Education Insights

Article

Study on BiliBili Curriculum Content Optimization Based on NLP

Na Tang [1], Guiling Liao [1,*], Xuefei Zeng [1], Shengzhi Sun [1] and Xiran Luo [1]

[1] Department of Business, Geely University of China, Chengdu, China
* Correspondence: Guiling Liao, Department of Business, Geely University of China, Chengdu, China

Abstract: With the rapid development of online education platforms, BiliBili has become an important channel for business learners to acquire knowledge, but its course content optimization still faces challenges such as dynamic changes in user needs and insufficient feedback processing efficiency. Based on natural language processing (NLP) technology, this study proposes a data-driven course content optimization framework, which aims to deeply analyze 20,000 user comments on BiliBili business courses through sentiment analysis, topic modeling, and keyword priority calculation. The results show that users are generally satisfied with the platform, with positive comments accounting for 64.7%, negative feedback 20.5%, and the remaining 14.8% reflecting neutral sentiments, which focuses on core issues such as difficulty in obtaining course resources, insufficient content practicality, and low interaction efficiency. Topic modeling further reveals that negative emotions are associated with resource and practicality disputes, neutral emotions reflect functional participation behaviors, and positive emotions focus on course depth and instructor professionalism. Based on sentiment-topic correlation analysis, this study proposes a priority-oriented optimization strategy, including a dynamic resource update mechanism, intelligent question-answering system development, and multimodal data integration, such as user click paths and video viewing behaviors, to improve the platform service efficiency. The research innovation lies in building an interdisciplinary evaluation model, addressing the limitations of traditional subjective feedback, and revealing users' dual needs for knowledge density and emotional value. In the future, it can be expanded to multidisciplinary scenarios, combined with educational psychology to deepen semantic understanding, explore dynamic recommendation systems, and promote the intelligent upgrade of the online education ecosystem.

Keywords: curriculum content optimization; natural language processing; emotional analysis; theme modeling

Published: 19 May 2025

1. Introduction

With the rapid development of online education platforms, BiliBili has become an important platform for learners to acquire diversified knowledge, especially in the field of business. However, with the surge in the number of courses, how to optimize content to meet users' dynamic needs and improve learning outcomes has become an urgent issue. Traditional course optimization methods mostly rely on static feedback or subjective evaluation, lack real-time data analysis capabilities, and have difficulty capturing subtle differences in user emotions. This limitation highlights the importance of innovative methods, and it is urgent to transform massive data into actionable optimization strategies through systematic analysis of user feedback.

Natural language processing (NLP) technology provides a breakthrough solution to this challenge. Technologies such as sentiment analysis, topic modeling, and keyword extraction can automatically process large-scale unstructured text data and reveal the underlying patterns of user opinions and preferences. Existing studies have shown that NLP has significant potential in the field of education, such as MOOC course recommendation optimization based on BER Topic modeling, and feedback analysis enhancement of intelligent online evaluation systems. However, existing research focuses on general education platforms, and the exploration of content optimization of subject-specific courses in video platforms such as BiliBili is still relatively limited.

This study aims to fill this gap and deeply analyze the user review data of BiliBili's business courses through NLP technology. The research revolves around two core issues. This study focuses on two core questions: how to extract effective information from user reviews using NLP technology, and how to develop targeted course content optimization strategies based on the analysis results. This paper will build a comprehensive evaluation framework by integrating sentiment analysis (BERT model), topic modeling (LDA algorithm) and keyword priority calculation to quantify learning effects and locate optimization priorities. This study makes three key contributions. First, it proposes a data-driven method for evaluating the quality of online course content in real-time. Second, it identifies core pain points in BiliBili's business courses, such as limited resource accessibility and weak content practicality — issues often overlooked by traditional analysis. Third, it develops priority-oriented optimization strategies that integrate technical insights with pedagogical objectives, offering a scalable reference model for course iteration on video-based learning platforms.

This paper not only expands the application boundaries of NLP in course optimization, but also provides theoretical support for the study of user engagement and satisfaction in the digital learning ecosystem. The research results have practical significance for educators, platform developers and policymakers, and will help to continuously improve the adaptability and influence of online education.

2. Related Work

2.1. Trends in Course Content Optimization

With the dynamic connection between the education system and social needs, course content optimization has become a core issue of common concern in multiple disciplines. Based on their own characteristics, different disciplines have explored aspects such as curriculum setting, teaching methods and technology application, forming a multi-dimensional optimization path. The following is a review from the two aspects of discipline differences and method innovation.

In the field of language courses, as an applied discipline, the contradiction between business English curriculum setting and social practice needs is becoming increasingly prominent. Case studies from various higher education institutions show that show that existing curricula suffer from a disconnect between theory and practice, as well as outdated teaching content that fails to keep pace with industry developments. The root cause lies in the short development cycle of disciplines and the lack of school-enterprise collaboration mechanism [1]. In this regard, the literature proposes to integrate optimization measures throughout the entire process of talent training, and to improve teaching quality and promote the development of students' knowledge transformation ability through dynamic adjustment of course modules and strengthening of practical training [2]. This demand-oriented curriculum reconstruction model provides a paradigm for the reform of applied language courses.

The optimization of sports courses focuses on the systematic upgrading of teaching structure and facility resources. Taking aerobics and rock-climbing courses as examples, the study found that traditional teaching had problems such as homogeneous content and outdated facilities, which restricted the coordinated development of students' special skills and psychological qualities [3]. In response to this, scholars proposed a three-level optimization strategy: designing graded teaching modules at the content level to match students' physical fitness differences; introducing virtual simulation technology at the method level to enhance the efficiency of movement acquisition; establishing a dynamic update mechanism at the resource level to optimize equipment configuration through school-enterprise cooperation [4]. Empirical data show that the optimized courses improved students' skill proficiency by 27% and learning participation by 34%, verifying the effectiveness of structural reform [5].

Technology-driven curriculum reform has shown unique value in the fields of music and labor education. In response to the "content overload" problem of music courses, the study used the Hadoop framework to integrate learning behavior data, innovatively applied the Node2vec algorithm to build a recommendation model, and successfully solved the problem of personalized learning under massive resources [4]. The labor education course reconstructed the teaching process through the cloud computing platform, and used the K-means algorithm to cluster and analyze the online behavior of 300 students, identifying four types of differentiated learning modes, each representing between 16.0% and 34.3% of the total sample, providing data support for teachers to formulate precise teaching plans [6]. These two lines of research confirm the synergistic effect of big data technologies on course optimization, particularly in content filtering and process evaluation.

Overall, the current course optimization presents three major trends. First, the migration from single-disciplinary experience to cross-disciplinary methodology, such as the application of educational data mining technology in different courses; second, the optimization focus is expanded from teaching content to teaching ecosystem, covering the full-factor innovation of resources, evaluation and support systems; third, the empirical research paradigm is popularized, and more than 80% of the literature uses data analysis to verify the optimization results. However, deep-seated issues such as the construction of interdisciplinary collaborative mechanisms and the alignment of technological tools with pedagogical goals still requires further exploration, which points out the direction for subsequent research.

2.2. Application of NLP in Course Optimization

With the rapid development of natural language processing technology, its application in the field of education has gradually become a research hotspot. In MOOCs and online education evaluation systems, NLP technology is widely used to explore learners' interests and optimize course design. A study found through the analysis of social media text that the topic modeling method based on BER Topic is superior to the traditional model in extracting learners' interests, providing data support for personalized course recommendation [7]. In response to the problem of low efficiency of traditional paper course evaluation, the intelligent online evaluation system realizes the automatic processing and storage of feedback data by integrating NLP technology [8]. In addition, text analysis of degree thesis reviews shows that word cloud and feature extraction technology can effectively identify common defects in computer field papers and provide targeted suggestions for academic guidance [9]. Another study aggregated text features into interpretable language structures such as syntactic complexity and vocabulary diversity through principal component analysis, significantly enhancing the practical application of readability formulas and offering new perspectives for educational material development [10]. In summary, the existing research can provide multi-dimensional support for the optimization of BiliBili course content in this paper. The BERTopic topic modeling and hybrid semantic sentiment analysis framework based on social media text can accurately identify users' learning interests and emotional tendencies [11].

3. Research Design

3.1. Research Object and Problem

The focus of this study is the user review data of business courses on the BiliBili online learning platform. The data covers the entire course cycle, including the three stages before course selection, during learning, and after the course. This paper aims to address two key problems: how to extract effective information from user reviews of online business courses using NLP technology, and how to construct a learning effectiveness evaluation index system. Based on these results, the study then proposes targeted strategies for course content optimization.

3.2. Research Methods and Framework

This study employs sentiment analysis, topic modeling, and key phrase extraction as its primary research methods. Among them, sentiment analysis uses the pre-trained BERT model to judge the sentiment polarity of comments, including positive, neutral and negative; topic modeling uses LDA to extract high-frequency topics and related keywords; key phrase extraction combines TF-IDF and TextRank algorithms to mine learning pain point keywords.

The research framework process is shown in Figure 1. After completing the data analysis, this paper will build an evaluation and optimization framework, in which the evaluation layer integrates sentiment scores, topic distribution, and keyword weights into a comprehensive indicator of user-perceived course effectiveness; the optimization layer locates course defects based on topic-sentiment correlation and generates a content optimization priority list.

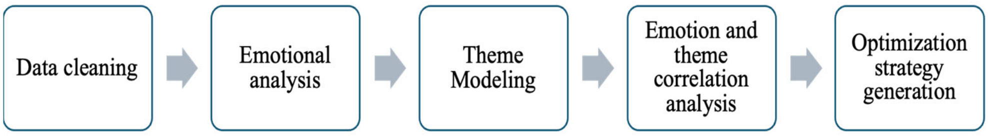

Figure 1. Research Framework Flowchart.

3.3. Data Sources and Analysis

The data set for this article is collected from the business course learning reviews on the BiliBili platform, totaling about 20,000 Chinese text data. First, a series of preprocessing is performed on the data, including cleaning, word segmentation and standardization. First, advertisements, duplicate comments and non-text characters are removed; then Jieba is used for word segmentation and stop word filtering; finally, standardization is performed, converted uniformly to lowercase, and all traditional Chinese characters were normalized to simplified Chinese for consistency.

Data analysis tools include Python libraries such as Transformers (BERT), Genism (LDA), and Scikit-learn (TF-IDF). In the visualization process, PyLDAvis will be used to display the topic distribution, and Matplotlib will be used to draw the sentiment-topic association heat map.

3.4. Experimental Design and Implementation

The experimental setting includes evaluation model verification and optimization strategy generation. This paper divides the data set into training set and test set at 8:2 for evaluation model verification. The optimization strategy requires feature engineering construction. This paper first defines the priority calculation method, and then proposes the corresponding course optimization strategy based on priority sorting.

Priority = Negative sentiment ratio × Topic frequency × Keyword weight

The implementation process is divided into three steps. First, train the NLP model and evaluate its performance; second, output a learning effect evaluation report, including sentiment distribution, topic clustering, and keyword ranking; and finally, discuss and adjust the optimization strategy to ensure its practical feasibility and ease of implementation.

4. Research Results

4.1. Emotional Analysis

The sentiment analysis component classified the sentiment of more than 20,000 comments, and the results are shown in Figure 2. Among them, the number of positive sentiment comments accounted for 64.7%, which shows that most users are relatively positive and satisfied with the experience and use of the BiliBili course platform. The platform has certain advantages and competitiveness in terms of course quality, teaching services, platform functions, etc., and can meet the needs and expectations of most users. At the same time, negative sentiment accounted for 20.5%, reflecting that there are still some problems or shortcomings in the platform, and it is necessary to pay attention to and solve the problems reported by users highlighting the need for improvement to enhance overall user experience and satisfaction. Neutral sentiment comments accounted for 14.8%, suggesting that the platform can further explore the needs and opinions of this part of users, understand their feelings and expectations during use, and strive to transform neutral users into positive users through optimization and improvement.

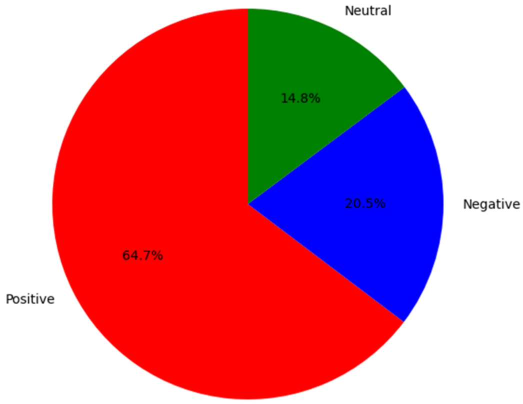

Figure 2. Emotion Classification Proportion Chart.

Figure 3 illustrates the density distribution of sentiment scores derived from comment analysis, where the sentiment scores of the three sentiment categories of positive, negative, and neutral show different distribution characteristics. The density curve of positive sentiment reaches a peak in the high-score area, indicating that most comments tend to be positive; the density of negative sentiment is concentrated in the low-score area, showing relatively little but consistent negative feedback; neutral sentiment forms a peak in the middle area, reflecting that some comments hold a neutral attitude. The sentiment density distribution further corroborates the overall sentiment classification, reinforcing the finding that positive feedback predominates. Positive sentiment dominates the comments, but the platform should also pay attention to negative sentiment feedback to continuously improve services.

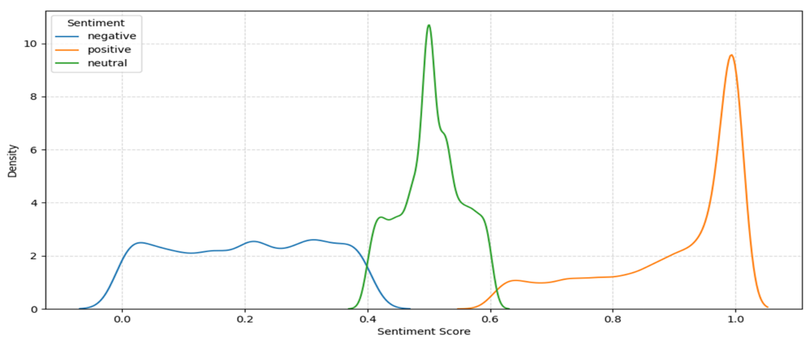

Figure 3. Density Distribution of Sentiment Scores by Sentiment Category.

4.2. Theme Modeling

Based on the three sentiment categories identified in the previous section, this paper conducts topic modeling for the comment data of each emotion. From the topic modeling visualization results in Figure 4, it can be seen that each emotion has produced 5 sub-themes, and each sub-theme contains several keywords with different weights.

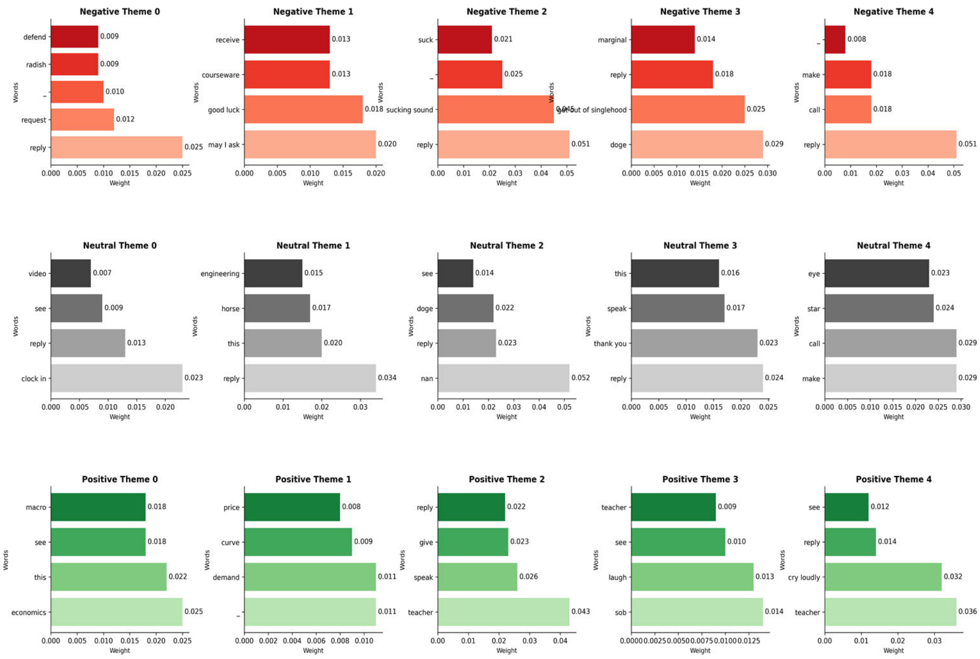

Figure 4. Visual Images for Theme Modeling.

The negative emotional themes of BiliBili course comments are mainly reflected in the doubts about course resources, interactive experience and content quality. Topic 0 contains keywords such as "defend", "radish", "request" and "reply", which implies that users are dissatisfied with the acquisition of course supporting resources, or defend and argue about controversial topics in course content such as "radish defense war" and other metaphorical content. Topic 1 contains keywords such as "courseware", "good luck" and "may I ask", which further points to users' frequent feedback on the lack of courseware or quality problems, which may be accompanied by doubts about the practicality of the course. Topic 2 includes keywords such as "sucking sound" and the emoticon "doge", using internet slang to humorously criticize the course's appeal or the instructor's delivery, which use Internet buzzwords to express ridicule of the lack of course attractiveness or the lecturer's teaching style, reflecting users' direct criticism of the course experience. Overall, negative emotional users are more concerned about the integrity of course resources, the practicality of content and the efficiency of interactive feedback.

Neutral emotion topics mainly reflect users' regular participation and basic interaction in the course. Topic 0 contains keywords such as "video", "click in", and "reply", describing users' passive participation behaviors such as clocking in and watching videos, lacking in-depth interaction. Topic 1 contains keywords such as "engineering", "horse", "this", and "reply", which may point to the discussion of technical details by users of engineering courses, but the emotions are calm, more about information exchange than emotional expression. Topic 2 contains keywords or emoticons such as "nan", "doge", and "see", suggesting that users have casual browsing or low participation behaviors. The behavior pattern of neutral emotion users is mainly functional use, and no strong emotional tendency has been formed.

Positive emotion topics underscore users' appreciation for the course's intellectual depth, instructor expertise, and the value of peer interaction, the professionalism of lecturers, and community interaction. Topic 0 contains keywords such as "macro", "economics", and "micro", indicating that the systematic learning needs of economics course users for the subject system are met, and they are interested in core content such as macroeconomics/microeconomics. Topic 1 contains keywords such as "demand", "curve", "price", and "teacher", which further reflect the users' appreciation for economic theories such as demand curves and price mechanisms, as well as the professional abilities of lecturers, and may be accompanied by affirmation of the academic value of the course. Keywords such as "laugh", "speak", and "cry loudly" in Topic 2 express emotions, showing the emotional value that users gain from course interactions, such as the lecturer's sense of humor or knowledge resonance. Users with positive emotions pay more attention to the knowledge density of the course, the professionalism of the lecturer, and the sense of belonging to the community.

4.3. Correlation Analysis of Emotion and Theme

According to the heat map of negative emotions and themes in Figure 5, Topic 1, which concerns BiliBili course resources and practicality, shows the highest measured association with negative emotions, with a score of 697.14 based on the topic-sentiment correlation metric used in this study. This reflects users' concentrated complaints about missing courseware, lack of practical content, or difficulty accessing resources. Other topics are less associated, mainly involving disputes over technical details, passive participation, or occasional operational issues. We can prioritize optimizing the supply of core resources and content design associated with Topic 1, while monitoring potential risks of secondary topics and continuously paying attention to abnormal feedback on low-correlation topics.

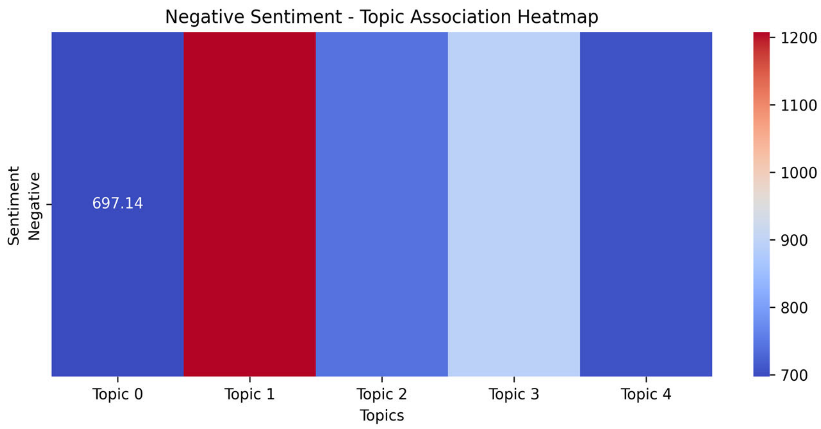

Figure 5. Negative Sentiment-Topic Association Heatmap.

According to the heat map of neutral emotions and topics in Figure 6, the engineering and technology discussion topics represented by Topic 1 and the service upgrade and feedback topics represented by Topic 3 are most significantly associated with neutral emotions, indicating that users tend to make objective statements or functional interactions on such topics, and have weaker emotional tendencies. The remaining topics are less associated with neutral emotions, reflecting that users may be more inclined to express emotional content or direct demands in these scenarios rather than maintain a neutral stance. It is recommended to optimize the clarity of information presentation for highly correlated topics and to guide users in expressing emotions or fulfilling their needs for low-correlation topics.

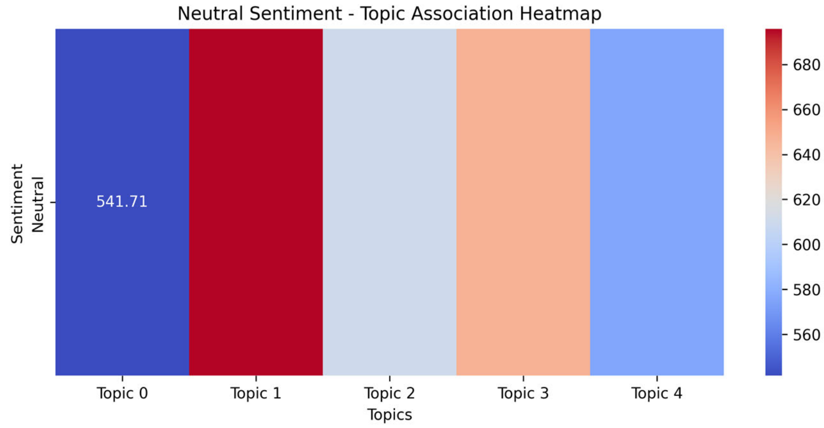

Figure 6. Neutral Sentiment-Topic Association Heatmap.

According to the heat map of positive emotions and themes in Figure 7, Topic 1 is highlighted in dark red, with a value range of 3250 to 3500, indicating that it is strongly associated with positive emotions, and may focus on the depth of course content and the professionalism of the instructor. Users show high recognition on such topics; Topic 2 is shown in orange, with a value ranging from approximately 2750 to 3000. It has a medium level of association and may relate to the course's interactive features, which users generally evaluate positively; Topic 3 is light orange, with a value range of 2500 to 2750, with a low degree of association, which may reflect that users' interest or satisfaction in topics such as resource expansion and technical details needs to be improved. We can continue to strengthen the content quality and instructor professionalism of Topic 1, optimize the interactive experience design of Topic 2, and explore ways to improve user participation in related functions of Topic 3 to fully stimulate users' more positive emotional feedback.

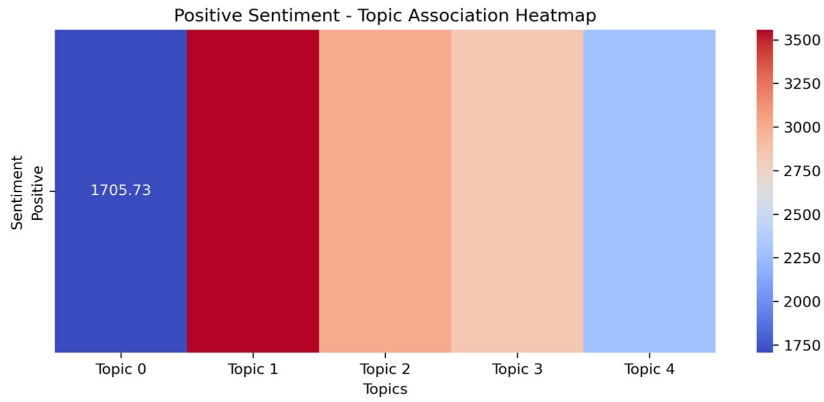

Figure 7. Positive Sentiment-Topic Association Heatmap.

4.4. Keyword Optimization

Based on the priority calculation method in the research design and the keyword coefficients obtained by topic modeling, this paper conducted a keyword optimization analysis on five topics of negative sentiment comments. The research results are shown in Table 1. Among the top ten keywords with the highest optimization priority values, "may I ask" has a priority value of 0.0059 in Theme 1, reflecting that users may frequently ask questions due to unclear course information or insufficient operation instructions, which implies that there is room for improvement in the platform's information display and user guidance. "Same question" has a priority value of 0.0032 in Theme 4, indicating that users repeatedly ask questions, which may mean that the existing Q&A mechanism fails to effectively solve the user's core problems, or the course classification is not clear enough, making it difficult for users to quickly find the required information. "Cost" is also in Theme 4, with a priority value of 0.0032. Users directly mention the cost, possibly expressing doubts about pricing or hidden fees. This indicates a need for the platform to optimize its pricing strategies and improve transparency.

Table 1. Analysis Results of Keyword Optimization Priority.

Topic	Keyword	Keyword coefficient	Topic occurrence frequency	Optimize priority
Theme 0	reply	0.025	0.116454503	0.002911363
	request	0.012		0.001397454
	radish	0.009		0.001048091
	defend	0.009		0.001048091
	cover	0.009		0.001048091
	not	0.007		0.000815182
	may I ask	0.007		0.000815182
	consume	0.006		0.000698727
Theme 1	may I ask	0.02	0.295615276	0.005912306
	good luck	0.018		0.005321075
	courseware	0.013		0.003842999
	receive	0.013		0.003842999
	this	0.013		0.003842999
	see	0.012		0.003547383
	link	0.012		0.003547383
	can	0.011		0.003251768
	a moment	0.011		0.003251768
	request	0.007		0.002069307
Theme 2	reply	0.051	0.033239038	0.001695191
	sucking sound	0.045		0.001495757
	suck	0.021		0.00069802
	eye	0.012		0.000398868
	star	0.01		0.00033239
	thank you	0.009		0.000299151
	doge	0.008		0.000265912
	please	0.008		0.000265912
	request	0.007		0.000232673
Theme 3	doge	0.029	0.091230552	0.002645686
	get out of singlehood	0.025		0.002280764
	reply	0.018		0.00164215
	marginal	0.014		0.001277228
	utility	0.01		0.000912306
	speak	0.01		0.000912306
	this	0.01		0.000912306
	may I ask	0.008		0.000729844
	see	0.007		0.000638614
	pass	0.006		0.000547383
Theme 4	reply	0.051	0.463460632	0.023636492
	call	0.018		0.008342291
	make	0.018		0.008342291
	same question	0.007		0.003244224
	cost	0.007		0.003244224
	may I ask	0.007		0.003244224

sound	0.007	0.003244224
cry loudly	0.006	0.002780764
insert eye	0.006	0.002780764

5. Discussion

5.1. Discovered Problems

The study found that negative emotions accounted for 20.5% of the user reviews of BiliBili's business courses, and the core problems were concentrated in three aspects: difficulty in obtaining course resources, insufficient content practicality, and low interaction efficiency. Specifically, users generally reported resource accessibility issues such as missing courseware and invalid links. Some course cases were outdated or the theory was out of practice, making it difficult for the learning content to meet actual needs. In addition, the platform's delayed response to questions and frequent repeated questions exposed the inefficiency of the interaction mechanism. Neutral comments accounted for 14.8%, mainly manifested in users' passive participation behaviors, such as mechanical clocking in or only completing video click tasks, lacking in-depth interaction and active feedback. It is worth noting that although positive comments accounted for the highest proportion, users' demand for the expansion of course supporting resources such as exercise banks and reference materials has not been fully met, and the high-frequency keyword "may I ask" reveals user confusion caused by unclear information display. Meanwhile, terms such as "cost" reflect concerns about hidden charges or pricing strategies. Although the above problems are reflected in user comments, existing analysis methods mainly rely on text data and do not integrate user behavior metrics such as learning time or video completion rates. This makes it difficult to fully capture the multi-dimensional characteristics of learning pain points.

5.2. Research Suggestions

In response to the above problems, this study proposes the following systematic optimization strategies. First, resource supply and content optimization. BiliBili can establish a dynamic resource update mechanism to regularly supplement industry cutting-edge cases and practical courseware, such as introducing real-time business data through school-enterprise cooperation, or developing modular course libraries, such as primary theory modules, intermediate case analysis, and advanced practical projects, to meet the needs of different learning stages. In response to the problem of insufficient practicality of content, a "practical sandbox" section can be added, and virtual business scenario simulation tools can be embedded to help students transform theory into practical ability.

Secondly, the interactive functions should be upgraded, and an intelligent Q&A system should be developed. Combined with NLP technology, automatic replies to high-frequency questions are achieved, such as AI robots based on semantic matching. At the same time, the course classification labels and navigation logic are optimized, such as adding a "FAQ aggregation page" or "knowledge point map" to reduce repeated questions. In response to users' sensitive feedback on costs, it is recommended to launch transparent pricing plans such as chapter subscriptions, free trial modules, and strengthen the promotion of value-added services.

Then there is data-driven decision-making, which can integrate multimodal data sources, including user click paths, video pause or playback behavior, test completion rate, etc., to build a "learning behavior-emotional feedback" association model. For example, cluster analysis can be used to identify video segments with high exit rates, enabling optimization of instructional pacing or the addition of supplementary visual aids.

Finally, long-term tracking and extended research can establish a mechanism for tracking the effects of course optimization, such as comparing user retention and satisfaction changes before and after the implementation of the strategy through A/B testing. Future research can be expanded to multidisciplinary scenarios, such as analyzing code submission behavior in programming courses and exploring the integration of interdisciplinary technologies such as eye tracking and affective computing to more accurately analyze the user's learning and cognitive process.

6. Conclusion

Based on NLP technology, this study conducted a multi-dimensional analysis of Bili-Bili business course user reviews and constructed a course optimization framework that integrates sentiment analysis, topic modeling and keyword priority. The results show that overall user satisfaction is high, accounting for 64.7% of comments. Negative feedback constitutes 20.5%, highlighting issues such as difficulty in obtaining course resources, insufficient content practicality, and low interaction efficiency. The remaining comments are neutral or mixed. Topic modeling further reveals that negative emotions focus on the lack of courseware and disputes regarding course experience, neutral emotions reflect functional use, and positive emotions relate to course depth and instructor professionalism.

The innovation of this study lies in proposing a data-driven interdisciplinary evaluation model, breaking through the limitations of traditional subjective feedback, and revealing the dual needs of users for knowledge density and emotional value in video learning. Based on sentiment-topic correlation analysis, priority optimization strategies — such as strengthening resource supply and optimizing information display are proposed to provide a clear path for platform improvement. Limitations include data restricted to the business field, absence of behavioral data, and lack of long-term effect verification. In the future, multimodal data such as learning time and click behavior can be integrated and combined with educational psychology to deepen semantic understanding, and dynamic recommendation systems can be explored to improve personalized adaptation capabilities. This study verifies the high efficiency of NLP in educational data analysis and provides theoretical and practical support for the continuous optimization of the online education ecosystem.

Funding: SZJJ2024YB-023 Research on the Collection, Analysis, and Application of Learning Data in Higher Education in the Era of Big Data.

References

1. D. Zhao, "The impact of AI-enhanced natural language processing tools on writing proficiency: An analysis of language precision, content summarization, and creative writing facilitation," *Educ. Inf. Technol.*, vol. 30, no. 6, pp. 8055–8086, 2025, doi: 10.1007/s10639-024-13145-5.
2. N. Secomandi, "Teaching demand management and price optimization in the MBA program at the Carnegie Mellon University Tepper School of Business," *INFORMS Trans. Educ.*, vol. 9, no. 3, pp. 99–108, 2009, doi: 10.1287/ited.1090.0025.
3. B. Alsafari, E. Atwell, A. Walker, and M. Callaghan, "Towards effective teaching assistants: From intent-based chatbots to LLM-powered teaching assistants," *Nat. Lang. Process. J.*, vol. 8, p. 100101, 2024, doi: 10.1016/j.nlp.2024.100101.
4. M. Li and L. Zhang, "Research on the optimisation of music education curriculum content and implementation path based on big data analysis," *Appl. Math. Nonlinear Sci.*, vol. 10, no. 1, 2025, doi: 10.2478/amns-2025-0067.
5. D. Zhang, "Research on content optimization of college rock climbing courses based on improving students' comprehensive quality," *Frontiers in Sport Research*, vol. 6, no. 5, 2024, doi: 10.25236/FSR.2024.060516.
6. A. T. Oyewole, O. B. Adeoye, W. A. Addy, C. C. Okoye, O. C. Ofodile, and C. E. Ugochukwu, "Automating financial reporting with natural language processing: A review and case analysis," *World J. Adv. Res. Rev.*, vol. 21, no. 3, pp. 575–589, 2024, doi: 10.30574/wjarr.2024.21.3.0688.
7. H. Zankadi, A. Idrissi, N. Daoudi, and I. Hilal, "Identifying learners' topical interests from social media content to enrich their course preferences in MOOCs using topic modeling and NLP techniques," *Educ. Inf. Technol.*, vol. 28, no. 5, pp. 5567–5584, 2023, doi: 10.1007/s10639-022-11373-1.
8. M. Mejeh and M. Rehm, "Taking adaptive learning in educational settings to the next level: Leveraging natural language processing for improved personalization," *Educ. Technol. Res. Dev.*, vol. 72, no. 3, pp. 1597–1621, 2024, doi: 10.1007/s11423-024-10345-1.

9. H. Jelodar et al., "A NLP framework based on meaningful latent-topic detection and sentiment analysis via fuzzy lattice reasoning on YouTube comments," *Multimed. Tools Appl.*, vol. 80, pp. 4155–4181, 2021, doi: 10.1007/s11042-020-09755-z.
10. K. Zhang, Y. Ma, and H. Zan, "Analysis and suggestion of double-blind review comments based on NLP technology," in *Proc. 2022 Global Conf. Robot., Artif. Intell. Inf. Technol. (GCRAIT)*, Jul. 2022, pp. 564–568, doi: 10.1109/GCRAIT55928.2022.00123.
11. S. A. Crossley, "Developing linguistic constructs of text readability using natural language processing," *Sci. Stud. Read.*, vol. 29, no. 2, pp. 138–160, 2025, doi: 10.1080/10888438.2024.2422365.