Postprint: Evaluating the Effectiveness of Sentiment Analysis for User-Generated Content in Mobile Libraries

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Abstract

[Purpose/Significance] Through sentiment analysis of mobile library user-generated content, this study predicts the impact of user sentiment orientation on the evaluation effectiveness of mobile library resources, thereby facilitating improved resource promotion and precision recommendation services. [Method/Process] An analytical framework for evaluating the effectiveness of mobile library user-generated content is proposed based on sentiment analysis. Taking user-generated content for 15 annual bestsellers from "Zhangyue Library" as the research sample, data preprocessing is performed, followed by analysis encompassing three key processes: domain dictionary construction, sentiment classification, and evaluation effectiveness assessment. [Result/Conclusion] The data analysis reveals that user sentiment orientation in mobile library UGC demonstrates both diversity and consistency, with neutral evaluations proving significant in relatively accurately predicting resource ratings. Integrating sentiment analysis theories and methods into mobile library UGC research can provide valuable insights for mobile libraries to refine their service measures and enhance service quality.

Full Text

Preamble

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Research on the Evaluation Effect of Mobile Library User-Generated Content Based on Sentiment Analysis

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Abstract

[**Purpose/Significance**] This study aims to predict the evaluation effect of user sentiment tendencies on mobile library resources through sentiment analysis of mobile library user-generated content (UGC), thereby facilitating better resource promotion and precision recommendation services. [**Method/Process**] Based on sentiment analysis, this paper proposes an analytical process for evaluating mobile library UGC. Taking user-generated content for 15 annual bestsellers from "Zhangyue Library" as the research sample, the study conducts data preprocessing and analyzes three key aspects: domain dictionary construction, sentiment classification, and evaluation effectiveness. [**Result/Conclusion**] Data analysis reveals that mobile library UGC exhibits both pluralistic and consistent user sentiment tendencies, with neutral evaluations playing an important role and enabling accurate prediction of resource ratings. Introducing sentiment analysis theories and methods into mobile library UGC research provides valuable references for improving service measures and quality.

Keywords: sentiment analysis; mobile library; user-generated content; evaluation effect
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Introduction

Mobile library services, enabled by smartphones and other mobile terminals, have gradually blurred the boundaries of user reading behaviors. Reading is no longer simply a process of obtaining book content but has evolved into a community-based activity integrating reading, creation, sharing, and social interaction. In this mobile library community service model, users are no longer mere content readers but have become content producers and disseminators [1]. User-generated content (UGC) has emerged as an important resource for mobile libraries, and its management and utilization have become crucial for meeting user needs and building user loyalty. Rich and demand-specific mobile library UGC reflects the collective wisdom of mobile reading users [2]. Conducting text mining and sentiment analysis on UGC in mobile library community services to discover user evaluations and sentiment tendencies toward resources has become a new research hotspot for better resource promotion and precision recommendation.

Although scholars have conducted relevant research on UGC mining and sentiment analysis, studies specifically focusing on the evaluation effectiveness of mobile library UGC based on sentiment analysis remain relatively scarce. L. Siguenza-Guzman et al. comprehensively reviewed text mining applications in libraries, highlighting their importance for identifying problems in library operations and predicting future user needs [3]. Q. Zhou et al. demonstrated that rich online academic book review resources could be used for deeper information and content mining by identifying sentiment polarity and values [4]. Zhu Zhenyuan

analyzed online book reviews as product evaluation texts using information classification-based content mining methods to examine linguistic characteristics, patterns, and content structures [5]. Hou Yinxiu et al. utilized sentiment analysis to obtain user book attribute preferences through attribute-level text mining of book reviews, thereby optimizing personalized book recommendations [6]. These studies collectively demonstrate that UGC, rich in user opinions and emotions, holds significant analytical value [7]. Through sentiment and content mining of UGC, libraries can not only understand user sentiment tendencies and value preferences but also provide precision recommendation services based on personalized needs, ultimately improving service models.

This study applies sentiment analysis to construct a mobile library UGC sentiment dictionary, classify UGC sentiment, and analyze evaluation effectiveness using the BP neural network method. The research addresses three key questions: How to effectively construct a sentiment dictionary for mobile library UGC? How to effectively classify sentiment in mobile library UGC? How to analyze the evaluation effectiveness of mobile library UGC based on sentiment classification? Theoretically, this research extends the applicability of sentiment analysis theory to mobile library UGC classification. Practically, it provides references for mobile libraries to improve service measures and quality by deeply mining and analyzing evaluation content and sentiment tendencies in user-generated content.

2 Related Concepts

2.1 User-Generated Content

The Organisation for Economic Co-operation and Development (OECD) defined user-generated content (UGC) in its 2007 report as publicly available internet content created by non-professionals with a certain degree of innovation [8]. In terms of manifestation, UGC refers to diverse forms of text, images, audio, and video publicly published online by users [9]. UGC represents collective benefits generated from aggregated content contributions under conditions of effective personal information sharing. Its core advantage lies in leveraging the highly experiential nature of individual knowledge and information, making such concentrated personal experiences applicable to a broader audience [10]. UGC is both static web information resources produced by users and a dynamic behavioral pattern of user creation, as well as an order closely related to user communities and social networks [9].

Although definitions of UGC vary among scholars, its non-authoritative nature and characteristics of reflecting collective wisdom and collaborative creation are widely recognized. The Web 2.0 model of openness and participation has made the internet increasingly dependent on user participation and contribution [11], extending UGC and its potential benefits to the library domain [16]. C. Dezela-tiedman explored whether user-provided tags in British literary works could enhance or supplement subject indexing for the same works in academic

library catalogs [17]. Y. Naik and B. Trott examined how users assist others in discovering "good books" through discussion and evaluation in library online reader communities [18]. L.F. Spiteri noted that current library discovery systems have Web 2.0 social functions, allowing users to enhance bibliographic records by adding their own tags, ratings, and reviews [19]. Through insights into work themes, characters, and reader impact, library UGC provides a rich dataset that clearly connects with known reader advisory access points [16]. Y.J. Moon et al. indicated that user-generated social bookmarks can serve as effective intelligent search engines in information acquisition processes [20]. Other researchers have explored rich user-generated content as a supplementary source for supporting personalized recommendations [13].

Mobile library services, built upon mobile networks and digital library technologies, not only enable users to access library information resources anytime and anywhere via various mobile devices but also foster a user-centered, participation-encouraging community service model through continuous innovation. UGC generated in community behaviors such as "user-user," "user-librarian," and user-collection" interactions has become an important component of the mobile library knowledge ecosystem [21]. Mobile library UGC is publicly available content produced by users in community service models, reflecting collective wisdom and personalized creativity with stronger natural language logic and ideation. Deep mining and analysis of its evaluation effectiveness can effectively capture mobile library users' rational evaluations and sentiment tendencies toward resources.

2.2 Definition and Methods of Sentiment Analysis

Sentiment analysis emerged as a research field in the late 1990s and rapidly became an active research topic. It is a research method that uses natural language processing and text analysis techniques to explore subjective information from raw corpora, achieving extensive development and successful applications in data mining, information retrieval, and natural language processing [13]. Opinion mining and sentiment analysis provide a computational approach for processing unstructured data, primarily used for opinion extraction and sentiment identification [14].

Mainstream sentiment analysis methods can be divided into dictionary-based approaches and machine learning-based approaches. This study adopts the dictionary-based approach, which essentially treats sentiment analysis as a matching problem between a sentiment dictionary and the text to be processed [15]. This method requires a predefined sentiment dictionary to determine text polarity, making the effectiveness of sentiment polarity identification highly dependent on dictionary quality. Dictionary-based approaches offer strong universality, enabling simple and rapid identification of sentiment tendencies in corpora. However, they heavily depend on sentiment dictionaries, requiring domain-specific, targeted, and comprehensive dictionaries as a foundation.

2.3 Sentiment Analysis of Mobile Library UGC

While domestic and international scholars have conducted relevant research on UGC mining and sentiment analysis, studies on the evaluation effectiveness of mobile library UGC based on sentiment analysis remain relatively limited.

3 Data Preprocessing

3.1 Evaluation Effectiveness Analysis Process

This study focuses on mobile library UGC, analyzing sentiment to extract positive, neutral, and negative emotions. These serve as input data for the evaluation model, which compares predicted output data with actual data to examine how sentiment tendencies in UGC affect actual user evaluations. Based on the above discussion, this paper proposes an analysis process for mobile library UGC evaluation effectiveness, consisting of three stages: domain dictionary construction, sentiment classification, and evaluation effectiveness analysis, following data acquisition and cleaning. As shown in Figure 1 [Figure 1: see original paper].

3.2 Research Sample Selection

Mobile libraries attract numerous readers who generate rich UGC during reading and commenting, making them representative for sample research. Through comprehensive investigation of 2017 bestseller lists and considering data accessibility, this study selected 15 annual bestsellers and used the Gooseeker web crawler to extract user reviews for these books from the "Zhangyue Library" mobile platform. Since review volumes varied significantly across books, the first 20 pages of reviews were collected for each to ensure comparability. Target book titles and their comprehensive user ratings are shown in Table 1 .

Table 1 Target Book Titles and Ratings

Book Title	User Rating
I Understand Your Knowledge Anxiety	9.3
Rich Dad Poor Dad	8.7
Speak Well: Fresh and Interesting Communication Skills	8.7
The Miracles of the Namiya General Store	9.3
Fall of Giants	8.9
The Kite Runner	9.2

Note: User ratings are on a 10-point scale.

The user ratings in Table 1 represent average scores calculated by the mobile library based on actual user ratings, reflecting user endorsement levels. Higher scores indicate greater user recognition. Since all selected books were 2017

bestsellers, ratings are generally high. However, ratings only show overall evaluation and cannot capture detailed individual reading experiences, necessitating further mining of sentiment tendencies in UGC.

3.3 Data Cleaning

The crawled review text data were saved in TXT format. The R language `gsub` function was used to clean English letters, symbols, spaces, and other elements from raw data that might hinder subsequent analysis. Processed data is shown in Figure 2 [Figure 2: see original paper]. The cleaned data removed symbols and characters that could affect processing, preventing incomplete data reading and enabling subsequent segmentation.

4 Evaluation Process

4.1 Domain Sentiment Dictionary Construction

Sentiment tendencies in mobile library UGC are primarily expressed through sentiment words. The comprehensiveness of the sentiment dictionary significantly affects classification effectiveness. While many mature Chinese sentiment dictionaries exist (e.g., HowNet, NTUSD), relying solely on basic dictionaries is insufficient for identifying sentiment words in specific domains. Some words not included in basic dictionaries also carry sentiment tendencies in particular contexts, making domain dictionary construction essential and foundational for sentiment analysis.

4.1.1 Basic Sentiment Dictionary This study uses the HowNet sentiment dictionary as its foundation, removing uncommon words and adjusting sentiment orientations of some words based on mobile library UGC characteristics. The final basic sentiment dictionary composition is shown in Table 2 .

Table 2 Basic Sentiment Dictionary

Word Set Name	Word Count
Positive sentiment words	4,560
Negative sentiment words	4,370

4.1.2 Domain Sentiment Dictionary For domain dictionary construction, this study uses Pointwise Mutual Information (PMI) to extract domain-specific sentiment words. PMI measures the similarity between two words x and y in natural language processing. The basic principle is that higher co-occurrence probability indicates stronger correlation and consistent sentiment orientation. The formula is:

$$PMI(x;y) = \log\left[\frac{p(x,y)}{p(x)p(y)}\right] = \log\left[\frac{p(x|y)}{p(x)}\right]$$

where $p(x, y)$ represents the probability of x and y co-occurring, and $p(x)$ and $p(y)$ represent individual occurrence probabilities. In this study's data, these probabilities can be obtained through corpus statistics. Let N be the total word count in the corpus, d_x and d_y be the occurrence counts of two words in the review corpus, and d_{xy} be their co-occurrence count. The PMI formula becomes:

$$PMI(x; y) = \log \left[\frac{N \cdot d_{xy}}{d_x d_y} \right]$$

By calculating PMI values, the correlation between x and y can be determined based on value ranges, as shown in Table 3 .

Table 3 PMI Correlation Degree

PMI(x;y) Range	Relationship
>0	Words are correlated
=0	Words are independent (neither correlated nor mutually exclusive)
<0	Words are mutually exclusive

This study introduces PMI into sentiment analysis to calculate word sentiment orientation and identify domain sentiment words: Select benchmark word sets containing positive benchmark words $Pwords$ and negative benchmark words $Nwords$; Calculate PMI between a word x and both $Pwords$ and $Nwords$; Determine sentiment orientation based on the difference between the two PMI values, following the rules in Table 4 .

Table 4 PMI Word Sentiment Orientation Criteria

PMI(Pwords;x) - PMI(Nwords;x)	Sentiment Orientation
>0	Positive sentiment word
<0	Negative sentiment word

Through manual selection of 20 positive and 20 negative sentiment words with clear orientation, domain-specific words were identified. After deduplication against the basic sentiment dictionary, 160 positive and 49 negative words were obtained and added to the basic dictionary to form the mobile library UGC domain sentiment dictionary.

4.1.3 Negation Analysis Negation words express negative meaning and typically reverse the sentiment polarity of modified sentiment words. When a negation modifies a positive word, the expressed sentiment becomes negative, and vice versa. In the algorithm, when a sentiment word is preceded by a negation, its weight is multiplied by -1. Common negation words are shown in Table 5 .

Table 5 Common Negation Words

Count	Weight	Negation Words (Examples)
24	-1	甭、别、并非、并未、不、不必、不曾、非、否、弗、毫不、毫无、很少、极少、几乎不...

4.1.4 Degree Adverb Analysis Degree adverbs modify or limit verbs/adjectives to express scope or degree. Given the generally short length of mobile library UGC, degree adverbs significantly impact sentiment expression, creating substantial variations in emotional intensity. This study constructs a degree adverb table based on "Chinese Degree Level Words" from CNKI, assigning weights according to intensity, as shown in Table 6 .

Table 6 Degree Adverbs

Intensity Level	Weight	Degree Adverbs (Examples)
"Extremely/Most"	2	非常、极、极度、极端、极其、极为
"Very"	1.75	不少、出奇、大为、分外、格外、颇为、太、特别、着实
"More"	1.25	更、更加、更进一步、更为、还、还要、较、较比、较为、进一步
"Slightly"	0.5	或多或少、略、略加、略略、略微、略为、稍、稍稍、稍微、稍为、稍许

4.2 Sentiment Classification

For each book's cleaned reviews, individual files were created. For each review: (1) Text preprocessing was performed; (2) Reviews were segmented into n sentences using punctuation as delimiters (single-sentence reviews were not split); (3) Sentiment words were extracted and matched against the domain dictionary; (4) For each matched sentiment word, degree adverbs and negations were identified sequentially forward with corresponding weight calculations; (5) Sentiment scores for words in each clause were summed, and scores across all clauses were aggregated to obtain the final review score.

4.2.1 Segmentation and Sentence Splitting

(1) Python's jieba segmentation was employed with the domain sentiment dictionary and stopword dictionary to segment mobile library UGC files and remove stopwords; (2) Sentiment words were tagged with part-of-speech to form word-POS tuples; (3) Sentences were split based on punctuation.

4.2.2 Sentiment Scoring Building on the previous step, sentiment scoring was performed on split sentences: (1) The domain sentiment dictionary, negation word list, and degree adverb list were loaded; (2) Different weights were applied based on negation and degree adverb types. For a sentiment word w_i, its sentiment orientation O_i is calculated as:

$$O_i = N_{w_i} \cdot V_{w_i}$$

where N_{w_i} is the negation weight. When degree adverbs are present:

$$O_i = A_{w_i} \cdot V_{w_i}$$

where A_{w_i} is the degree adverb weight and V_{w_i} is the sentiment word weight. The sentiment orientation OS_i for each sentence S_i is:

$$OS_i = \sum_{i=1}^{k} O_i$$

The final sentiment orientation score O for a review split into n sentences is:

$$O = \sum_{i=1}^{n} OS_i$$

The process loops through all sentiment words, rounding the final score to enhance intuitiveness.

Sentiment orientation statistics for the 15 books are shown in Table 8 , with three levels defined in Table 7 .

Table 7 Sentiment Orientation Grading Criteria

Score Range	Sentiment Level
score < 0	Negative comment
$0 \leq$ score ≤ 1	Neutral comment
score > 2	Positive comment

Table 8 Sentiment Orientation Analysis Results

Book Title	User Rating	Negative (%)	Neutral (%)	Positive (%)
I Understand Your Knowledge Anxiety	9.1	9.677%	29.677%	60.645%
Rich Dad Poor Dad	8.7	5.556%	29.630%	64.815%

Book Title	User Rating	Negative (%)	Neutral (%)	Positive (%)
Speak Well: Fresh and Interesting Communication Skills	8.7	12.195%	8.943%	78.862%
The Miracles of the Namiya General Store	9.7	8.429%	45.977%	45.594%
Fall of Giants	8.6	14.286%	30.519%	51.948%
The Kite Runner	9.2	16.820%	19.266%	63.914%

Sample sentiment orientation scores are shown in Figure 3 [Figure 3: see original paper].

4.3 Evaluation Effectiveness

The BP neural network, developed by D.E. Rumelhart et al. in 1986 [22], is an artificial neural network algorithm typically using a multi-layer feedforward structure. A typical BP network consists of input, hidden, and output layers.

This study obtained user sentiment tendency data from mobile library UGC, using percentages of positive, neutral, and negative sentiments as BP network inputs and book ratings as output data for training and testing. By comparing actual scores with predicted scores, the study examines whether user sentiment tendencies in UGC can predict book popularity.

Using R's neuralnet package with 3 input attributes and 1 output attribute, the hidden layer neuron count $m = \sqrt{n+1} + \alpha$ (where n is input nodes, α is 1-10) was determined to be 8 through iterative testing for minimal error. The BP neural network program is as follows:

```
[1] library(grid)
[2] library(MASS)
[3] library(neuralnet)
[4] p <- matrix(c(0.097,0.297,0.606,0.166,0.231,0.603,0.114,0.276,0.610,0.068,0.195,0.737,0.
# Input layer: 10$\times$3 matrix, randomly selecting 10 groups for training
[5] t <- c(9.1,8.9,8.9,9.3,8.7,8.7,9.7,8.6,9.2,9.2) # Output layer values
[6] trainingdata <- cbind(p,t) # Combine input and output
[7] colnames(trainingdata) <- c("Input1","Input2","Input3","Output")
[8] net <- neuralnet(Output~Input1+Input2+Input3, trainingdata, hidden=8, threshold=0.001, l
[9] print(net) # Output network computation process
```

```
[10] plot(net) # Display network structure
[11] testdata <- matrix(c(0.084,0.305,0.611,0.113,0.155,0.732,0.125,0.118,0.757,0.115,0.252,
[12] net.results <- compute(net, testdata) # Predict results
[13] ls(net.results) # Return result object names
[14] print(net.results$net.result) # Output predicted values
```

Prediction results are shown in Table 9 .

Table 9 Prediction Results

Book Title	Actual Score	Predicted Score
Book 1	9.1	9.056783248
Book 2	8.9	8.987550379
Book 3	8.9	8.877180627
Book 4	9.3	8.982631021
Book 5	9.2	9.225526503

The errors between actual and predicted values are small. The BP neural network successfully predicted book scores by learning from three feature attributes (positive, neutral, negative sentiments) extracted from UGC, with the largest prediction error being only 4.5% across five books. This demonstrates that user sentiment tendencies in mobile library UGC can serve as a basis for predicting book popularity.

5 Analysis and Discussion

5.1 Pluralism of Sentiment Tendencies

Table 8 shows that UGC for all books contains positive, negative, and neutral sentiments. Even highly-rated books like *The Miracles of the Namiya General Store* and *The Kite Runner* have some "negative sentiment" reviews, indicating diverse user preferences and personalized demands. Mobile library UGC services encourage users to become content contributors, enabling free expression of opinions and interactive communication. This reflects an inclusive, personalized, and pluralistic service model that allows different voices to coexist and collectively drive service development.

5.2 Consistency of Sentiment Tendencies

Highly-rated books show larger proportions of positive and neutral sentiments in their UGC. While dictionary-based analysis introduces some classification errors, the data demonstrates that user sentiment tendencies accurately reflect preferences for mobile library resources. Users express their views on content and acceptance of UGC services through active contribution. Mobile libraries can thus use UGC sentiment tendencies to understand user needs and address service issues promptly, making UGC a reliable evaluation metric.

5.3 Importance of Neutral Evaluations

Table 8 reveals that neutral evaluations significantly impact user ratings. For highly-rated books like *The Miracles of the Namiya General Store*, neutral comments often constitute 30% or more of UGC. Analysis shows that low-scoring neutral comments typically discuss writing techniques, narrative structure, and frameworks—rational content without strong emotional coloring. Such neutral UGC represents high-value user knowledge that helps others understand books and improve appreciation skills. Books with higher proportions of neutral reviews tend to receive higher ratings, demonstrating that knowledge sharing through UGC is a key driver of user interaction.

5.4 Reasonableness of Evaluation Effectiveness

The BP neural network successfully predicted ratings for five books with high accuracy, confirming that UGC sentiment tendencies represent user evaluation attitudes. The community service process involves information exchange and interaction among users and between users and the platform, embodying collective wisdom and value creation. As the most representative manifestation of collective intelligence, UGC serves as both an important information resource and reliable data for evaluating service effectiveness, providing references for improving mobile library services.

6 Research Conclusions

This study predicts the evaluation effect of user sentiment tendencies on mobile library resources through sentiment analysis of mobile library UGC. The proposed evaluation model was validated through domain dictionary construction, sentiment classification, and effectiveness analysis. Results show that mobile library UGC sentiment tendencies are pluralistic and consistent, with neutral evaluations playing a crucial role. UGC sentiment can predict book popularity, helping libraries understand user recognition of collections and adjust service strategies.

The main limitation lies in the dictionary-based method's dependence on dictionary comprehensiveness. Future research will further improve domain dictionary coverage.

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Author Contributions

Wang Xiwei: Responsible for research design and revision;
Yang Mengqing: Responsible for data collection and paper writing;
Wei Yanan: Participated in data collection;
Wang Duo: Participated in data collection.

Research on the Evaluation of Mobile Library User-Generated Content Based on Sentiment Analysis

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Abstract: [Purpose/significance] This study aims to analyze the evaluation effect of mobile library user-generated content (UGC) through sentiment analysis to improve resource recommendation and promotion. [Method/process] An evaluation model based on sentiment analysis was constructed. After preprocessing UGC from 16 bestsellers in Zhangyue Library, analysis was conducted in three stages: dictionary construction, sentiment classification, and evaluation. [Result/conclusion] Results show that UGC sentiment tendencies are pluralistic and consistent, with neutral evaluation being important and final evaluation results being reasonable. This paper introduces sentiment analysis theory into mobile library UGC research, providing references for improving social service measures and quality.

Keywords: sentiment analysis; mobile library; user-generated content; evaluation effect

Note: Figure translations are in progress. See original paper for figures.