Sentimental Analysis in Online Learning Environment: A Review

Varalakshmi N[1], Dr. Hanumantappa M[2]
[1]*Full-time Guest Faculty, Department of Computer Science and Applications*, *Bangalore University, Bangalore, Karnataka, India*
[2]*Senior Professor, Department of Computer Science and Applications*, *Bangalore University, Bangalore, Karnataka, India*

Abstract- The surge in online learning platforms has led to a significant increase in user-generated feedback through course reviews and ratings. These reviews serve as a valuable source for improving course quality, teaching methods, and learner engagement. This survey paper provides a comprehensive review of existing online course review systems, focusing on their underlying methodologies, including sentiment analysis, machine learning models, and feedback classification techniques. The paper presents a taxonomy of approaches used to process and analyze student reviews, highlights existing challenges such as review bias and data sparsity, and outlines future directions in developing intelligent and interpretable review systems. This survey aims to help researchers and educators understand the current landscape and identify potential areas for improvement.

Keywords: Course review and ratings, Sentimental Analysis, Machine learning models, data Sparsity, interpretable review system.

I.INTRODUCTION

Online classes offer flexibility and convenience, allowing students to learn at their own pace and schedule, which can be particularly beneficial for those with demanding schedules or who prefer self-directed learning. However, they also require strong self- discipline and motivation, as it can be easy to fall behind or lose focus without the structure of a traditional classroom.

ADVANTAGES OF ONLINE CLASSES:

Flexibility and convenience
Online classes can be accessed from anywhere with an internet connection, making them ideal for students with busy schedules or those who prefer to learn at their own pace.

Cost-Effectiveness
Online courses can be more affordable than traditional courses, as they may eliminate the need for commuting and on-campus living expenses.

Wider Range of Options
Online platforms offer a vast array of courses and programs, often unavailable in local institutions.

Personalized Learning:
Online courses can be adapted to individual learning styles and paces, allowing students to focus on areas where they need more support.

Self-Paced Learning:
Students can progress through the material at their own speed, revisiting lessons as needed and taking breaks when necessary.

Improved Concentration:
For some students, the lack of distractions in a home environment can lead to better focus and concentration.

Development of Self-Discipline:
Online learning can foster self-discipline and time management skills, as students are responsible for managing their own learning schedules.

Enhanced Technology Skills:
Online learning provides opportunities to develop proficiency in various digital tools and platforms.

Access to Notes and Materials:
Online platforms often provide easy access to lecture notes, assignments, and other learning materials.

Online classes can be a valuable and effective learning option, especially when students are prepared for the challenges and actively engage with the material. However, it's crucial to acknowledge the potential drawbacks and ensure that students have the necessary resources, support, and self-discipline to succeed.

SENTIMENTAL ANALYSIS

Sentiment analysis, also referred to as *opinion mining*, is an approach to natural language processing (NLP) that identifies the emotional tone behind a body of text. This is a popular way for organizations to determine and categorize opinions about a product, service or idea. Sentiment analysis involves the use of data mining, machine learning (ML), artificial intelligence (AI) and computational linguistics to mine text for sentiment and subjective information, such as whether it's expressing positive, negative or neutral feelings.

Sentiment analysis systems help organizations gather insights into real-time customer sentiment, customer experience and brand reputation. Generally, these tools use text analytics to analyze online sources, such as emails, blog posts, online reviews, customer support tickets, news articles, survey responses, case studies, web chats, tweets, forums and comments. Algorithms are used to implement rule-based, automatic or hybrid methods of scoring whether the customer is expressing positive, negative words or neutral words.

Sentiment analysis can also extract the polarity or the amount of positivity and negativity, as well as the subject and opinion holder within the text. This approach is used to analyze various parts of text, such as a full document or a paragraph, sentence or sub sentence.

How does sentiment analysis work?

Sentiment analysis uses ML models and NLP to perform text analysis of human language. The metrics used are designed to detect whether the overall sentiment of a piece of text is positive, negative or neutral.

Sentiment analysis generally follows these steps:

1. Collect data. The text being analyzed is identified and collected. This involves using a web scraping bot or a scraping application programming interface.
2. Data preprocessing. In this stage, the data is processed to identify keywords that highlight the core meaning of the text. Other preprocessing steps include the following:

tokenization is used to break a sentence down into multiple elements, called tokens.

Stop-word removal is performed to remove parts of speech that don't have meaning relevant to the sentiment of the text. This includes contractions, such as *i'm*, and words that have little information such as *is*, articles such as *the*, punctuation, urls, special characters and capital letters.

lemmatization then converts keywords into their root form.

3. Keyword analysis. ML and NLP algorithms automatically extract text features to identify negative or positive sentiment. Ml approaches used include the bag-of-words technique that tracks the occurrence of words in text and the more nuanced word-embedding technique that uses neural networks to analyze words with similar meanings.
4. Text scoring. A sentiment analysis tool scores the text using a rule-based, automatic or hybrid ml

model. Rule-based systems perform sentiment analysis based on predefined, lexicon-based rules and are often used in domains such as law and medicine, where a high degree of precision and human control is needed. Automatic systems use ml and deep learning techniques to learn from data sets. A hybrid model combines both approaches and is generally considered the most accurate model. These models offer different approaches to assigning sentiment scores to pieces of text.

5. Sentiment classification. Once a model is picked and used to analyze a piece of text, it assigns a sentiment score to the text, including positive, negative or neutral. Organizations can also decide to view the results of their analysis at different levels, including document level, which pertains mostly to professional reviews and coverage; sentence level for comments and customer reviews; and sub-sentence level, which identifies phrases or clauses within sentences.

BENEFITS OF SENTIMENT ANALYSIS IN ONLINE COURSES

Improved Course Quality: Sentiment analysis helps identify areas where students are struggling or find content confusing, allowing for adjustments to improve clarity and effectiveness.
Enhanced Student Satisfaction: By addressing negative feedback and enhancing positive aspects, sentiment analysis can lead to increased student satisfaction and engagement.
Data-Driven Decisions: Sentiment analysis provides objective data that can inform decisions about course design, teaching methods, and resource allocation.
Early Warning System: Sentiment analysis can identify potential issues early on, allowing for timely intervention and preventing negative experiences from escalating.
Personalized Learning: By understanding individual student sentiments, educators can personalize learning experiences and provide targeted support.

Aspect based sentimental analysis
Online classes can be a valuable and effective learning option, especially when students are prepared for the challenges and actively engage with the material. However, it's crucial to acknowledge the potential drawbacks and ensure that students have the necessary resources, support, and self-discipline to succeed. Sentiment analysis of online course reviews involves using techniques to determine the emotional tone (positive, negative, or neutral) expressed in student feedback, which can help in understanding course quality and student satisfaction. By analysing review data, educators can gain insights into areas of strength and weakness, allowing for targeted improvements to course content, teaching methods, and overall learning experience.

How Sentiment Analysis Works in Online Courses:

1. Data Collection:
Collect online course reviews from various platforms, including learning management systems, social media, and dedicated review sites.
2. Text Preprocessing:
Clean the review text by removing noise (e.g., irrelevant characters, HTML tags), converting text to lowercase, and handling stop words (common words like "the", "a", etc.).
3. Sentiment Lexicons and Machine Learning:
Utilize sentiment lexicons (dictionaries that map words to sentiment scores) or machine learning models (like deep learning models such as BERT) to classify the sentiment of each review.
4. Analysis and Visualization:
Analyze the sentiment distribution (e.g., percentage of positive, negative, and neutral reviews) and visualize the results to identify trends and patterns.
5. Actionable Insights:
Use the sentiment analysis results to improve courses by addressing areas of concern, highlighting strengths, and tailoring course content and teaching strategies.

LITERATURE REVIEW

1.Latha Nagesh, K. S. Madhuri, D. R. Reddy, J. V. Reddy, K. M. N. Vardhini, and M. Ramesh, "Online Course Review System Using Aspect Based Sentimental Analysis and Opinion Mining Using Deep Learning," *Int. Res. J. Adv. Sci. Hub*, vol. 7, no. 5, pp. 490–497.
[1] Latha Nagesh et.al. (2025) proposes a novel Online Course Review System that applies Aspect-Based Sentiment Analysis (ABSA) and deep learning to analyse user reviews from Reddit and YouTube. The system targets the challenge faced by learners in evaluating the quality of online courses due to the large volume and unstructured nature of user comments.
The proposed model uses PyABSA's pretrained ABSA models (e.g., FAST-LCF-ATEPC) to extract aspect-specific sentiments for course features such as cost, content quality, difficulty, and duration. Web scraping tools like PRAW (for Reddit) and Playwright (for YouTube) are used to collect real-time feedback. The extracted sentiments are then visualized in a user-friendly interface with aspect-wise star ratings and summaries.
The system achieves an accuracy of 88.1%, and provides users with detailed, real-time, and actionable insights, improving the course selection process. Despite limitations like handling sarcasm and ambiguous language, the framework is modular, scalable, and suitable for future enhancements.

2.S. Gul, M. Asif, F. Amin, K. Saleem, and M. Imran, "Advancing Aspect-Based Sentiment Analysis in

Course Evaluation: A Multi-Task Learning Framework with Selective Paraphrasing," *IEEE Access*, vol. XX, pp. 1–30.

[2] S.Gul et.al. (2025) study presents a novel approach for Aspect-Based Sentiment Analysis (ABSA) in educational course evaluations by integrating Selective Paraphrasing (SP) within a Multi-Task Learning (MTL) framework using transformer-based models (BERT, RoBERTa, XLNet). The authors propose a SP mechanism that augments training data while preserving semantic and sentiment consistency through nuance control. Experimental results on a custom student feedback dataset reveal that the proposed SP-MTL-BERT model outperforms traditional and baseline models significantly, achieving up to 96.2% F1-score for aspect classification and 98.4% for sentiment classification. Comparative evaluations also show that SP surpasses other data augmentation techniques like back translation and Easy Data Augmentation (EDA). The work demonstrates the efficacy of combining nuanced paraphrasing and multi-task learning for robust ABSA in academic settings.

3.A. Baqach and A. Battou, "A new sentiment analysis model to classify students' reviews on MOOCs," Education and Information Technologies, vol. 29, no. 1, pp. 1–35.

[3] Adil Baqach and Amal Battou (2024) proposes a deep learning model named BLC (BERT– LSTM–CNN) to analyze student sentiments in online course reviews. It addresses the challenge of low engagement and dropout rates in MOOCs by enabling tutors to understand student feedback through sentiment classification.

The model integrates:

- BERT for context-rich embeddings,
- BiLSTM for semantic relationship capture,
- CNN for local feature extraction.

Using a scraped Coursera dataset (22,812 labeled reviews), BLC achieved state-of-the-art performance with an accuracy of 79.75% and F1- score of 79.57%, outperforming several traditional and deep learning baselines.

4.H. Iqbal, M. O. Beg, and A. Khan, "An Explainable AI-Enabled Sentiment Analysis Framework for Online Learning Using Aspect- Based Attention and BiGRU," Educ. Inf. Technol., vol. 29.

[4] H.Iqbal (2024) et.al. Study shows how deep contextual embeddings significantly enhance the performance and reliability of ABSA in educational settings, offering actionable insights for course quality improvement.

This paper presents an interpretable deep learning framework for sentiment analysis in online learning environments, leveraging aspect-based attention and Bidirectional Gated Recurrent Units (BiGRU). The goal is to extract fine-grained insights from student feedback and support adaptive, personalized learning.

Key features of the study:

- Development of an explainable AI (XAI) model integrating aspect-term extraction with BiGRU and an attention mechanism to highlight sentiment-bearing words.
- Utilization of a real-world student feedback dataset labeled with five key aspects: Instructor, Content, Assessment, Platform, and Interaction.
- Visualization tools and attention heatmaps to offer transparency into the model's decision-making process.
- The proposed model achieved superior performance (accuracy, F1-score) compared to traditional LSTM and BERT-based baselines.

The study emphasizes the significance of explainability in educational NLP applications to support decision-making by instructors and platform designers.

5.Z. Khanam, "Sentiment Analysis of User Reviews in an Online Learning Environment: Analyzing the Methods and Future Prospects," European Journal of Education and Pedagogy*,* vol. 4, no. 2, pp. 209–217.

[5] Zeba Khanam (2023) presents a systematic review of sentiment analysis (SA) methods used in e-learning environments. With the transition to online education, especially post-pandemic, the paper emphasizes how SA helps educators assess and improve teaching quality based on student feedback, reviews, discussions, and content.

The author categorizes sentiment analysis methods into:

- Machine learning techniques like SVM, Random Forest, Naive Bayes, LSTM.

- Lexicon and deep learning-based models using CNN and attention mechanisms.
- Hybrid approaches combining topic modeling (LDA) with probabilistic classifiers.
- Multimodal SA using facial expressions, speech, and text.

Sentiment analysis is becoming a powerful tool for improving the quality and personalization of e-learning. While current systems show promise, future development should focus on integrating multimodal inputs, real-time analysis, and handling data privacy more robustly.

6.T. Shaik, X. Tao, C. Dann, H. Xie, Y. Li, and L. Galligan, "Sentiment Analysis and Opinion Mining on Educational Data: A Survey," Nat. Lang. Process. J., vol. 2, p. 100003.

[6] T.Shaik et.al (2023) comprehensive survey explores the application of sentiment analysis (SA) and opinion mining in educational contexts. The paper examines the effectiveness of sentiment analysis in improving teaching and learning by analyzing student feedback at multiple granularity levels—document, sentence, entity, and aspect levels.

Key contributions of the paper include:

- A classification of sentiment analysis tasks based on granularity: document-level (overall sentiment), sentence-level (fine- grained sentiment), entity-level (opinions about entities like instructors or courses), and aspect-level (opinions about features/aspects).
- An extensive review of sentiment annotation methods:
  - Unsupervised techniques like lexicon-based (e.g., SentiWordNet, VADER) and corpus-based methods.
  - Supervised machine learning techniques such as SVM, Naive Bayes, Random Forest, etc.
  - Deep learning models (e.g., CNN, LSTM) and transformer-based models (e.g., BERT, BERT-CNN).
- A summary of the impact of SA on educational outcomes including learning evaluation, pedagogical improvement, decision-making, and assessment analysis.
- Identification of major challenges like negation handling, opinion spam, multi- polarity, and polysemy in student feedback.
- Suggestions for future research include developing domain-specific annotation techniques, improving deep learning models for multimodal data, and using reinforcement learning for personalized education.

7.V. N. Vedavathi and K. M. Anil Kumar, "E- learning course recommendation based on sentiment analysis using hybrid Elman similarity," Knowledge-Based Systems, vol. 259.

[7] V. N. Vedavathi (2023) proposes a hybrid recommendation system for e-learning course suggestions using sentiment analysis and deep learning. It integrates Elman Recurrent Neural Network (ERNN) with a Minimal Redundancy Maximum Relevance (MRMR) model and optimizes using Enhanced Aquila Optimization (EAO). The model processes social media data through pre-processing, extracts features using Improved TF-IDF, Word2Vec, and Hybrid N-gram, then classifies sentiments (positive, negative, neutral) to recommend courses. Evaluation demonstrates a high accuracy of 99.98%, outperforming traditional methods. The use of hybrid similarity measures (cosine, Jaccard, Euclidean) strengthens course recommendation relevance and precision

8.B. Ramkumar, R. Subhashini, and K.Chithra, "An Effective Online Learning Course Recommendation Using Improved Deep Active Convolutional Neural Network-Based Sentiment Analysis and Ranking," J. Soft Compute. Paradigm, vol. 4, no. 1, pp. 1–10.

[8] B. Ramkumar (2022) et.al proposes an intelligent course recommendation system for online learners by leveraging sentiment analysis using an Improved Deep Active Convolutional Neural Network (IDACNN). The system aims to enhance the accuracy and relevance of course recommendations by interpreting user-generated reviews on e-learning platforms.

Key contributions and methodology include:

- Implementation of an IDACNN model that captures semantic and contextual features from student reviews.
- Use of sentiment polarity (positive/negative) and opinion strength to improve course ranking.

- Integration of pre-processing techniques (tokenization, stemming, stop word removal) for optimal input formatting.
- Evaluation using performance metrics like accuracy, precision, recall, and F1-score, showing superior performance over traditional CNN and LSTM models.

The proposed system demonstrates an efficient and scalable approach for online course recommendation, especially valuable in MOOCs where user feedback plays a vital role in guiding learner decisions.

9.V. Arnaiz, M. Sokolova, and C. von Nest, “Aspect-Based Sentiment Analysis for Online Course Evaluation Using BERT Embeddings,” Future Internet, vol. 14, no. 7, p. 218.

[9] V. Arnaiz (2022) presents a novel approach for evaluating online courses using aspect-based sentiment analysis (ABSA) powered by BERT embeddings. The authors focus on extracting fine-grained opinions from students' open-ended feedback to support data-driven decision-making in higher education.

Key contributions include:

- Development of a labelled dataset for ABSA based on student feedback from the University of Ottawa.
- Application of BERT for both aspect and sentiment classification, outperforming traditional machine learning models like SVM and Naive Bayes.
- Evaluation across five manually annotated aspect categories: learning content, delivery, instructor, tools, and assessment.
- Demonstrated improvement in F1-scores and interpretability, enabling better understanding of students’ needs and priorities.

10.X. Pu, G. Yan, C. Yu, X. Mi and C. Yu, "Sentiment Analysis of Online Course Evaluation Based on a New Ensemble Deep Learning Mode: Evidence from Chinese," *Applied Sciences*, vol. 11, no. 23, p. 11313.

[10] The study by Pu (2021) et al. proposes a novel sentiment analysis model for online course evaluations written in Chinese. The model combines two word embedding techniques (Word2Vec and GloVe) with deep learning models (CNN and BiLSTM), further enhanced through an ensemble approach using Multi-Objective Gray Wolf Optimization (MOGWO). This hybrid model improves classification accuracy by capturing both local and global textual features. The proposed method outperforms traditional models and other ensemble techniques, achieving over 91% F1 score, and demonstrates high stability and precision in multi-class sentiment recognition.

11.T. V. Ngoc, M. N. Thi and H. N. Thi, “Sentiment Analysis of Students’ Reviews on Online Courses: A Transfer Learning Method,” in Proceedings of the International Conference on Industrial Engineering and Operations Management (IEOM), Harbin, China, Jul. 2021, pp. 306–314.ss

[11] T. V. Ngoc et.al. (2021) provide an extensive overview on a sentiment analysis framework using BERT (Bidirectional Encoder Representations from Transformers), a powerful transfer learning model, to classify student reviews of online courses from Coursera. The study aimed to evaluate the sentiments—positive, negative, or neutral—and classify them based on different course-related aspects: instructor, content, structure, design, and general impression.

A dataset of 21,940 English-language student reviews was preprocessed and analyzed. The model's performance was compared with conventional machine learning techniques like SVM and Decision Trees. Results show that BERT achieved higher F1-scores in both aspect category classification (82.68%) and sentiment polarity classification (88.94%) compared to other methods.

The study concludes that BERT is highly effective for sentiment classification tasks in e-learning environments and recommends its application for future work involving multi-label classification and datasets across diverse domains.

CONCLUSION

The collection of research papers demonstrates that Aspect-Based Sentiment Analysis (ABSA), powered by advanced deep learning and transformer models, is an effective tool for understanding and enhancing the online course experience. Across various methodologies— including BERT, BiLSTM, CNN, BiGRU, hybrid models like BERT-LSTM-CNN, and explainable AI frameworks—researchers consistently show that fine-grained analysis of student feedback can significantly inform course design, instructor performance, and learning content quality.

Several models (e.g., PyABSA, SP-MTL-BERT, BLC, and IDACNN) achieved high classification accuracy (ranging from 79% to 99%), proving their ability to extract meaningful insights even from noisy or unstructured data. The integration of attention mechanisms, transfer learning, and multi-task learning further enhances the models' robustness, particularly in capturing contextual nuances and aspect-level sentiments such as content difficulty, cost, instructor quality, or course design.

Moreover, the studies emphasize the importance of explainability, real-time processing, and multimodal analysis for future systems. Explainable AI and visualization tools help stakeholders understand model decisions, promoting trust and actionable outcomes in educational environments.

A recurring challenge noted across papers includes the handling of sarcasm, ambiguous language, and opinion spam, which suggest the need for continuous improvement in data preprocessing and domain-specific modeling. Several authors advocate for personalized course recommendations, privacy-aware architectures, and multilingual support as key directions for future development.

In summary, ABSA and deep learning techniques are revolutionizing the analysis of online course reviews, leading to data-driven decision-making and personalized learning pathways that cater to diverse learner needs.

REFERENCE

[1] Latha Nagesh, K. S. Madhuri, D. R. Reddy, J. V. Reddy, K. M. N. Vardhini, and M. Ramesh, "Online Course Review System Using Aspect Based Sentimental Analysis and Opinion Mining Using Deep Learning," Int. Res. J. Adv. Sci. Hub, vol. 7, no. 5, pp. 490–497, May 2025, doi: 10.47392/IRJASH.2025.055.

[2] S. Gul, M. Asif, F. Amin, K. Saleem, and M. Imran, "Advancing Aspect-Based Sentiment Analysis in Course Evaluation: A Multi-Task Learning Framework with Selective Paraphrasing," IEEE Access, vol. XX, pp. 1–30, 2025, doi: 10.1109/ACCESS.2025.3527367.

[3] A. Baqach and A. Battou, "A new sentiment analysis model to classify students' reviews on MOOCs," Education and Information Technologies, vol. 29, no. 1, pp. 1–35, Feb.2024, doi: 10.1007/s10639-024-12526-0.

[4] H. Iqbal, M. O. Beg, and A. Khan, "An Explainable AI-Enabled Sentiment Analysis Framework for Online Learning Using Aspect-Based Attention and BiGRU," Educ. Inf. Technol., vol. 29, 2024, doi: 10.1007/s10639-024-12526-0.

[5] Z. Khanam, "Sentiment Analysis of User Reviews in an Online Learning Environment: Analyzing the Methods and Future Prospects," *European Journal of Education and Pedagogy*, vol. 4, no. 2, pp. 209–217, Apr. 2023, doi:10.24018/ejedu.2023.4.2.531.

[6] T. Shaik, X. Tao, C. Dann, H. Xie, Y. Li, and L. Galligan, "Sentiment Analysis and Opinion Mining on Educational Data: A Survey," Nat. Lang. Process. J., vol. 2, p. 100003, 2023, doi: 10.1016/j.nlp.2022.100003.

[7] V. N. Vedavathi and K. M. Anil Kumar, "E-learning course recommendation based on sentiment analysis using hybrid Elman similarity," *Knowledge-Based Systems*, vol. 259, p. 110086, 2023. [Online]. Available: https://doi.org/10.1016/j.knosys.2022.110086

[8] B. Ramkumar, R. Subhashini, and K. Chithra, "An Effective Online Learning Course Recommendation Using Improved Deep Active Convolutional Neural Network-Based Sentiment Analysis and Ranking," J. Soft Comput. Paradigm, vol. 4, no. 1, pp. 1–10, 2022, doi: 10.36548/jscp.2022.1.001.

[9] V. Arnaiz, M. Sokolova, and C. von Nest, "Aspect-Based Sentiment Analysis for Online Course Evaluation Using BERT Embeddings," Future Internet, vol. 14, no. 7, p. 218, Jul. 2022, doi: 10.3390/fi14070218.

[10] X. Pu, G. Yan, C. Yu, X. Mi and C. Yu, "Sentiment Analysis of Online Course Evaluation Based on a New Ensemble Deep Learning Mode: Evidence from Chinese," *Applied Sciences*, vol. 11, no. 23, p. 11313, Nov. 2021, doi: 10.3390/app112311313.

[11] T. V. Ngoc, M. N. Thi and H. N. Thi, "Sentiment Analysis of Students' Reviews on Online Courses: A Transfer Learning Method," in Proceedings of the International Conference on

Industrial Engineering and Operations Management (IEOM), Harbin, China, Jul. 2021, pp. 306–3