and Xia (2023) discovered that sentiment analysis could accurately capture users' emotional responses to brands by analyzing social media data, offering crucial support for brand management. Additionally, Alfonso et al. (2008) and Zhang (2023) highlighted the critical role of sentiment analysis in crisis management, aiding companies in identifying and responding to potential public relations crises promptly.

In terms of user profile construction, Hu (2020) and Qiu (2024) proposed a dynamic user profiling model based on sentiment analysis. This model analyzes user behavior and emotional changes on social media, building more refined user profiles. Park (2012) and Liu (2023) explored data-driven user profiling methods, finding that combining multiple data sources can significantly improve the accuracy and practicality of user profiles. Konstan (2012) pointed out that applying user profiles in personalized recommendation systems greatly enhances user experience and satisfaction. Moreover, Tan (2011) demonstrated that integrating sentiment analysis with user profiling strategies can increase the precision and effectiveness of ad targeting.

Despite these advancements, several limitations remain. Firstly, most studies focus primarily on single data sources, lacking comprehensive analysis across multiple data sources. Secondly, existing sentiment analysis models still face challenges in handling complex and subtle emotional variations. Lastly, traditional user profiling methods are relatively static, failing to reflect users' dynamic changes in real-time. These limitations underscore the need for further research on combining multiple data sources and dynamic sentiment analysis methods to construct more accurate and real-time user profiles and apply them to product iteration design.

By collecting and analyzing 178,563 user comments and 42,786 social media posts from various platforms, the research utilized advanced sentiment analysis algorithms such as BERT and Transformer to extract user sentiment features and construct user profiles. Significant differences in product needs and preferences among different user groups were identified. Based on the user profiles, three product iteration schemes were designed and validated, including function improvements, interface optimization, and personalized recommendations. Through A/B testing and user feedback, the results showed that user satisfaction increased from 3.8 to 4.35 (out of 5), monthly market sales rose from 1.975 million to 2.183 million yuan, and user retention rates improved from 74.6% to 82.9%.

The findings provide empirical support for optimizing product design and enhancing marketing effectiveness through sentiment analysis and data-driven methods, demonstrating the significant role of combining sentiment analysis with data-driven user profiles in improving product design quality and user satisfaction.

2. Methodology

2.1. Data Collection and Preprocessing

The data for this study were sourced from user comments and social media posts, specifically including 178,563 user comments and 42,786 social media posts. After data collection, a comprehensive data cleaning and preprocessing process was undertaken to ensure accuracy and completeness. The data cleaning steps are as follows:

Noise Removal: Texts containing advertisements and irrelevant information were removed.

Deduplication: Duplicate comments and posts were eliminated.

Text Preprocessing: This involved tokenization, removal of stop words, and stemming.

Regular expressions and natural language processing (NLP) techniques, such as the NLTK library, were employed for text preprocessing. The preprocessed text was then used for subsequent sentiment analysis and user profiling.

2.2. Sentiment Analysis Model Construction

To extract user sentiment features, advanced sentiment analysis algorithms such as BERT (Bidirectional Encoder Representations from Transformers) and Transformer were employed. The specific steps are as follows:

•Text Preprocessing: Tokenization and stemming were performed on the cleaned text data.

•Feature Representation: The BERT model was used to represent the text features, yielding contextual semantic vectors for each word. The input representation of the BERT model is as follows:

$$\mathrm{E} = \left[\mathrm{E}_{[\mathrm{CLS}]}, \mathrm{E}_1, \mathrm{E}_2, \ldots, \mathrm{E}_\mathrm{N}, \mathrm{E}_{[\mathrm{SEP}]}\right]$$

Where $E_{[CLS]}$ and $E_{[SEP]}$ represent the embedding vectors for the classification token and the separator token, respectively, and E_i represents the embedding vector for the i-th word.

•Model Training: Sentiment-labeled data were used to fine-tune the BERT model for the sentiment analysis task. The loss function employed was the cross-entropy loss function:

$$\mathcal{L} = -\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}[\mathrm{y_i}\log(\widehat{y_i}) + (1-\mathrm{y_i})\log(1-\widehat{y_i})]$$

Where y_i is the true label, and $\hat{y_i}$ is the predicted probability by the model.

•Sentiment Classification: The fine-tuned BERT model was used to classify new data, extracting user sentiment features with an accuracy of 92.7%.

2.3. User Profiling

In the user profiling phase, the K-means clustering algorithm was employed to segment users and extract their features. The steps involved are:

•Feature Extraction: Sentiment analysis results and user behavior data (e.g., purchase records, click behavior) were used to construct user feature vectors. The feature vector is represented as:

$$X = [x_1, x_2, \dots, x_{10}]$$

Where xi represents the i-th feature.The feature dimensions include ten dimensions such as user sentiment score, purchase frequency, click-through rate.

•K-means Clustering: The goal is to minimize the within-cluster sum of squares (WCSS):

$$J = \sum_{k=1}^{K} \sum_{i=1}^{N_k} |x_i - \mu_k|^2$$

where K is the number of clusters, x_i is the i-th sample, and μ_k is the centroid of the k-th cluster.

•Cluster Number Selection: The elbow method was used to determine the optimal number of clusters by plotting the WCSS against different numbers of clusters and identifying the "elbow point":

$$SSE = \sum_{i=1}^{N} |x_i - c_{k(i)}|^2$$

•Where $ck_{(i)}$ is the centroid of the cluster to which the k-th sample belongs. The optimal number of clusters was determined to be five.

•User Profile Presentation: The results of user profiles are visualized using tools like Tableau and Matplotlib, including the distribution of user sentiment, behavior characteristics, and clustering results. The final five user groups each exhibit different sentiment tendencies and behavior patterns. Group A has an average sentiment score of 0.75, while Group B has an average sentiment score of 0.45.

2.4. Product Iteration Design

Based on the results of user profile analysis, we conducted three iterations of product design with the following specific steps:

•Requirement Analysis: Analyze user needs and preferences according to the profile results of different user groups to determine the direction of product improvement. For example, Group A requires a high level of interface friendliness, while Group B has a strong demand for personalized recommendations.

•Scheme Design: Propose design schemes for different user groups, including functional improvements, interface optimization, and personalized recommendations. For instance, an interface optimization scheme was designed for Group A, while a personalized recommendation system was created for Group B.

•A/B Testing: Implement A/B testing to compare the effects of different design schemes. The test metrics include user satisfaction, usage rate, and retention rate. The statistical test for A/B testing uses a t-test, with the formula as follows:

$$t = \frac{\overline{X_A} - \overline{X_B}}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}}$$

Where $\overline{X_A}$ and $\overline{X_B}$ are the sample sizes for Group A and Group B respectively. s_A^2 and s_B^2 are the variances for Group A and Group B respectively, and n_A and n_B are the sample sizes for Group A and Group B respectively. The test results showed that user satisfaction increased from 3.8 to 4.35 out of 5 after interface optimization, and the usage rate improved by 12.5%.

•User Feedback: Collect user feedback to analyze the acceptance of the iterative design and suggestions for improvement. A total of 3,237 user feedback responses were collected, with 80% being positive.

•Continuous Optimization: Continuously optimize product design based on user feedback and test results to enhance user satisfaction and market performance. For example, further optimizing the personalized recommendation algorithm based on user feedback increased the recommendation accuracy by 8.4%.

3. Empirical Analysis and Results

3.1. Case Selection

For the empirical study, a highly active mobile application on social media was selected. This application targets a young demographic, offering features such as social networking, entertainment, and shopping. The selection was motivated by the rich user comments and social media interaction data available, which provide ample support for sentiment analysis and user profiling. Data sources include comments from the App Store and Google Play, as well as related social media posts. A total of 178,563 user comments and 42,786 social media posts were collected.

3.2. Data Analysis and Results

3.2.1. Sentiment Analysis Results

Sentiment analysis was performed on user comments and social media posts using the BERT model, achieving an accuracy of 92.7%. The analysis revealed that 62.5% of the comments were positive, while 37.5% were negative. Key sentiment features extracted included user satisfaction with the app interface, the practicality of the app's functionalities, and aversion to advertisements.

Table 1. Sentiment Analysis Result Distribution

Emotion Type	Comment Count	Percentage (%)
Positive Comments	111,352	62.5
Negative Comments	67,211	37.5

3.2.2. User Profiling Results

Based on the sentiment analysis results and user behavior data (such as purchase records and click behavior), user feature vectors were constructed and clustered using the K-means algorithm. Five primary user groups were identified, each representing distinct user needs and sentiment tendencies. The main characteristics of these groups are as follows:

Group A: Average sentiment score of 0.75, primarily concerned with the app's interface.

Group B: Average sentiment score of 0.45, mainly focused on personalized recommendations.

Group C: Average sentiment score of 0.60, interested in the app's comprehensive functionality.

Group D: Average sentiment score of 0.50, focused on social features.

Group E: Average sentiment score of 0.40, exhibiting aversion to advertisement content.

Table 2. Characteristics of User Profiles

User Group	Average Sentiment Score	Main Focus
Group A	0.75	Interface Design
Group B	0.45	Personalized Recommendation
Group C	0.60	App Functionality
Group D	0.50	Social Features
Group E	0.40	Advertisement Content

3.2.3. Implementation and Results of Product Iteration Design

Based on the user profile results, three product iteration schemes were designed, including interface optimization, functionality improvements, and personalized recommendations. After each iteration, A/B testing and user feedback were collected.

First Iteration: Targeting Group A, the app interface was optimized. A/B test results showed that user satisfaction increased from 3.82 to 4.10, and usage rates improved by 10.2%.

Second Iteration: Focused on Group B, personalized recommendation features were added. User satisfaction increased from 4.10 to 4.25, with an 8.7% increase in usage rates.

Third Iteration: Aimed at Groups C and D, core functionalities and social features of the app were enhanced. User satisfaction rose from 4.25 to 4.35, usage rates increased by 9.3%, and retention rates improved from 74.6% to 82.9%.

Table 3. Results of Regression Analysis

Parameter	Estimate	Std. Error	t Value	p Value
Intercept	3.2	0.15	21.33	<0.01
Sentiment Score (X_1)	0.85	0.07	12.14	<0.01
User Behavior (X_2)	0.45	0.05	9.00	<0.01
User Behavior (X_3)	0.30	0.04	7.50	<0.01

3.3. Discussion

3.3.1. Role of Sentiment Analysis in User Profiling

Sentiment analysis played a crucial role in constructing user profiles by extracting detailed user sentiment features. It captured users' emotional tendencies towards different functionalities, providing a significant basis for user segmentation.

3.3.2. Impact of Data-Driven Methods on Product Iteration

Data-driven methods significantly enhanced user satisfaction and market performance in product iteration design. By analyzing user needs based on profiles and validating iteration schemes through A/B testing, the iterations closely aligned with user demands, improving user experience and product competitiveness.

3.3.3. Enhancements in Marketing

Combining sentiment analysis with data-driven user profiling proved effective not only in product design but also in supporting marketing strategies. Accurate user profiles allowed for more targeted marketing strategies, improving the effectiveness of ad placement and overall marketing efficiency.

4. Conclusion and Future Directions

The study effectively constructed user profiles through sentiment analysis and data-driven methods, yielding significant results in product iteration design. By analyzing 178,563 user comments and 42,786 social media posts, user sentiment features were extracted and combined with behavioral data to develop user profiles. The K-means clustering algorithm was used to segment users into five primary groups, each representing distinct needs and sentiment tendencies. Based on these profiles, three product iterations were designed and implemented, with the effectiveness of each iteration validated through A/B testing. The results demonstrated substantial improvements in user satisfaction and market performance.

The innovative integration of sentiment analysis with data-driven methods introduced a novel approach to user profiling and product iteration design. The application of sentiment analysis technology enabled the creation of more precise and detailed user profiles, capturing dynamic changes in user sentiment. Data-driven product iteration design, informed by user profile analysis and validated through A/B testing, ensured that iteration schemes closely aligned with user needs, thereby enhancing user experience and product competitiveness.

Future research should focus on optimizing sentiment analysis algorithms to improve accuracy and robustness in handling complex and subtle emotions. Expanding the diversity and breadth of data sources will enhance the comprehensiveness and accuracy of user profiles. Additionally, developing real-time user profile models will enable the capture of dynamic user changes, providing more precise product design and marketing strategies. These improvements and expansions will enable sentiment analysis and data-driven user profiling methods to play an even greater role in product design and marketing, offering stronger support for enhancing competitiveness and user satisfaction.

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