Elementaria: Journal of Educational Research

Journal website: https://elementaria.my.id/

E-ISSN: 2988-5949 Vol. 3 No. 1 (2025)
DOI: https://doi.org/10.61166/elm.v2i1.89 pp. 105 - 131

Research Article

Sentiment Analysis and its Application in the Education Sector: A Comprehensive Review

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Received	: March 12, 2025	Revised	: June 15, 2025
Accepted	: July 20, 2025	Available online	: July 31, 2025

How to Cite: Fahima, M., & Prasanna Sumathipala. (2025). Sentiment Analysis and its Application in the Education Sector: A Comprehensive Review. *Elementaria: Journal of Educational Research*, *3*(1), 105–131. https://doi.org/10.61166/elm.v3i1.89

Sentiment Analysis and its Application in the Education Sector: A Comprehensive Review

Abstract. Sentiment analysis has become an essential tool across various domains, including the education sector, where its application remains relatively underexplored. This study presents a comprehensive review of sentiment analysis in educational contexts, evaluating traditional machine learning models such as Support Vector Machines (SVM) and Naive Bayes, as well as advanced deep learning approaches like Long Short-Term Memory (LSTM) networks and transformer-based models such as BERT. These methods have been applied to analyze student feedback, predict academic performance, and improve teaching strategies. Model performance is assessed using accuracy, precision, recall, and F1-score, though challenges persist related to data quality, annotation consistency, and the contextual complexity of student language. The review identifies significant research gaps, particularly the lack of multilingual and culturally diverse datasets, which limits the generalizability of current models. Furthermore, real-time sentiment tracking and adaptive feedback systems remain underdeveloped. To address these issues, the study proposes the integration of AI-enabled adaptive learning environments capable of dynamically responding to learners' emotional and cognitive states, thus enhancing personalization and educational effectiveness. Overall, sentiment analysis holds significant promise for transforming educational practices, provided future research focuses on inclusivity, contextual awareness, and scalability.

Keywords: Sentiment Analysis, Education Sector, Machine Learning, Natural Language Processing, Student Feedback, Deep Learning, Multilingual Sentiment Analysis, Educational Technology

Abstrak. Analisis sentimen telah menjadi alat penting di berbagai bidang, termasuk sektor pendidikan yang hingga kini masih tergolong kurang dieksplorasi. Studi ini menyajikan tinjauan komprehensif tentang penerapan analisis sentimen dalam konteks pendidikan, dengan mengevaluasi model pembelajaran mesin tradisional seperti Support Vector Machines (SVM) dan Naive Bayes, serta pendekatan pembelajaran mendalam yang lebih canggih seperti Long Short-Term Memory (LSTM) dan model berbasis transformer seperti BERT. Metode-metode ini telah digunakan untuk menganalisis umpan balik siswa, memprediksi performa akademik, dan meningkatkan strategi pengajaran. Kinerja model dievaluasi menggunakan metrik akurasi, presisi, recall, dan F1-score, meskipun masih terdapat tantangan terkait kualitas data, konsistensi pelabelan, dan kompleksitas konteks bahasa siswa. Tinjauan ini mengidentifikasi sejumlah kesenjangan penelitian yang signifikan, terutama kurangnya dataset multibahasa dan beragam budaya yang membatasi generalisasi model saat ini. Selain itu, pelacakan sentimen secara real-time dan sistem umpan balik adaptif masih belum berkembang optimal. Untuk mengatasi hal tersebut, studi ini mengusulkan integrasi lingkungan pembelajaran adaptif berbasis AI yang mampu merespons kondisi emosional dan kognitif peserta didik secara dinamis, sehingga meningkatkan personalisasi dan efektivitas pembelajaran. Secara keseluruhan, analisis sentimen memiliki potensi besar untuk mentransformasi praktik pendidikan, dengan catatan bahwa riset ke depan perlu lebih fokus pada inklusivitas, kesadaran konteks, dan skalabilitas solusi.

Kata Kunci: Analisis Sentimen, Sektor Pendidikan, Pembelajaran Mesin, Pemrosesan Bahasa Alami, Umpan Balik Siswa, Pembelajaran Mendalam, Analisis Sentimen Multibahasa, Teknologi Pendidikan.

INTRODUCTION

Throughout the years, advancements in information technology, such as intelligence (AI) and machine learning (ML), have significantly impacted areas such as education, healthcare, arts, and finance by enhancing their performance. Integrating AI and sentiment analysis (SA), also known as opinion mining, has emerged as an asset across industries, particularly in education since the emotions/sentiments of human beings play a vital role in interaction and communication between individuals (B. Saju, 2020), in decision-making, finding the correct ways to correct mistakes and finding the possible solutions. Also, "identifying the primary emotions from the text is beneficial in deciding the axioms of human-computer interaction that governs communication and many additional key factors (B. Saju, 2020)".

Generally, "Sentiment analysis (SA) is the process of using natural language processing (NLP) techniques, text analysis, and statistics to analyze (Obeleagu, 2019) subjective information such as opinions, attitudes, impressions, and feelings (Aldowah, 2020)". Generally, it is the Application of NLP, text analysis, and statistical tools to understand the sentiment of the text (B. Saju, 2020). This technique used to identify and extract thoughts from written content (such as feedback, news reports, user reviews on movies, education systems etc...., social media updates, etc.) has become increasingly important in marketing, healthcare, and education industries. Its effectiveness in evaluating opinions and emotions has been widely recognized (Reddy, 2017) (Obeleagu, 2019). Sentiment analysis is vital in education for improving communication between students and teachers and helping to understand how students feel about the study materials and teaching methods (Aldowah, 2020). And the student's learning experience depends on the activities, interactions, courses, programs, or other experiences in their learning environment (Obeleagu, 2019). The figure below illustrates the various components contributing to the student's learning experience. Generally, educational institutions get feedback and comments regarding these components. However, due to several reasons, such as the lack of a clerical workforce and other ethical concerns, this qualitative feedback and comments are often not properly analyzed and used in decision-making to overcome the issues that impact students' learning experience. Sentiment analysis can be used in the education sector to process qualitative data from student feedback, peer reviews, social media comments, and any other education-related text data to analyze and extract opinions and sentiments. Applying Sentiment analysis can easily improve the student's learning experience with those constraints.

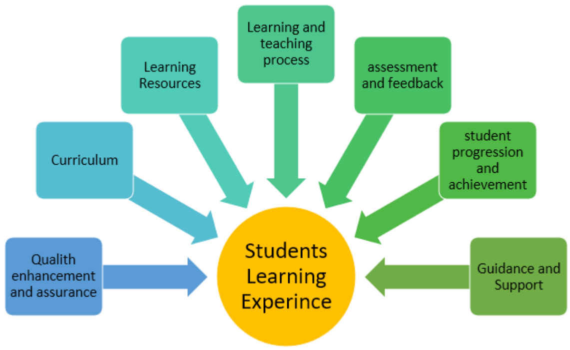

Figure 1. Components of Student Learning Experience (Obeleagu, 2019)

Furthermore, AI, ML, and Sentiment Analysis technologies empower institutions to gain insights into the viewpoints and sentiments of students, faculty members, and other key stakeholders. (B. Saju, 2020). It allows administrators to make effective decisions. The manual sentiment analysis process is time-consuming, and there is a high possibility of losing essential data when analyzing it due to human errors. "Appropriate and timely reporting can help identify opportunities for quality improvement and deployment of mitigation steps, but many of these processes remain manual (Piyush Mathur, 2021)". By fully using ML techniques, Educational organisations can analyze qualitative written comments, feedback, and documents within a few minutes with minimal human interactions. This enables them to categorize sentiments as positive, negative, neutral or many more, which enhances decision-making processes and elevates the quality of Education (Aldowah, 2020). Additionally, utilizing Natural Language Processing (NLP) and ML techniques can significantly simplify this analysis, offering insights without the need for extensive resource allocation in traditional feedback evaluation procedures (Piyush Mathur, 2021) (B. Saju, 2020).

Furthermore, growth in the use of sentiment analysis across Higher Education has also been witnessed to allow a more comprehensive view of student satisfaction with teaching quality, one emerging dominant theme within this area and reinforcing institutions' capability for data-driven changes (Aldowah, 2020) Sentiment analysis has come a long way. Many computational methods are used to measure the sentiment of individual texts, such as advanced ML techniques (Piyush Mathur, 2021). These strategies improve the sensitivity of sentiment classification and enable capturing feedback for finer granularity along with unique context, providing a better understanding of user sentiments under the education domain (Piyush Mathur, 2021) (B. Saju, 2020). In addition, leveraging ML approaches (e.g., supervised classifiers and aspect-based sentiment analysis) has also boosted the reliability and agility of mining student feedback (Hu, 2021). Automating the feedback process makes educational institutions better understand student experiences and solve their problems, resulting in more tailored teaching improvement and enhancement (Reddy, 2017) (R. Nandakumar, 2022).

Literature Review

A. Sentiment Analysis and its techniques

"Sentiment analysis is an automated process to extract and understand the opinion about a given subject from a written or spoken language by using NLP and AI (Obeleagu, 2019)". Based on the input type, sentiment analysis can be performed in Document level, Sentence Level, and Word level (Reddy, 2017).

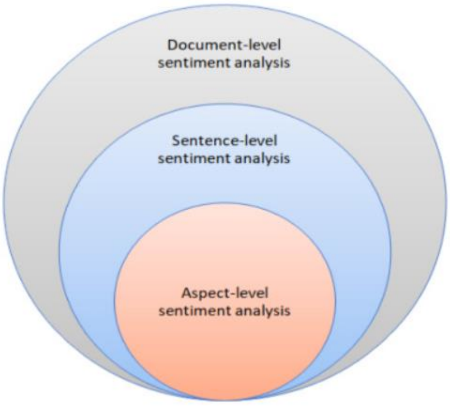

Figure 2.Levels of sentiment analysis (Marouane Birjali, 2021) (Thanveer Shaik X. T., 2023)

This sentiment analysis includes several steps such as data collection, pre-processing, data analysis, sentiment classification, evaluation of accuracy, etc. The below image illustrates those steps.

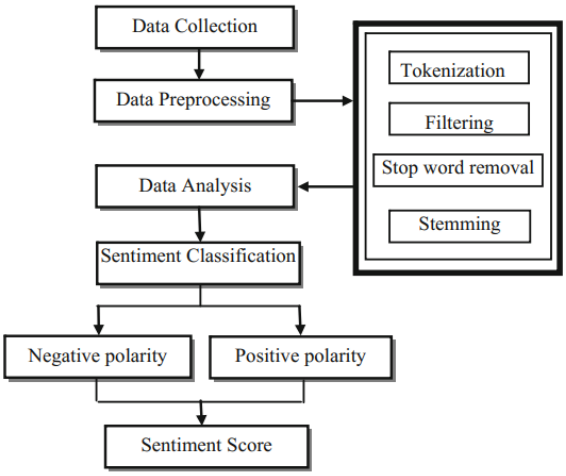

Figure 3. Process flow of the sentiment analysis (Thakur, 2018)

- Data Collection: Sentiment analysis can be performed on various data sets and collected from multiple sources. For instance, student feedback and comments on Twitter, Facebook (Reddy, 2017) (B. Saju, 2020) .
- Data Pre-processing: the collected data must be pre-processed to extract the sentiment accurately. This involves:
  - ➢ Tokenisation is "the process of breaking sentences into pieces such as words, phrases, symbols, and keywords (tokens) (Reddy, 2017)". This process guides the other pre-processing processes (B. Saju, 2020) (Obeleagu, 2019) (de Paula Santos, 2016).
  - ➢ Stop word removal and Filtering involve "removing words such as on, at, how, which, etc., to extract meaningful information from the data (Reddy, 2017) (B. Saju, 2020) (Obeleagu, 2019).

- Stemming "is the process of chopping or cutting of the ends of the words (derivational affixes) (Reddy, 2017) (B. Saju, 2020) (Obeleagu, 2019)" and lemmatization "is the proper way of word processing that uses vocabulary and morphological analysis of words typically aiming to remove inflectional endings and return the base or dictionary form of a word (Reddy, 2017) (B. Saju, 2020) (Obeleagu, 2019) (de Paula Santos, 2016)".

B. Types of Sentiment Analysis

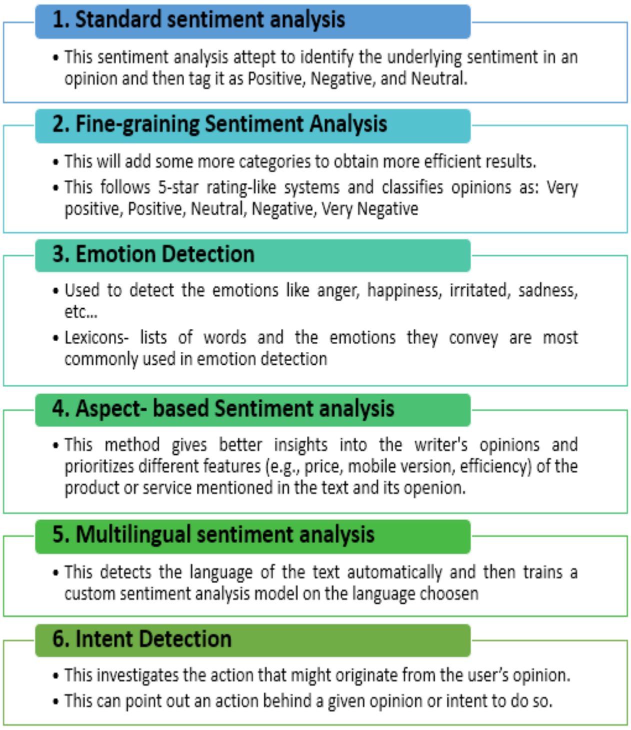

Figure 4. Types of Sentiment Analysis (B. Saju, 2020)

C. Artificial Intelligence-based Techniques for Sentiment Analysis

Furthermore, Artificial intelligence-based sentiment analysis approaches can be categorized into three categories: Machine learning (ML), Lexicon/Rule-based approach, and Hybrid (B. Saju, 2020) (Obeleagu, 2019).

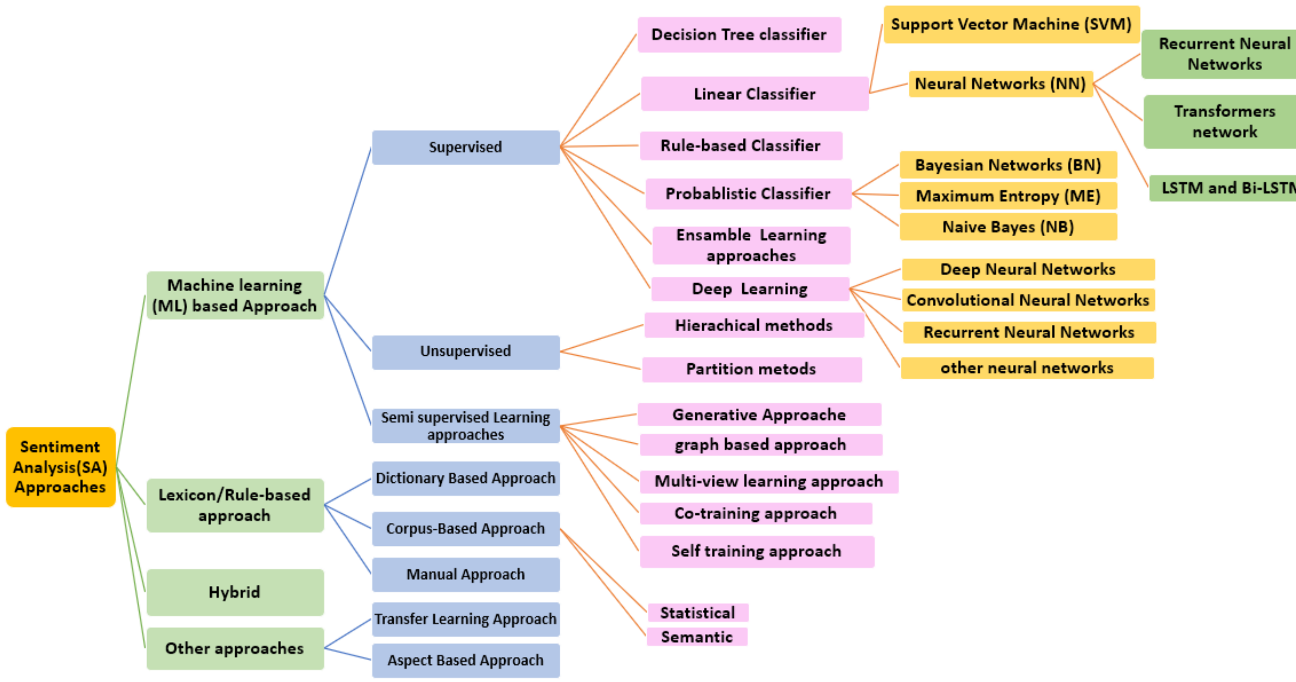

Figure 5. Artificial Intelligence-based techniques used in Sentiment Analysis (Marouane Birjali, 2021)

i. *Machine Learning (ML) Approach:*

"In this approach, sentiment analysis works as a classifier problem, where the text is fed to the classifier model, and it returns a specific category or tag like positive, negative, or neutral (B. Saju, 2020)". and "they perform well for the domain on which they are trained (Thakur, 2018)". To do this classification, "it applies a set of statistical techniques for identifying parts of speech. entities, sentiments and other aspects of the text. This includes part-of-speech (POS) tagging. (Obeleagu, 2019) (Aldowah, 2020)".

a. Supervised Learning

This approach uses labelled training data to train the model. A classification model predicts the class of the text based on the pre-trained or predefined category.

- Naïve Bayes: "This classification algorithm works based on Bayes' Theorem. This assumes there is strong independence between the features. The Bayes hypothesis is a method of computing for distinguishing the likelihood (Reddy, 2017)". (Thakur, 2018). This can be effectively used in "classifying student feedback text according to the two classes, such as positive and negative (Reddy, 2017)".

- Support Vector Machines: Support Vector Machines (SVM) support well in sentiment analysis applications. This information from the analysis is provided, and then the limits of choice are characterized. "this plots the data points in two-dimensional space based on predefined classes. It predicts the class based on the side of the spaces where the points lie. Here, various possible hyperplanes are drawn. Among these hyperplanes, one will be chosen which has the maximum margin that classifies data points effectively ". The SVM classifier has proven its better performance on various text classification problems (B. Saju, 2020)".

- **Deep Learning (DL) Approaches**: These models, particularly Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and transformers, have shown remarkable promise in sentiment analysis due to their ability to capture complex linguistic patterns. For example, (V. Naveen, 2024) Utilized Bi-LSTM for analysing sentiment in online course reviews, demonstrating superior performance compared to traditional methods. Transformers, such as BERT, have further enhanced sentiment analysis by capturing context more effectively, as evidenced by their application in analyzing student emotions from social media data (K. A. Alshaikh, 2024)

- Decision tree Induction: This is a supervised learning method. "It assumes all input values have a fine set of domains. Each non-leaf node is labelled with an input feature. Each leaf of the tree is labelled with a class. So, a decision tree can be used for sentiment analysis by labelling leaf nodes with different classes, such as positive, negative, or neutral (Reddy, 2017) (Thakur, 2018)".

Generally, Supervised learning models such as Support Vector Machines (SVM) and Naive Bayes are widely used for sentiment analysis in educational settings due to their effectiveness in classification tasks. For instance, a study by Nismah Panjaitan. et al. applied SVM to analyze sentiment in feedback on Google Classroom, achieving high accuracy in classifying sentiments into positive, negative, and neutral categories (Manurung, 2022). Similarly, Naive Bayes has been utilized to predict student satisfaction levels, showing significant performance in handling large datasets (Almonte, 2022).

b. Unsupervised Learning

Unsupervised Learning approaches don't need to be retrained. This including clustering and topic modelling, are employed to discover patterns in unstructured educational data. used clustering techniques to group similar sentiments from student discussions, facilitating the identification of common concerns and suggestions (Aldowah, 2020). Topic modelling has also been applied to extract themes from large volumes of feedback data, providing insights into areas needing improvement (Thanveer Shaik X. T., 2022) (Khalid, 2024).

- K-Mean Algorithm: "It is an unsupervised learning clustering algorithm that effectively clusters a large data set into a specified number of clusters. It clusters a given sentence into positive and negative sentences. So, this method can be used to generate reports with a count of positive and negative sentences about a particular topic (Reddy, 2017)"

ii. *Lexicon/ Rule-Based Approach:*

The lexicon-based text sentiment analysis is a data analysis activity involving compiling and collecting opinion-bearing words and phrases without knowledge (Obeleagu, 2019) (Lazrig & Humpherys, 2022). "Opinion lexicons include all the positive and negative terms that also mean opinion expressions. The lexicon-based technique made use of unlabeled data. Words present in the text are matched with an opinion lexicon to find out the orientation of words and, hence, the sentiment of the text. Opinion lexicons are usually built using three methods (Thakur, 2018)". It has three approaches, those are:

- Manual Approach

Opinion words are manually collected based on the individual's topic expertise and linguistics comprehension. It is a very time-consuming process. Combining it often with the automated approach will make up for the shortcomings in the latter approach (Thakur, 2018).

- Dictionary-based approach

It collects opinion words of known orientations from lexicographical sources such as an online dictionary. It bases word feelings using synonyms, antonyms, and opinion lexicon hierarchies. The dictionary-based techniques have problems recognizing context-specific sentiment since they do not possess domain expertise. The used dictionary can be VADER (Bisan Salem, 2024) (Thanveer Shaik X. T., 2023) (Robert Kasumba, 2024) (Lazrig & Humpherys, 2022) (Charalampos Dervenis, 2024) (Mërgim H. HOTI, 2023), WordNet, SentiWordNet, SecticNet, and Sentiful, amongst others (Thakur, 2018) (Thanveer Shaik X. T., 2023).

- Corpus-based approach

Co-occurrence and opinion words are used in the corpus-based technique for the syntactic pattern of opinion-term detection and construction in huge corpora. The corpus-based technique overcomes the limitation of context-specific categorization of opinion words in a dictionary. However, dictionary-based approaches are more efficient. The corpus-based technique employed labeled data (Thakur, 2018).

iii. *Hybrid approach:*

This "Combining ML with software rules across the entire text analytics function stack, from low-level tokenization and syntax analysis to the highest level of sentiment analysis (Thakur, 2018) (Obeleagu, 2019)". (Li, 2019) implemented a hybrid model combining SVM and LSTM to analyze sentiment in reviews, resulting in improved accuracy and robustness. However, these methods often increase model complexity and pose challenges in interpretability (K. A. Alshaikh, 2024). The list below shows the AI-based sentiment analysis methods used or discussed in the literature review of this study. This table contains various AI-based techniques and methods used for sentiment analysis and related tasks across multiple papers. Here's a summary of the key techniques mentioned:

Supervised techniques, such as Support Vector Machine (SVM), Naive Bayes, and Random Forest, require labelled datasets for training and have shown high accuracy, with SVM achieving up to 98.63% in some studies (Manurung, 2022). While efficient in dynamic environments, unsupervised techniques often sacrifice accuracy due to the need for more training data (Yaakub, 2019). Additionally, hybrid approaches that combine rule-based and automatic methods have been explored, with algorithms like the Levenshtein algorithm providing effective pre-processing and achieving accuracy rates of around 81.23% (M. S. Hossen, 2022). Overall, the choice of technique depends on the specific requirements of the sentiment analysis task and the nature of the data involved (Yaakub, 2019).

Table 1. Reference for Sentiment Analysis

Reference	Rule-based Systems	Naive Bayes Classifier (NB)	SVM	Decision Trees (DT)	Lexicon-based SA	Neural Networks	VADER	LDA	BERT	KNN	RF	ABSA	Clustering	GloVe	Multimodal	Hybrid
Saju (2020)	√	√	√													
Reddy (2017)		√		√												
Aldowah (2020)		√	√		√					√						
Yaakub (2019)		√	√								√					
Almonte (2022)		√														√
Kumar (2017)		√	√													
Mehmood (2017)		√									√					
Shandana (2023)		√								√	√					
Manurung (2022)			√													
Mathimagal (2021)			√													
Khan (2023)				√												
Sultana (2018)				√		√										
Piyush Mathur (2021)					√		√	√								
Santos (2016)					√											
Hossen (2022)					√											
Kim (2023)					√		√						√			
Naveen (2024)					√		√			√						
Li (2019)					√				√							
Hu (2021)						√			√			√	√	√		
Anwar (2023)						√										
Srivastav (2023)						√			√							
Fang (2024)						√										
Rääf (2021)							√									
Salem (2024)							√									
Shaik (2023)							√									
Kasumba (2024)							√									
Lazrig (2022)							√									
Dervenis (2024)							√									
Hoti (2023)							√									

Reference	Rule-based Systems	Naive Bayes Classifier (NB)	SVM	Decision Trees (DT)	Lexicon-based SA	Neural Networks	VADER	LDA	BERT	KNN	RF	ABSA	Clustering	GloVe	Multimodal	Hybrid
Cunningham (2019)								√								
Ozyurt (2023)								√								
Akash (2024)									√					√	√	
DSouza (2023)															√	
Zahidi (2020)																√

D. Evaluation Metrics and Performance Analysis

Since the sentiment analysis models, especially in the educational contexts, have been considered necessary in their performance analyses for effectiveness and reliability through certain metrics of evaluation, here are some critical evaluations based on the provided contexts:

i. *Key Evaluation Metrics*
- Accuracy: This metric provides the proportion of true results, both true positives and true negatives, concerning the total number considered. While accuracy is an intuitively clear measure, it can sometimes be misleading when working with an imbalanced dataset where one class of sentiment dominates the others (Reddy, 2017).
- Precision: Precision is the ratio between true positives relative to all the positive predictions that occur from a model. In an education setting, this precision rate would be highly imperative so that models can confidently find the true positives, thus reducing the number of false positives (Reddy, 2017).
- Recall: Recall or sensitivity measures the proportion of correctly identified positives. In education, high recall is desired to capture every relevant student sentiment, especially negative feedback that might need attention (Reddy, 2017).
- F1-Score: The F1-score is the harmonic mean of precision and recall and gives a balance between the two. This can be especially helpful in the case of uneven class distributions; it provides overall, balanced perspectives toward model performance (Reddy, 2017).

ii. *Performance Analysis Methods*
- Cross-Validation: The technique involves data partitioning into subsets, on which the model is trained and others on which it is validated. The idea behind cross-validation is to estimate how the results will generalize with an independent dataset and thus increase performance metrics' reliability.
- Confusion Matrix: this forms a visual chart of the performance of different sentiment classes in the model. It also helps establish some finer

wrongdoings by the model, such as classifying negative sentiments as positive.

iii. Reliability of Metrics

- Data Quality Impact: Most of the metrics for the evaluation depend mainly on the quality of data fed into them. Noisy or wrongly labelled data can lead to wrong performance evaluations; hence, high-quality datasets must be guaranteed for training and testing.
- Inconsistency in Labeling: Human judgment in labelling sentiment can introduce inconsistencies that may affect the reliability of metrics. This can result in different performance outcomes, making the evaluation process more complex.

Need for Comprehensive Evaluation: Complete dependence on quantitative metrics may show only an incomplete picture of model performance. Qualitative assessments- such as understanding the context of the predictions- will be needed to continue improving the reliability of evaluations.

This review seeks to provide a comprehensive overall understanding of sentiment analysis techniques used in the education sector and the improvements and constraints encountered within its application in industries and revisit its relevance when used for sentiment analysis embodied with ML applied towards a context of education that is essential to fostering conducive conditions suitable for efficient learning. This article consists of an introduction, research question, objective of the research, and methodology, followed by a literature review, discussion, and conclusion. This research is organized accordingly to provide a better understanding to its readers. In the following sections, we will discuss the findings of the literature review individually.

RESEARCH QUESTION

To address the previously mentioned essential concerns of this research, our study is driven by the following research question:

RQ1: What machine learning techniques are used for sentiment analysis in education?

RQ2: What are the Impacts of implementing machine learning techniques for sentiment analysis in the education sector, and how do these impact creating a supportive learning environment?

RESEARCH OBJECTIVE

The research has set the following objectives to assess and answer the above-mentioned research questions effectively. The objective is: To identify and analyze the effectiveness of various machine learning sentiment analysis algorithms used in the education sector, To identify the possible impacts and limitations of applying sentiment analysis in education.

METHOD

To achieve the objective of this research, A comprehensive systematic literature review was conducted along with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) technique (A. Anwar, 2023) to do this critical review research. According to research, "Mulrow (1994) claimed that Systematic Literature Review (SLR) provides utilised information that is done based on decision making, policy-making, and research (Narges Rezaee, 2023)." This research paper follows a systematic approach to analyze the literature.

To conduct this research, Research articles from IEEE, Elsevier, Google Scholar, Research Gate, Web of Science, and ACM Digital Library were used and systematically analyzed to conduct this research. To search in these databases, We searched the keywords: "Machine learning in education", "sentiment analysis in education", and "impact of applying sentiment analysis in education", we used. Furthermore, The selection of research articles and documents was based on relevance to the topic and theme, focusing on recent studies published between the 08-year gap from 2016 to 2024 that discuss the Application of ML techniques for sentiment analysis in educational contexts. The selection criteria included English-language articles relevant to the application of sentiment analysis in the education sector. The other language papers and full-text-unavailable papers are excluded from the research. This study aims to provide a comprehensive review of how ML sentiment analysis models are used in the education sector and their impact. The following figures show the filtering process for the study's articles and the selected articles based on the application of sentiment analysis in the education system year-wise distribution.

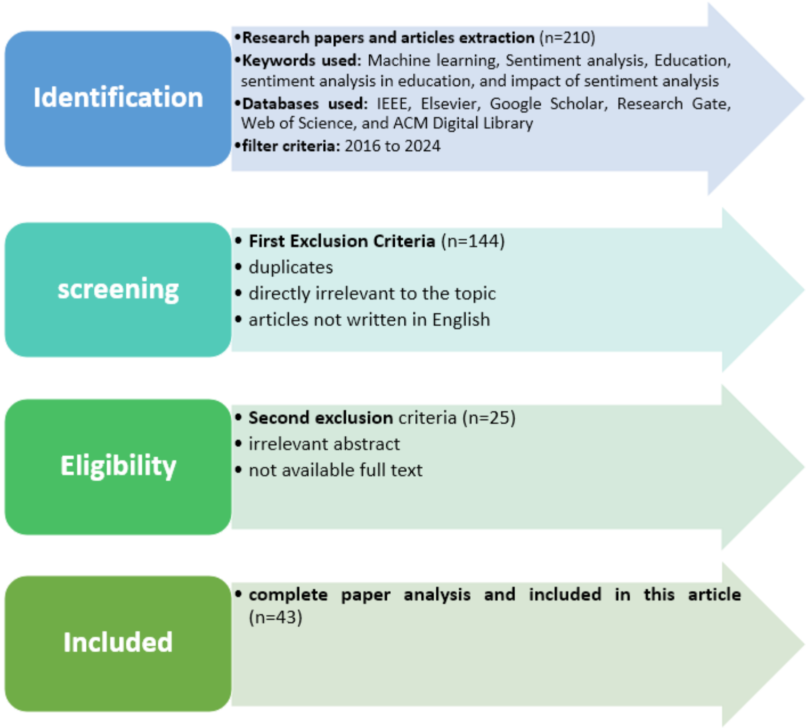

Figure 6. Relevant articles selection process using the PRISMA technique

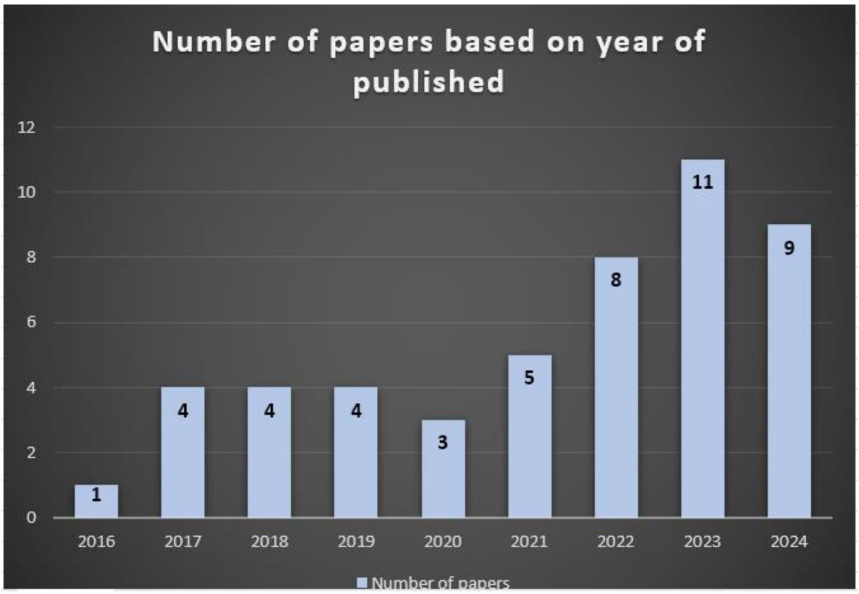

Figure 7. Research articles matrix is based on the year of publication.

RESULTS AND DISCUSSION

We conduct a comprehensive review of sentiment analysis and its application in education by synthesizing data from various studies and tracing the application of sentiment analysis in education, as well as its impact, challenges, major trends, techniques, research gaps, and prospects. The review findings highlight the importance of sentiment analysis in comprehending and improving educational processes using a combined ML-NLP approach.

A. Sentiment Analysis in Education: Applications

Sentiment analysis has become a vital tool in the education sector, where insights can be drawn that might help find avenues for improvement in teaching-learning experiences. Sentiment analysis in education has been explored across dimensions such as student feedback analysis, performance prediction, and improvement of teaching strategies. For example, reference (N. Mathimagal and S, 2021) showed the SVM algorithm's potential to analyze students' intellectual behaviour through social media activities with 93% accuracy. This also positions sentiment analysis as a predictor of student learning behaviour and offers educators data on the cognitive processes in which students engage. Reference (Kumar, 2017) also explored NLP and ML algorithms, such as Naive Bayes and SVM, to analyze student feedback to provide more robust sentiment-based assessments. These two examples reflect the growing importance of sentiment analysis in driving data-informed decisions within educational contexts.

Meanwhile, some new approaches that incorporate sentiment analysis into educational systems are identified in this review. Reference (Fang, 2024) developed an improved text emotion classification framework using a combination of TextCNN, LSTM, and BI-GRU networks for sentiment recognition in an English reading course. Applications of these methods in corresponding educational tools manifest the promising result of individualizing learning strategy and shortening the talent training cycle. Here are some key applications based on the literature review:

- Enhancing Student Learning Experience

The students' feedback about courses, teaching methodology, and learning tools can be done through sentiment analysis. This will help educators know about the students' sentiments on specific aspects and find further areas to improve, thus helping educators adjust their teaching methodology. Therefore, this application contributes to a responsive learning environment responsive to its student needs (Reddy, 2017) (Hu, 2021) (R. Nandakumar, 2022) (Devi, 2022) (N. Mathimagal and S, 2021) (Kumar, 2017) (Thanveer Shaik X. T., 2022).

- Predicting Student Performance

By integrating academic and social variables, sentiment analysis can predict students' performance. This will exclude subjective judgments of students' learning experiences and provide a data-based intervention. (Obeleagu, 2019) (J. Sultana, 2018) (Kumar, 2017) (M. Khan, 2023).

- Evaluating Teaching Practices

Sentiment analysis can be carried out in the assessment of teaching practices through the perception and sentiment of students about the instructors. It may, therefore, bring a greater nuance to understanding effective teaching rather than traditional evaluation methods. This allow targeted improvements in teaching strategies (de Paula Santos, 2016).

- Monitoring Online Learning Platforms

Sentiment analysis can be utilized in digital education to analyse user reviews and feedback on virtual learning platforms (Devi, 2022). In addition, this analysis of sentiments stated in the reviews will allow educational institutions to measure user satisfaction and other areas in which they may want to make adjustments. For example, a study analyzed 6,000 reviews, with accuracy in sentiment classification at about 88%, proving the efficiency of ML algorithms for such an application (M. S. Hossen, 2022) .

- Addressing Challenges in Education

Whereas sentiment analysis may indicate students' problems during their learning processes, such sentiments based on mood, attitudes, and perception may provide insight into emotional factors affecting successful student outcomes. This understanding would hopefully lead to the development of strategies to mitigate negative sentiments and enhance overall student well-being (Cunningham-Nelson, 2019).

B. Approaches and Methods

The different ML models and techniques of sentiment analysis that are used within the reviewed studies include a shallow BERT-CNN model with self-attentive pooling in reference (Li, 2019); it was used to carry out sentiment analysis on MOOC comments, hence giving an impressive F1 score of 92.8%. This proves that DL models can handle much educational data for sentiment analysis. Reference (Kim, 2023) has utilized cluster analysis and VADER for summarizing student feedback about the course of physics as presented. It points out the usefulness of NLP in giving instructors useful insight.

However, it also pointed out some limitations in the current methodologies. Reference (Kim, 2023) demonstrated that the effectiveness of VADER was somewhat compromised because it is trained on social media datasets which may fail to show all the peculiarities of educational content. The work in reference (O. Ozyurt, 2023) discussed the limitation of topic modelling and bibliometric analysis concerning capturing an overview of EDM research in terms of what influences real educational practices and indicated a need for more robust analysis frameworks.

C. Impact of Sentiment analysis in education

- *How does sentiment analysis impact decision-making in education?*

Sentiment analysis (SA) significantly impacts decision-making in education by providing insights into students' opinions and emotions regarding their learning experiences. By analyzing feedback collected from various platforms, such as social media and online surveys, educational institutions can identify areas for improvement in teaching methodologies and course content (Reddy, 2017) (Almonte, 2022). Additionally, aspect-based sentiment analysis allows for a more nuanced understanding of specific elements affecting student satisfaction, such as teaching style and course materials (R. Oramas-Bustillos, 2018) (Y. Zahidi, 2020). This data-driven approach not only helps in enhancing the quality of education but also fosters a responsive educational environment that addresses students' needs effectively, ultimately leading to improved retention and recruitment of students (K. DSouza, 2023) (Almonte, 2022).

- *What role does sentiment analysis play in student engagement?*

Sentiment analysis enhances student engagement by providing insights into students' feelings and perceptions regarding their educational experiences. By analyzing sentiments expressed through various platforms, such as social media and feedback forms, educational institutions can better understand student satisfaction and areas needing improvement (Almonte, 2022). Techniques like the Perceptual Neural Boltzmann Machine (PNBM) and Naive Bayes (NB) algorithm have demonstrated high accuracy in classifying student sentiments, with PNBM achieving 87% accuracy compared to traditional methods (Devi, 2022) (Almonte, 2022). This analysis not only helps in identifying positive and negative sentiments but also aids in tailoring educational services to meet student needs, thereby fostering a more engaging learning environment (de Paula Santos, 2016) (J. Sultana, 2018). Furthermore, sentiment analysis can inform strategic planning within institutions, ensuring that student voices are considered in decision-making processes, ultimately leading to improved educational outcomes and student retention (Almonte, 2022) (de Paula Santos, 2016).

- *Impact sentiment analysis in student motivation levels*.

Sentiment analysis (SA) significantly influences student motivation levels by providing insights into their emotional responses and feedback regarding educational experiences. By analyzing student sentiments, educators can identify positive emotions such as enthusiasm and satisfaction, which are crucial for fostering motivation and engagement in learning environments (A. Anwar, 2023). Moreover, sentiment analysis helps understand students' concerns and preferences, allowing instructors to adapt their teaching methods accordingly, and enhancing the overall learning experience (Rääf, 2021). ML techniques, such as the Perceptual Neural Boltzmann Machine, have shown improved accuracy in sentiment classification, enabling more effective feedback mechanisms (Devi, 2022). Additionally, sentiment analysis can reveal negative emotions, such as frustration, which may hinder motivation, prompting timely interventions to address these issues (Hu, 2021) (N. Mathimagal and S, 2021). Overall, leveraging sentiment analysis in educational settings can improve student motivation and satisfaction by aligning teaching strategies with student needs.

D. Challenges of implementing machine learning for sentiment analysis in the education sector

While a powerful tool, sentiment analysis faces many challenges in educational settings and beyond. Some key challenges relate to the following contexts.

- Data Quality and Cleaning: The leading challenges are poor data quality. Poor quality may lead to incorrect sentiment classification, the most crucial task in effective analysis. Clean data pre-processing methods are usually tiresome and take more time, generally affecting the overall efficiency in the tasks of Sentiment Analysis (Manurung, 2022).
- Feature Selection: Choosing appropriate features is an important step in sentiment analysis. Feature selection in educational contexts includes specifying relevant variables that usefully reflect the sentiment of students. Feature selection becomes difficult in educational data because of the variety and complexity presented by both academic and social factors in the data (R. Nandakumar, 2022) (Yaakub, 2019) (K. DSouza, 2023) (Fang, 2024) .
- Sentiment Classification Accuracy: The challenge to surge ahead for a higher accuracy level in the classification of sentiment remains strong. Many current models are weak against subtle variations of language, like sarcasm or mixed sentiments, that often mislead the data interpretation process. This becomes even more important in education, where misunderstanding student feedback may affect teaching behaviour.
- Limited Translation to Practice: There is often a gap between the insights gained from sentiment analysis and their practical application. For instance, positive beliefs about teaching practices may not always translate into actual improvements in educational outcomes (Hu, 2021). This disconnect can hinder the effectiveness of sentiment analysis in driving meaningful changes.
- Neglect of Negative Sentiment: Most methods of sentiment analysis return positive sentiments, and much less attention is paid to the negative. That skews the perception of the general landscape of sentiment at least in academic contexts, where negative feedback is quite relevant for improvement (Yaakub, 2019) (Manurung, 2022).
- Subjectivity and Variability of Context: Sentiment analysis might be a pretty subjective area since it usually deals with individual interpretations of words and language. The educational environment contains students whose moods, attitudes, and perceptions can vary within a wide spectrum, which makes the analysis very complicated.
- Inaccurate sentiment detection can lead to misinterpretations, negatively affecting decision-making. The use of sentiment analysis raises ethical concerns, particularly regarding student privacy and the potential for data misuse. The ethical implications of sentiment analysis, emphasizing the need for transparency and consent when analyzing student data (Thanveer Shaik X. T., 2022) (Ahmad, 2024).

The following section shows the summary of the challenges found in the literature review.

E. Challenges of sentiment analysis

This section outlines challenges across various AI and sentiment analysis papers, particularly in educational and other domains. Here's a summary of the main challenges mentioned:

1. Data Challenges:
    - Unstructured Data: Varying lengths, irregularities, and complexity in text data make processing and model performance challenging (Hu, 2021), (R. Nandakumar, 2022), (N. Mathimagal and S, 2021), (Li, 2019), (M. Khan, 2023).
    - Data Scarcity: Limited labeled data, particularly in education and healthcare sectors, hinders experimentation and model training (Lazrig & Humpherys, 2022), (Mërgim H. HOTI, 2023).
    - Language and Context: Challenges arise with sentiment analysis in non-English languages (Arabic, Persian, Bangla), and domain-specific language issues like sarcasm, ambiguity, and emoticons (Y. Zahidi, 2020), (K. T. Shandana, 2023), (Srivastav, 2023).
    - Multimodality: The need to handle multiple data formats (text, audio, video) poses a challenge for accurate analysis (Lazrig & Humpherys, 2022), (Mërgim H. HOTI, 2023).
    - Manual Processes: Collecting and labeling data is time-consuming and subject to human judgment errors (Reddy, 2017), (Hu, 2021), (Piyush Mathur, 2021).
2. Model Performance and Accuracy:
    - Model Limitations: Challenges include achieving high classification accuracy, especially in Naive Bayes models due to its independence assumption and SVM's sensitivity to feature dimensionality (Almonte, 2022), (Yaakub, 2019).
    - Negation Handling: Negation words distort the results of sentiment and aspect-based analysis (Hu, 2021).
    - Overfitting and Feature Selection: Overfitting risks arise from irrelevant attributes, and feature selection techniques need improvement to boost performance (Yaakub, 2019), (O. Ozyurt, 2023), (Thanveer Shaik X. T., 2022).
3. Challenges in Educational Domain:
    - Sentiment Analysis in Education: Limited research in applying sentiment analysis to education, with challenges including subjectivity in feedback, and extracting actionable insights (Obeleagu, 2019), (Aldowah, 2020), (Mërgim H. HOTI, 2023).

  - Student Feedback: Processing large amounts of unstructured student feedback and extracting meaningful insights poses a challenge (Papers (N. Mathimagal and S, 2021), (J. Sultana, 2018), (Ahmad, 2024)).
  - Technology Barriers: Limited access to technology, motivation, and engagement in online learning environments negatively affects student outcomes (A. Anwar, 2023), (K. A. Alshaikh, 2024).
4. Complexity in Sentiment Analysis:
  - Aspect-Based Sentiment Analysis: Difficulty in accurately extracting aspects and polarity from open-ended responses (Hu, 2021), (Thanveer Shaik X. T., 2023).
  - Handling Negative Sentiments: Balancing negative opinions in datasets to ensure classifier accuracy is complex (R. Oramas-Bustillos, 2018).
  - Multilingual and Multiclass Challenges: The complexity of developing multilingual sentiment analysis systems and accounting for multiple emotions or sentiment categories (Kumar, 2017), (Li, 2019), (Devi, 2022).
5. Real-World Application and Scalability:
  - AI System Limitations: Lack of real-time data processing, scalability, and agility in AI systems, along with privacy concerns and bias in educational AI systems (R. Mehmood, 2017), (Mërgim H. HOTI, 2023), (V. A. Pulikonda, 2023).
  - Real-World Impact: Challenges in translating technical success to real-world classroom impact, and in creating dynamic AI-driven content for education (M. Akash Rahman, 2024), (Mërgim H. HOTI, 2023).

E. Identified Research Gaps

Recent improvements have been observed in sentiment analysis in the educational domain; however, some critical research gaps were identified. One of the significant recurring themes was that sentiment analysis in exploring multilingualism was somewhat limited. For example, as mentioned in (M. S. Hossen, 2022), little or no work has been done on sentiment detection for non-English languages when customized training is unavailable, which, in most cases, limits the scope of sentiment analysis in linguistically diverse environments. Reference (V. Naveen, 2024) also reported the absence of broad sentiment analysis studies in multilingual education during the COVID-19 pandemic, in which e-learning environments have critically changed.

Another critical gap was the underutilization of sophisticated ML techniques for more accurate predictions and analyses. References (N. Mathimagal and S, 2021) and (V. A. Pulikonda, 2023) recommend further advanced models to consider long-term effects, such as the long-term impact of behavioral changes induced by social media on the student's learning. Besides, references (Fang, 2024) and (M. Khan, 2023) incorporate further features including temporal data and multimodal inputs—to improve the accuracy and applicability of sentiment analysis models in education.

F. Future Directions

These findings from the review provide several promising future directions. Among them, the most important is developing a more comprehensive and multilingual sentiment analysis model that accommodates diverse educational contexts. Reference (Li, 2019) suggests exploring fine-grained sentiment analysis or opinion mining techniques in MOOCs, while reference (Srivastav, 2023) claims that there is an imperative need to have AI-enabled learning environments that can use such an advanced toolkit.

Other key trends include sentiment analysis integrated with other cutting-edge technologies, such as speech recognition and IoT, references (Fang, 2024) and (R. Mehmood, 2017). This will give more of a global view of the processes involved around students' engagement and learning, thus enabling educators to conduct more personalized and effective educational interventions.

Finally, an urgent need was established in collaboration among educational institutions and these technology developers for open datasets and scalable solutions. This would hopefully provide a boost for more innovative applications of the approaches surveyed herein, giving more individuals within the educational sector access to the benefits. The table below discusses the potential gaps and future research in this field as indicated in the literature.

Table 2. Summary Table

Reference	Multilingual Limitations in Sentiment Analysis	Advanced Emotion Recognition and Detection	Real-Time Sentiment Feedback Systems	Comparative Evaluation of Sentiment Analysis Models	Incorporation of Multimodal and Non-Textual Data	Ethical Considerations in AI-Driven Sentiment	Sentiment Analysis for Crisis and Emergency Contexts	Integration of Social Media Sentiment Analysis in Education
B. Saju (2020)	✓	✓			✓			✓
Reddy (2017)			✓					
Obeleagu (2019)				✓				
Aldowah (2020)				✓				✓
Piyush Mathur (2021)				✓				
Hu (2021)	✓							
R. Nandakumar (2022)				✓				
Manurung (2022)				✓				
Yaakub (2019)								✓
de Paula Santos (2016)								
M. S. Hossen (2022)	✓						✓	
Almonte (2022)	✓			✓				

Reference	Multilingual Limitations in Sentiment Analysis	Advanced Emotion Recognition and Detection	Real-Time Sentiment Feedback Systems	Comparative Evaluation of Sentiment Analysis Models	Incorporation of Multimodal and Non-Textual Data	Ethical Considerations in AI-Driven Sentiment	Sentiment Analysis for Crisis and Emergency Contexts	Integration of Social Media Sentiment Analysis in Education
R. Oramas-(2018)								
Y. Zahidi (2020)	✓							
K. DSouza (2023)			✓					
Devi (2022)				✓				
J. Sultana (2018)				✓				
A. Anwar (2023)		✓						
Rääf (2021)								✓
N. Mathimagal (2021)								✓
M. Akash(2024)	✓				✓			
Chen (2018)				✓				
K. A. Alshaikh (2024)	✓							
Ahmad (2024)						✓		
V. A. Pulikonda (2023)	✓							
V. Naveen (2024)	✓			✓				
Barrón-Estrada (2017)					✓			
K. T. Shandana (2023)				✓				

CONCLUSION

In summary, sentiment analysis has proven to be a high-value tool within the education sector. It provides insight into students' behaviour, feedback, and performance, which might offer teaching strategies and educational policies. However, future research shall overcome noted gaps, especially those associated with a multilingual context and integration of advanced machine learning techniques. Sentiment analysis can thus help in framing a responsive future for education, meeting diverse learner needs. I hope this research may provide necessary guidance to the researchers who wish to apply sentiment analysis in the education sector.

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