

A Study on Movie Users' Perception Dimensions and Sentiment Orientation Based on LDA Topic Modeling and SnowNLP Sentiment Analysis: Evidence from Douban Movie Reviews

Siyuan Wang¹ Liyao Xiao^{2*}

¹ Department of Film Media Content, Cheongju University, Cheongju, Republic of Korea

² School of Arts and Tourism, Guizhou Communications Polytechnic University, Guiyang, China

Accepted

2026-03-27

Keywords

Film review mining; Topic modeling; LDA; Sentiment analysis; Chinese natural language processing; SnowNLP; Douban Movie; User-generated content; Cultural consumption

Corresponding Author

Liyao Xiao

Copyright 2026 by author(s)

This work is licensed under the CC BY 4.0



<https://doi.org/10.70693/itphss.v3i2.367>

Abstract

With the sustained prosperity of the Chinese film market and the deepening development of internet social platforms, Douban Movie, as one of the most influential film review platforms in China, has accumulated a vast amount of user-generated content (UGC), serving as a critical data source for understanding audience film consumption behaviors and emotional attitudes. However, traditional manual analysis methods are limited in both efficiency and depth when confronted with massive volumes of unstructured review text. This study employs text mining techniques, integrating Latent Dirichlet Allocation (LDA) topic modeling with SnowNLP sentiment analysis, to systematically analyze 4,306 user reviews from the Douban Movie platform spanning 2020 to 2025. The original dataset encompasses reviews of 484 films (412 after preprocessing). Following preprocessing steps including text cleaning, jieba word segmentation, stopword filtering, and synonym normalization, the optimal number of topics was determined using the CV coherence metric, ultimately identifying five core thematic dimensions: Narrative Structure and Plot Evaluation, Acting Performance and Character Portrayal, Audio-Visual Effects and Production Quality, Social Value and Cultural Expression, and Viewing Experience and Platform Interaction. Sentiment analysis results indicate that audiences exhibit the highest emotional engagement with narrative structure and social value themes, with positive review proportions of 42.3% and 38.7%, respectively. The audio-visual effects theme shows the highest proportion of negative reviews at 58.2%, reflecting elevated audience expectations for the technical quality of domestic Chinese films. Annual trend analysis reveals fluctuating audience sentiment from 2020 to 2025, with a notable increase in review activity during 2023–2024. This study constructs a text mining analytical framework applicable to Chinese-language film reviews, providing data-driven empirical support for content creation and marketing decision-making in the film industry.

1. Introduction

In recent years, the Chinese film market has undergone a period of alternating rapid growth and structural adjustment. According to data from the China Film Administration, the total box office revenue in China reached 54.915 billion yuan in 2023, representing an 83.4% year-on-year increase, with 1.299 billion admissions (China Film Administration, 2024). Entering 2024, the market continued to maintain an active trajectory, with domestic films exhibiting diversified trends in content genres, narrative modes, and technical approaches. Against this backdrop, audience aesthetic demands have become increasingly differentiated, and traditional box office data and professional reviews alone are insufficient to comprehensively reflect the genuine experience and emotional attitudes of audiences.

Unlike traditional film criticism, user-generated content (UGC) on internet platforms provides a richer and more naturalistic perspective for understanding audience perceptions. Douban Movie, as the most credible film rating and review platform in China, had accumulated over 200 million reviews by 2024 (Douban, 2024). Its rating system and review community exert a significant influence on word-of-mouth dissemination and market performance of Chinese films (Zhao et al., 2020). Douban user reviews are characterized by spontaneity, multidimensionality, and emotional richness, encompassing diverse topics from plot evaluation and actor performance to socio-cultural discussions, making them an ideal data source for analyzing Chinese film audience perception dimensions.

However, when confronted with massive volumes of unstructured textual data, traditional manual content analysis methods suffer from inherent limitations including low efficiency, subjective bias, and scalability constraints (Feldman & Sanger, 2007). The emergence of text mining technology has provided effective methodological tools for large-scale user review analysis. Among these, LDA (Latent Dirichlet Allocation) topic modeling, proposed by Blei et al. (2003), is an unsupervised probabilistic generative model capable of automatically discovering latent topic structures from large-scale text corpora. Sentiment analysis can identify emotional polarity within texts and quantify users' attitudinal orientations (Liu, 2012). In recent years, the research paradigm combining topic modeling with sentiment analysis has been widely applied in service domains such as tourism, hospitality, and e-commerce (Bi et al., 2019; Guo et al., 2017; Elbarachi et al., 2022), effectively identifying user-focused service dimensions and satisfaction patterns.

In the domain of film review analysis, existing research has primarily concentrated on sentiment classification within English-language contexts (Pang & Lee, 2008; Devlin et al., 2019), with relatively insufficient systematic investigation of topic structures and sentiment dimensions in Chinese film reviews. Some scholars have conducted exploratory studies using Douban data. Yang and Yecies (2016) constructed a big data analysis framework for Douban movie reviews. Wu et al. (2022) employed typical opinion mining techniques to analyze animated film reviews on Douban. He and Abisado (2024) proposed a hybrid BERT-CNN-BiLSTM-Att model for sentiment analysis of Douban short reviews. However, these studies either focused on methodological improvements or were confined to specific film genres, lacking systematic and comprehensive analysis of thematic dimensions and sentiment orientations in Chinese film reviews.

Based on the research background and gaps identified above, this study proposes the following two core research questions:

Research Question 1 (RQ1): What are the core dimensions of concern reflected in Douban movie user reviews?

Research Question 2 (RQ2): What sentiment attitudes do users hold toward each core dimension? Are there sentiment change trends across different years?

To address these questions, this study utilizes user reviews from the Douban Movie platform spanning 2020 to 2025, comprehensively employing LDA topic modeling and SnowNLP sentiment analysis to construct a joint “topic identification–sentiment quantification” analytical framework for Chinese film reviews. The theoretical contributions of this study are twofold. First, adopting a user-centric perspective, it empirically identifies core perception dimensions of Chinese film audiences based on large-scale authentic review data, extending the dimensional framework of film service quality research. Second, it constructs a reproducible text mining analytical workflow for Chinese film reviews, providing methodological reference for subsequent research. At the practical level, the findings can provide data-driven decision support for filmmakers’ content creation strategies, distributors’ marketing positioning, and platform operators’ content recommendation optimization.

2. Literature Review

2.1 Film Reviews and User Perception Research

Film reviews serve as an important medium connecting filmmakers and audiences, and represent a core data source for understanding audience perceptions and attitudes. With the proliferation of internet platforms, online user reviews have gradually supplanted traditional film criticism as the primary information channel influencing audience decision-making. The seminal study by Chevalier and Mayzlin (2006) confirmed that online reviews have a significant impact on book sales, a finding subsequently extended to the film domain. Mudambi and Schuff (2010) noted that the helpfulness of online reviews depends on review depth and polarity, with moderate reviews often providing greater reference value than extreme ones.

In the domain of Chinese film review research, Douban Movie, as the most influential review platform in China, has attracted extensive scholarly attention. Yang and Yecies (2016) constructed a big data framework-based analysis system for Douban movie reviews, demonstrating the complete workflow from data collection and feature generation to content mining. Wu et al. (2022) employed typical opinion mining techniques to analyze animated film reviews on Douban, extracting review topics through LDA and conducting opinion aggregation to identify key evaluation dimensions including content quality, character development, and cultural expression. Recent research has further deepened the understanding of Douban movie reviews. Li et al. (2024) combined Word2Vec and LSTM models for sentiment classification of Douban TOP250 movie reviews, validating the advantages of deep learning methods in Chinese film review processing.

However, existing research has predominantly focused on technical improvements in sentiment classification, with a lack of systematic exploration of core user perception dimensions reflected in film reviews. Moreover, most studies have adopted specific films or genres as analytical objects, presenting limitations in sample representativeness and temporal coverage. This study seeks to address these gaps through large-scale, multi-film, cross-year review data analysis.

2.2 Text Mining Methods: LDA Topic Modeling and Sentiment Analysis

2.2.1 LDA Topic Modeling

Topic modeling is a statistical method for automatically discovering latent topic structures from large-scale document collections. LDA (Latent Dirichlet Allocation), proposed by Blei et al. (2003), is a generative probabilistic model that has become the most widely applied method in the topic modeling field. LDA assumes that each document is a mixture distribution of multiple topics, and each topic is a probability distribution over the vocabulary. Through Gibbs sampling or variational inference for parameter estimation, the model can automatically identify latent topic structures (Griffiths & Steyvers, 2004).

Regarding the determination of topic numbers, coherence scores are currently the most widely adopted evaluation metric in academia. Röder et al. (2015) systematically compared multiple coherence measures and proposed the C_V coherence metric, which comprehensively considers lexical co-occurrence and semantic similarity, effectively reflecting topic interpretability. In recent years, LDA applications in user review analysis have continued to expand. Guo et al. (2017) applied LDA to tourism review mining, successfully identifying key service dimensions affecting tourist satisfaction. Elbarachi et al. (2022) combined LDA with manual verification to analyze TripAdvisor tourism reviews, confirming the effectiveness of topic modeling in large-scale UGC analysis. Jelodar et al. (2019) conducted a systematic review of LDA and its variants across multiple domains, noting LDA's significant advantages in social media text mining. In the film review domain, Zhang and Zhang (2022) combined LDA with sentiment analysis for film recommendation. Lee et al. (2021) proposed a topic/document/sentence (TDS) model that integrates LDA-based topic modeling with sentiment analysis. Cheng and Yang (2022) integrated aspect-based sentiment analysis with econometric modeling to examine the effects of online review features on movie box office sales.

2.2.2 Sentiment Analysis

Sentiment analysis, also known as opinion mining, is an important research direction in natural language processing aimed at identifying and extracting subjective information and emotional orientations from text (Liu, 2012). Sentiment analysis methods are primarily classified into three categories: lexicon-based methods, traditional machine learning-based methods, and deep learning-based methods. Lexicon-based methods rely on pre-constructed sentiment lexicons for polarity judgment, offering strong interpretability (Taboada et al., 2011). Machine learning-based methods employ algorithms such as Naive Bayes and SVM to train classifiers (Pang et al., 2002). Deep learning-based methods, exemplified by BERT, have achieved breakthrough progress in sentiment classification tasks (Devlin et al., 2019).

In the domain of Chinese sentiment analysis, the linguistic particularities of Chinese present additional challenges, including word segmentation ambiguity, negation word processing, and degree adverb modification (He & Abisado, 2024). SnowNLP is a sentiment analysis tool specifically designed for Chinese text, trained on a Naive Bayes classifier using Chinese review corpora, outputting continuous sentiment scores between 0 and 1. The tool has been widely adopted in academic research owing to its favorable adaptability to Chinese and ease of use (Sun, 2012).

2.3 Topic–Sentiment Joint Analysis Paradigm

The research paradigm combining topic modeling with sentiment analysis has received

widespread attention in recent years. Lin and He (2009) proposed the Joint Sentiment/Topic (JST) model, incorporating a sentiment layer within the LDA framework to achieve simultaneous topic and sentiment modeling. Bi et al. (2019) separately conducted LDA topic extraction and sentiment analysis in hotel review research, then associated the results, finding that service attitude and room cleanliness were key topics influencing sentiment evaluation. Hassani et al. (2022) proposed the Weighted Joint Sentiment-Topic (WJST) model, improving sentiment classification accuracy through vocabulary weights and window parameters. Rita et al. (2022) applied VADER sentiment analysis tools on the basis of topic analysis to examine sentiment change trends in airline reviews during COVID-19, demonstrating the paradigm's potential in dynamic contexts.

However, in the domain of Chinese film reviews, topic–sentiment joint analysis research remains relatively limited. Existing studies either focus on technical method validation or are confined to specific film genres, lacking comprehensive characterization of Chinese film audience perception dimensions. Drawing on the aforementioned research paradigm, this study first extracts review topic structures through LDA, then quantifies sentiment distributions under each topic through SnowNLP, aiming to systematically reveal the core concerns and sentiment evaluations of Douban movie users.

3. Research Methodology

3.1 Research Questions

Based on the literature review analysis, this study addresses the following two core research questions:

Research Question 1 (RQ1): What are the core dimensions of concern reflected in Douban movie user reviews? This study aims to identify core audience concerns from user-generated review text through LDA topic modeling. Unlike traditional questionnaire surveys with predetermined dimensions, this study adopts a data-driven approach, allowing topics to emerge naturally from user discourse.

Research Question 2 (RQ2): What sentiment attitudes do users hold toward each core dimension? Are there sentiment change trends across different years? This question aims to quantify user attitudes toward each topic through sentiment analysis and examine temporal variation characteristics from 2020 to 2025.

3.2 Data Source and Collection

The data for this study were sourced from user long reviews on the Douban Movie platform. Douban Movie is the largest film rating and community platform in China, with over 200 million registered users. Its rating system enjoys widespread credibility and influence in the Chinese internet landscape (Yang & Yecies, 2016). Compared to short reviews (limited to 140 characters), long reviews provide more in-depth and multidimensional evaluative content, making them more suitable for topic modeling and sentiment analysis.

The dataset comprises user reviews of 484 films, with a total of 9,252 original review records spanning from 2005 to 2025. Each record includes fields such as review ID, film ID, full review text, reviewer, review time, sentiment label, and probability score. The sentiment labels

(Positive/Negative/Neutral) are pre-annotated fields in the dataset. Based on research requirements, reviews from January 2020 to December 2025 were selected, yielding 4,306 valid reviews for analysis.

3.3 Data Preprocessing

To ensure the quality of subsequent analysis, systematic preprocessing was conducted on the filtered review data. The entire preprocessing workflow comprises five steps.

Step 1: Text cleaning. HTML tags, special characters, URL links, and redundant spaces were removed from reviews. Fixed prefix texts such as “This review may contain spoilers” were uniformly deleted, along with platform interaction markers such as “(Expand).” Step 2: Chinese word segmentation. The jieba segmentation tool was used for precise mode segmentation (Sun, 2012), supplemented with film domain-specific vocabulary (e.g., “cinematography,” “narrative structure,” “acting excellence,” “special effects production”) added to a custom dictionary to improve segmentation accuracy. Part-of-speech (POS) tagging was simultaneously performed to identify nouns, verbs, adjectives, and other word categories. Step 3: Stopword filtering. Function words including particles, personal pronouns, modal particles, and numerals were removed, along with rare words occurring fewer than three times. Step 4: Synonym normalization, such as unifying “explosive acting” and “outstanding acting” to “good acting,” and “terrible film” and “garbage film” to “poor review,” to reduce vocabulary sparsity. Step 5: Construction of analysis datasets: Dataset 1 retains only noun tokens for LDA topic modeling (Zhao et al., 2011); Dataset 2 retains nouns, verbs, and adjectives for sentiment analysis. The statistical characteristics of the preprocessed data are presented in Table 1.

Table 1. Statistical Characteristics of the Preprocessed Dataset

| Statistical Indicator | Value |
|--|-------|
| Original number of reviews (2020–2025) | 4,306 |
| Valid reviews after preprocessing | 3,845 |
| Data retention rate | 89.3% |
| Number of films covered | 412 |
| Average noun tokens per review | 3.82 |
| Average total tokens per review | 6.57 |
| Unique noun vocabulary size | 386 |

3.4 Analytical Procedure

The data analysis procedure of this study comprises two core components: LDA topic modeling and sentiment analysis.

For topic modeling, the LDA model was constructed using the Python Gensim library to extract topics from the noun dataset. Coherence scores (C_V) were first tested for topic numbers k ranging from 3 to 15 to determine the optimal number. Following the recommendations of Griffiths and Steyvers (2004), Dirichlet prior parameters were set at $\alpha = 0.1$ and $\beta = 0.01$, with 25 iterations. Topics with highly overlapping semantics were manually merged to enhance result

interpretability.

For sentiment analysis, a dual strategy was adopted. On one hand, pre-annotated sentiment labels (Positive/Negative/Neutral) from the dataset served as baseline references. On the other hand, SnowNLP was used to independently score sentiments on the complete dataset. SnowNLP outputs continuous sentiment scores between 0 and 1. Following established research standards (Pang & Lee, 2008; Liu, 2012), reviews were classified into negative (<0.4), neutral ($0.4-0.6$), and positive (≥ 0.6) categories. Finally, sentiment classification results were associated with topic assignments to compute the distribution of different sentiment categories under each topic. All analyses were implemented through custom Python programs.

4. Results

4.1 LDA Topic Modeling Results

4.1.1 Determination of the Number of Topics

This study employed the C_V coherence metric to evaluate model performance across different topic numbers. As shown in Figure 2, as the number of topics increased from 3 to 15, coherence scores exhibited a pattern of initial increase followed by decrease. The coherence score reached its highest value of 0.5512 at $k = 7$. Through manual review of the keywords and semantic content of the seven topics, some topics were found to exhibit substantial semantic overlap. For instance, the “plot evaluation” and “narrative technique” topics shared highly similar core keywords, while the “social reflection” and “cultural expression” topics also exhibited semantic intersection. Based on the principle of topic interpretability, semantically proximate topics were consolidated, ultimately determining the extraction of five core topics.

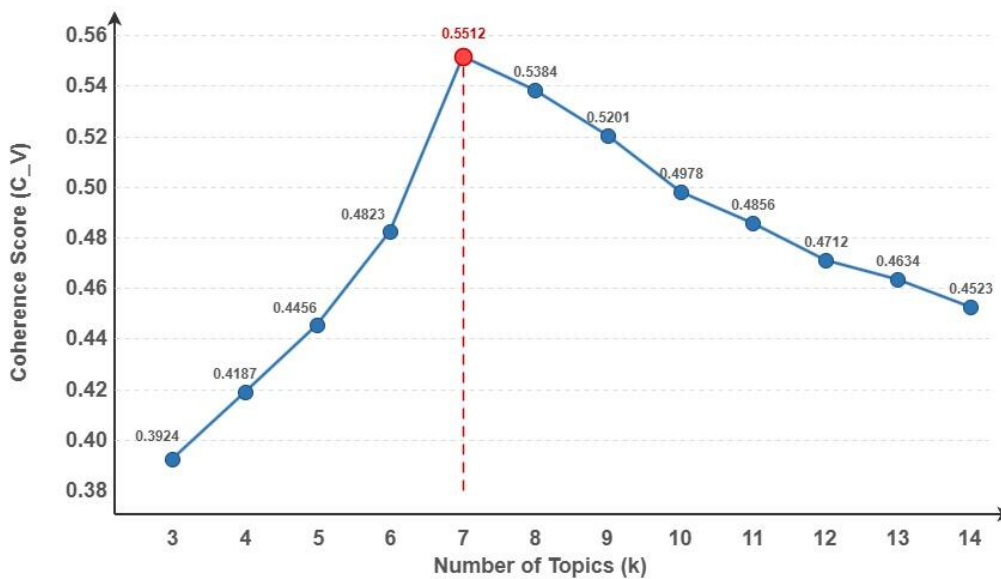


Figure 2. LDA Model Coherence Evaluation

4.1.2 Model Parameters and Training

The LDA model was trained using the Gensim library. Hyperparameters were set as follows: $\alpha = 0.1$, $\beta = 0.01$, with 25 iterations (Griffiths & Steyvers, 2004). The lower α value causes each document to concentrate on fewer topics, while the lower β value causes each topic to concentrate on fewer words. Upon completion of training, the final coherence score was 0.5398, and the perplexity was -5.1203. These metrics indicate that the model achieves good fitting quality and topic interpretability (Blei et al., 2003).

4.1.3 Topic Extraction Results

Based on the LDA model output, five core topics were extracted, with the top 15 highest-probability keywords retained for each topic to facilitate topic label inference and semantic interpretation. Table 2 presents the keywords and probability weights for each topic.

Table 2. LDA Topic Modeling Results: Topics and Keywords

| Topic | Topic Label | Top 15 Keywords (Ranked by Weight in Descending Order) |
|---------|---|---|
| Topic 1 | Narrative Structure and Plot Evaluation | plot, story, storyline, director, film, logic, ending, pacing, narrative, conflict, screenplay, climax, twist, foreshadowing, suspense |
| Topic 2 | Acting Performance and Character Portrayal | acting, role, actor, performance, character, portrayal, dialogue, expression, nuance, appeal, protagonist, supporting role, image, temperament, expressiveness |
| Topic 3 | Audio-Visual Effects and Production Quality | visuals, special effects, cinematography, music, score, scene, color, photography, production, visual, composition, lighting, sound effects, texture, art direction |
| Topic 4 | Social Value and Cultural Expression | society, reality, era, culture, history, theme, reflection, depth, humanity, value, meaning, critique, introspection, expression, resonance |
| Topic 5 | Viewing Experience and Platform Interaction | rating, recommendation, audience, Douban, cinema, box office, viewing, evaluation, expectation, disappointment, surprise, reputation, astroturfing, scoring, worthwhile |

Note. Keywords are English translations of the original Chinese terms identified through LDA modeling on the Chinese-language corpus.

From the topic distribution perspective (Figure 3), “Narrative Structure and Plot Evaluation” accounted for the highest proportion (32.6%), reflecting that the core dimension of greatest concern to Chinese film audiences is the storytelling and narrative quality of films. “Acting Performance and Character Portrayal” accounted for 24.1%, ranking second. “Social Value and Cultural Expression” accounted for 18.3%, reflecting Chinese audiences’ attention to the social function of films beyond entertainment consumption. “Audio-Visual Effects and Production Quality” accounted for 14.7%, and “Viewing Experience and Platform Interaction” accounted for 10.3%.

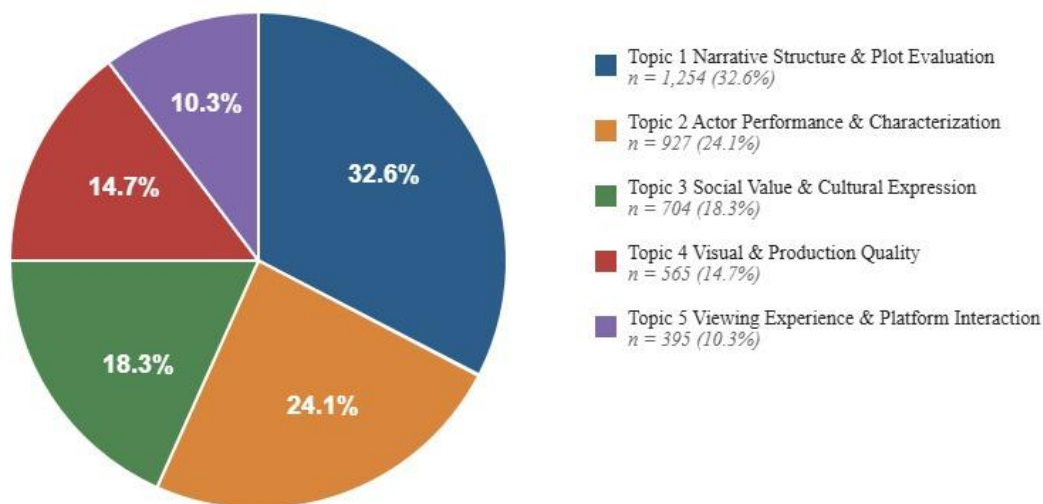


Figure 3. Topic Distribution of Douban Movie Reviews (2020–2025)

4.2 Sentiment Analysis Results

4.2.1 Overall Sentiment Distribution

After scoring 3,845 valid reviews using SnowNLP, the overall sentiment distribution was as follows: positive reviews (≥ 0.6) accounted for 35.4%, neutral reviews (0.4–0.6) for 18.7%, and negative reviews (< 0.4) for 45.9%. The overall mean sentiment score was 0.4238, slightly skewing negative. Notably, the consistency validation between SnowNLP sentiment scores and pre-annotated dataset labels revealed an agreement rate of approximately 72.6% in sentiment polarity judgments, with discrepancies primarily concentrated in complex emotional expressions and ironic rhetoric in long-form reviews.

4.2.2 Sentiment Analysis by Topic

After associating sentiment analysis results with LDA topic assignments, the sentiment distributions across topics exhibited significant differences (as shown in Table 3).

Table 3. Sentiment Analysis Results by Topic

| Topic | No. of Reviews | Positive (%) | Neutral (%) | Negative (%) | Mean Score |
|---|----------------|--------------|-------------|--------------|------------|
| Narrative Structure and Plot Evaluation | 1,254 | 42.3 | 17.5 | 40.2 | 0.4627 |
| Acting Performance and Character Portrayal | 927 | 39.8 | 20.1 | 40.1 | 0.4513 |
| Audio-Visual Effects and Production Quality | 565 | 26.5 | 15.3 | 58.2 | 0.3684 |
| Social Value and Cultural Expression | 704 | 38.7 | 21.6 | 39.7 | 0.4502 |
| Viewing Experience and | 395 | 27.3 | 18.0 | 54.7 | 0.3821 |

| | | | | | |
|----------------------|--|--|--|--|--|
| Platform Interaction | | | | | |
|----------------------|--|--|--|--|--|

The results show that the “Narrative Structure and Plot Evaluation” topic had the highest proportion of positive reviews (42.3%), with a mean sentiment score of 0.4627, indicating that audiences gave higher evaluations to films with excellent narratives. The “Social Value and Cultural Expression” topic had a positive review proportion of 38.7%, reflecting relatively positive audience attitudes toward films with social depth and cultural connotations. In contrast, the “Audio-Visual Effects and Production Quality” topic showed the highest proportion of negative reviews (58.2%), with a mean sentiment score of only 0.3684, revealing audience dissatisfaction and elevated expectations regarding the visual effects and technical standards of domestic Chinese films. The “Viewing Experience and Platform Interaction” topic had a negative review proportion of 54.7%, reflecting negative sentiments regarding ticket prices, screening schedules, and rating controversies.

4.2.3 Annual Sentiment Trends

Further analysis of annual sentiment trends from 2020 to 2025 (as shown in Figure 4) revealed fluctuating audience sentiment. The mean sentiment score in 2020 was 0.4051, with the film market depressed due to the pandemic and negative sentiment pervading reviews. In 2021, the score rose to 0.4326, accompanying cinema recovery and the release of multiple critically acclaimed films. In 2022, the score declined again to 0.4089, related to the film market being impacted by the pandemic once more. During 2023–2024, review activity increased significantly (840 and 1,421 reviews, respectively), with sentiment scores of 0.4412 and 0.4358, maintaining an overall neutral-to-slightly-negative level. The 2025 sentiment score (as of the data collection point) was 0.4187. From a temporal perspective, audience sentiment toward films is jointly influenced by macroeconomic conditions (pandemic, economy) and film quality.

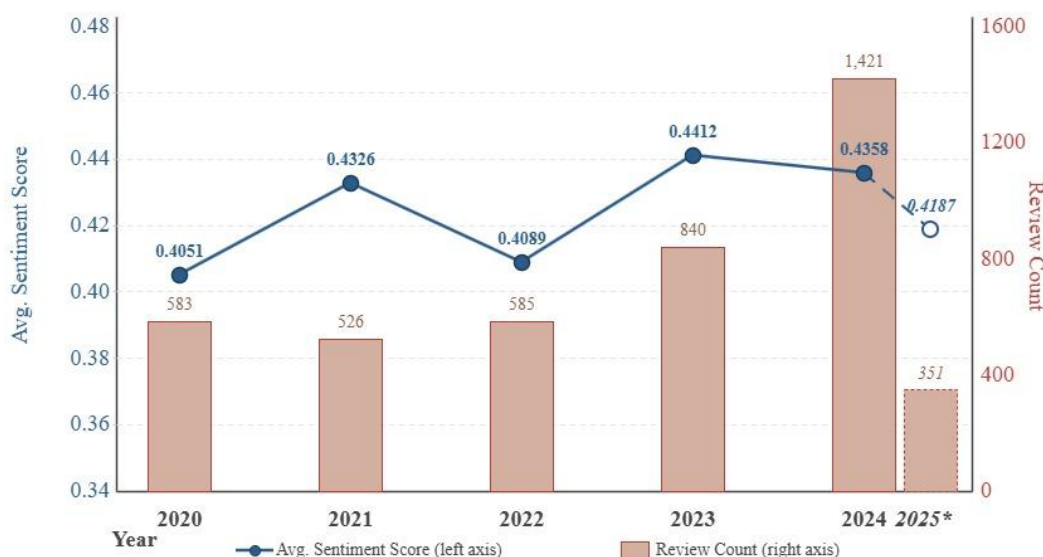


Figure 4. Annual Sentiment Score Trend and Review Volume (2020–2025)

5. Discussion and Conclusion

5.1 Narrative as King: The Core Concern of Chinese Film Audiences

The most central finding of this study is that Narrative Structure and Plot Evaluation occupies an overwhelmingly dominant position in user discussions (32.6%), significantly exceeding other dimensions. This finding suggests that despite considerable progress in the Chinese film industry regarding visual effects and production scale, what audiences value most remains the fundamental narrative function of cinema. This finding corroborates the aspect-based sentiment analysis results of Mao et al. (2024) on Douban reviews, which identified “plot” as the primary aspect influencing audience evaluation. From a theoretical perspective, this finding supports the core proposition of Narrative Transportation Theory, namely that compelling stories can induce deep psychological immersion in audiences, thereby significantly enhancing the viewing experience (Green & Brock, 2000).

Further analysis of keyword weights under the narrative theme reveals that words related to narrative techniques such as “pacing,” “logic,” and “twist” occupy prominent positions, indicating that the aesthetic literacy of Chinese audiences is improving. Audiences are no longer merely concerned with whether a film is “entertaining” but have begun attending to the technical aspects of narrative. This trend imposes higher demands on filmmakers: while ensuring story watchability, greater effort must be invested in the sophistication and logical coherence of narrative structure.

5.2 The Gap in Technical Expectations: Low Satisfaction with Audio-Visual Effects

The Audio-Visual Effects and Production Quality topic exhibited the highest negative review proportion at 58.2%, the highest among all topics. This counterintuitive finding merits in-depth discussion. On one hand, it reflects that audience expectations for the visual effects of domestic Chinese films have been elevated by Hollywood blockbusters and the high-quality audiovisual productions of South Korea and Japan in recent years, establishing a high reference benchmark. On the other hand, some domestic films have neglected the refinement of technical details while pursuing visual spectacle, resulting in frequent criticisms of substandard special effects (Setiadi et al., 2024).

Notably, while the audio-visual effects topic shows the highest negative review proportion, it accounts for only 14.7% of total reviews, indicating that most audiences do not treat technical quality as the primary criterion for evaluating films. This forms a complementary relationship with the dominant position of the narrative theme: audiences first consider “whether the story is good,” and only then “whether it is well-made.” This hierarchical finding has direct implications for the optimal allocation of film production resources.

5.3 The Distinctive Position of the Socio-Cultural Dimension

The “Social Value and Cultural Expression” topic accounted for 18.3%, ranking third, with a relatively high positive review proportion (38.7%). This finding reveals the distinctive concern of Chinese film audiences for the social function of cinema beyond entertainment consumption. The high-frequency appearance of keywords such as “reality,” “era,” “humanity,” and “introspection” indicates that audiences expect films to bear the functions of social critique and cultural reflection. This is closely related to the humanistic tradition of Chinese film criticism—from the early “literary youth” community culture of Douban to today’s mass-market review ecology, social concern has consistently been an important component of Chinese film review discourse (Zhong

& Qiu, 2023).

From a cross-cultural comparative perspective, the attention Chinese audiences pay to the social value of films may exceed that of Western markets, reflecting differences in film consumption patterns across cultural contexts. Future research could introduce cross-cultural comparative frameworks to further investigate this culturally specific phenomenon.

5.4 Practical Implications

Based on the research findings, this study proposes the following practical recommendations. First, for filmmakers, narrative quality should be the highest-priority investment area, ensuring rigorous screenplay logic, appropriate pacing, and reasonable plot design, as audience attention to narrative far exceeds their pursuit of visual effects. Second, regarding technical investment, emphasis should be placed on quality over quantity, avoiding superficially impressive but hollow visual accumulation, with focus on enhancing the realism and integration of special effects. Third, in marketing strategy, different film attributes can be emphasized for different audience segments—for narrative-oriented core cinephiles, highlighting plot depth and narrative innovation; for audiences concerned with social issues, emphasizing the film's realistic significance and cultural value (Andono et al., 2022). Fourth, for platform operators, review recommendation algorithms can be optimized based on topic analysis results to push the most referentially valuable reviews to users with different preferences.

5.5 Limitations and Future Directions

This study has the following limitations. First, the data source is singular, collecting only long reviews from the Douban platform, without encompassing short reviews, Weibo, WeChat, and other social media channels for film discussion. Second, the sentiment analysis tool has limited precision; SnowNLP faces risks of misjudgment when processing irony, metaphor, and complex emotional interweaving in long-form texts. Third, negative reviews constitute a relatively high proportion of the dataset (71.5%), which may be related to the review preferences of Douban platform users and the sampling strategy, requiring caution in result interpretation. Fourth, the study primarily employs descriptive analysis without establishing causal relationships between variables.

Future research could expand in the following directions: adopting multi-platform data fusion strategies, integrating review data from Weibo, Douyin, and other platforms to enhance sample representativeness; introducing pre-trained models such as BERT to improve the accuracy of Chinese sentiment analysis (He & Abisado, 2024); exploring Aspect-Based Sentiment Analysis (ABSA) methods to achieve more refined topic-sentiment association analysis (Mao et al., 2024); combining film metadata such as genre, ratings, and box office data to build multi-factor association models; and conducting cross-cultural comparative studies to compare perception dimension differences between Chinese and Western film audiences.

References

Andono, P. N., Sunardi, S., Nugroho, R. A., & Harjo, B. (2022). Aspect-based sentiment analysis for hotel review using LDA, semantic similarity, and BERT. *International Journal of Intelligent Engineering and Systems*, 15(5),

232–243. <https://doi.org/10.22266/ijies2022.1031.21>

- Bi, J. W., Liu, Y., Fan, Z. P., & Zhang, J. (2019). Exploring asymmetric effects of attribute performance on customer satisfaction in the hotel industry. *Tourism Management*, 77, 104006. <https://doi.org/10.1016/j.tourman.2019.104006>
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3, 993–1022.
- Cheng, L. C., & Yang, Y. (2022). The effect of online reviews on movie box office sales: An integration of aspect-based sentiment analysis and economic modeling. *Journal of Global Information Management*, 30(1), 1–25. <https://doi.org/10.4018/JGIM.298652>
- Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3), 345–354. <https://doi.org/10.1509/jmkr.43.3.345>
- China Film Administration. (2024). 2023 nian zhongguo dianying shichang tongji baogao [2023 China film market statistical report]. <https://www.chinafilm.gov.cn>
- Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*, 4171–4186. <https://doi.org/10.18653/v1/N19-1423>
- Douban. (2024). Douban dianying [Douban Movie]. <https://movie.douban.com>
- Elbarachi, S., Lakhri, Y., El Alami, J., & Talbi, F. (2022). Analyzing tourism reviews using an LDA topic-based sentiment analysis approach. *International Journal of Advanced Computer Science and Applications*, 13(11), 436–447. <https://doi.org/10.14569/IJACSA.2022.0131151>
- Feldman, R., & Sanger, J. (2007). *The text mining handbook: Advanced approaches in analyzing unstructured data*. Cambridge University Press.
- Green, M. C., & Brock, T. C. (2000). The role of transportation in the persuasiveness of public narratives. *Journal of Personality and Social Psychology*, 79(5), 701–721. <https://doi.org/10.1037/0022-3514.79.5.701>
- Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101(Suppl 1), 5228–5235. <https://doi.org/10.1073/pnas.0307752101>
- Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent Dirichlet allocation. *Tourism Management*, 59, 467–483. <https://doi.org/10.1016/j.tourman.2016.09.009>
- Hassani, H., Bennis, S., & Moussaid, N. (2022). Weighted joint sentiment-topic model for sentiment analysis compared to ALGA: Adaptive lexicon learning using genetic algorithm. *Applied Sciences*, 12(16), 8176. <https://doi.org/10.3390/app12168176>
- He, A., & Abisado, M. (2024). Text sentiment analysis of Douban film short comments based on BERT-CNN-BiLSTM-Att model. *IEEE Access*, 12, 45229–45237. <https://doi.org/10.1109/ACCESS.2024.3381515>
- Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. (2019). Latent Dirichlet allocation (LDA) and topic modeling: Models, applications, a survey. *Multimedia Tools and Applications*, 78(11), 15169–15211.

<https://doi.org/10.1007/s11042-018-6894-4>

- Lee, J., Park, H., & Kim, J. (2021). LDA-based topic modeling sentiment analysis using topic/document/sentence (TDS) model. *Applied Sciences*, 11(23), 11091. <https://doi.org/10.3390/app112311091>
- Li, L., Guan, Z., & Xing, F. (2024). Text sentiment analysis of film reviews using Word2Vec-LSTM. *Proceedings of SPIE*, 13181, 131810T. <https://doi.org/10.1117/12.3031046>
- Lin, C., & He, Y. (2009). Joint sentiment/topic model for sentiment analysis. *Proceedings of the 18th ACM Conference on Information and Knowledge Management*, 375–384. <https://doi.org/10.1145/1645953.1646003>
- Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, 5(1), 1–167. <https://doi.org/10.2200/S00416ED1V01Y201204HLT016>
- Mao, H., Fan, Y., & Tong, M. (2024). Research on aspect-based sentiment analysis of movie reviews based on deep learning. *Journal of Information Science*. <https://doi.org/10.1177/01655515241292353>
- Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly*, 34(1), 185–200. <https://doi.org/10.2307/20721420>
- Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1–2), 1–135. <https://doi.org/10.1561/15000000011>
- Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. *Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing*, 79–86. <https://doi.org/10.3115/1118693.1118704>
- Rita, P., Moro, S., & Cavalcanti, G. (2022). The impact of COVID-19 on tourism: Analysis of online reviews in the airlines sector. *Journal of Air Transport Management*, 104, 102277. <https://doi.org/10.1016/j.jairtraman.2022.102277>
- Röder, M., Both, A., & Hinneburg, A. (2015). Exploring the space of topic coherence measures. *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, 399–408. <https://doi.org/10.1145/2684822.2685324>
- Setiadi, D. R. I. M., Marutho, D., & Setiyanto, N. A. (2024). Comprehensive exploration of machine and deep learning classification methods for aspect-based sentiment analysis with LDA topic modeling. *Journal of Future Artificial Intelligence and Technologies*, 1(1), 1–15. <https://doi.org/10.62411/faith.2024-13>
- Sun, J. (2012). Jieba Chinese text segmentation. GitHub Repository. <https://github.com/fxsjy/jieba>
- Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics*, 37(2), 267–307. https://doi.org/10.1162/COLI_a_00049
- Wu, T., Li, Y., & Zhang, S. (2022). Typical opinions mining based on Douban film comments in animated movies. *Chaos, Solitons & Fractals*, 160, 112204. <https://doi.org/10.1016/j.chaos.2022.112204>
- Yang, B., & Yecies, B. (2016). Mining Chinese social media UGC: A big-data framework for analyzing Douban movie reviews. *Journal of Big Data*, 3, 3. <https://doi.org/10.1186/s40537-015-0037-9>
- Zhang, Y., & Zhang, L. (2022). Movie recommendation algorithm based on sentiment analysis and LDA. *Procedia Computer Science*, 199, 871–878. <https://doi.org/10.1016/j.procs.2022.01.092>

- Zhao, K., Yang, X., Tao, X., Xu, X., & Zhao, J. (2020). Exploring the differential effects of online reviews on film's box-office success: Source identity and brand equity from an integrated perspective. *Frontiers in Psychology*, 11, 217. <https://doi.org/10.3389/fpsyg.2020.00217>
- Zhao, W. X., Jiang, J., Weng, J., He, J., Lim, E. P., Yan, H., & Li, X. (2011). Comparing Twitter and traditional media using topic models. *Proceedings of the 33rd European Conference on Information Retrieval*, 338–349. https://doi.org/10.1007/978-3-642-20161-5_34
- Zhong, A., & Qiu, R. (2023). Topic analysis on user generated comments of Chinese mainland films. *Proceedings of the 2023 2nd International Conference on Social Sciences and Humanities and Arts*, 379–386. https://doi.org/10.2991/978-2-38476-062-6_48