Social Media Data Analysis for Enhancing Student Evaluation of Teaching Styles

Walaa Fouda[1,*], Najla M. Alnaqbi[2], Sanjar Mirzaliev[3], Dina Sabry Said[4]

[1]College of Arts, Sciences and Information Technology, Department of Communication, University of Khorfakkan, UAE

[2]Mohamed bin Zayed University for Humanities, UAE

[3]Department of Research and Innovations, Tashkent State University of Economics, Uzbekistan

[4] College of Business Administration, American University of the Middle East, Kuwait

Emails: Walaa.fouda@ukf.ac.ae; Najla.alnaqbi@mbzuh.ac.ae; s.mirzaliev@tsue.uz; dina.said@aum.edu.kw

Abstract

In the realm of education, understanding the impact of different teaching styles on student engagement and satisfaction is essential. Recent advancements in sentiment analysis provide new avenues for evaluating student feedback, particularly through informal channels such as social media. While formal student evaluations offer structured feedback on teaching styles, they may not fully capture the nuanced opinions and sentiments expressed by students in informal settings, such as social media. This research aims to address the gap by integrating sentiment analysis of social media data to evaluate teaching effectiveness across various styles and comparing it with formal evaluation results. This study employs sentiment analysis using the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool to analyze student posts on social media platforms. The analysis includes the extraction of sentiment distributions, identification of common keywords, and tracking of sentiment trends over time. Additionally, formal student evaluations (Likert scale) are collected to offer a direct comparison. The teaching styles analyzed include lecture-based teaching, project-based learning, flipped classrooms, online learning, hybrid learning, and traditional exam-based learning. The findings demonstrate that student sentiment varies significantly across teaching styles. Flipped classrooms and project-based learning received the highest positive sentiment scores, while traditional exam-based teaching showed the most negative sentiment. Social media feedback tended to align with formal evaluations for certain teaching styles, such as the flipped classroom and hybrid learning but showed divergence in others, like online learning, which received higher sentiment in social media feedback. Trends over time reveal evolving sentiments, with fluctuating satisfaction as the academic semester progressed. The integration of social media sentiment analysis provides a more dynamic and real-time understanding of student experiences, offering deeper insights into teaching style effectiveness.

Keywords: Social media analysis; Student Evaluation; Teaching styles; Sentiment analysis; VADER; Educational feedback,

1. Introduction

The increasing possibility of informal feedback on social networks and the need for further differentiation of assessments of educational approaches are currently stimulating the development of the area of social media data analysis for enhancing the student assessment of teaching styles [1]. A Real-time and full range of students' experiences and perceptions of their peers are frequently missed when using the standard tools for assessing the effectiveness of teaching, including formal questionnaires and course feedback at the end of a term. In response, to gain a better insight into the students' happiness and their level of engagement, educators, and academics are

DOI: https://doi.org/10.54216/FPA.170218

Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

incorporating social media information as additional feedback [2]. Due to recent advancements in sentiment analysis, especially VADER and machine learning technologies, it is now easier to pull out and analyze views from large volumes of social media messages [3]. This shift is happening as organisations face issues like the credibility of unstructured data, privacy, and the necessity for better approaches to ensure that insights derived from social media correspond to the standard assessments. Also, the COVID-19 crisis and the subsequent shift to online and hybrid learning models, have made the evaluation of teaching even more challenging since students' experiences in these settings are not similar to face-to-face learning [4]. Thus, the appeared developments to confirm the necessity of the integration of social media data analysis with traditional evaluation methods because the former can provide a more comprehensive and dynamic picture of the teaching effectiveness [5].

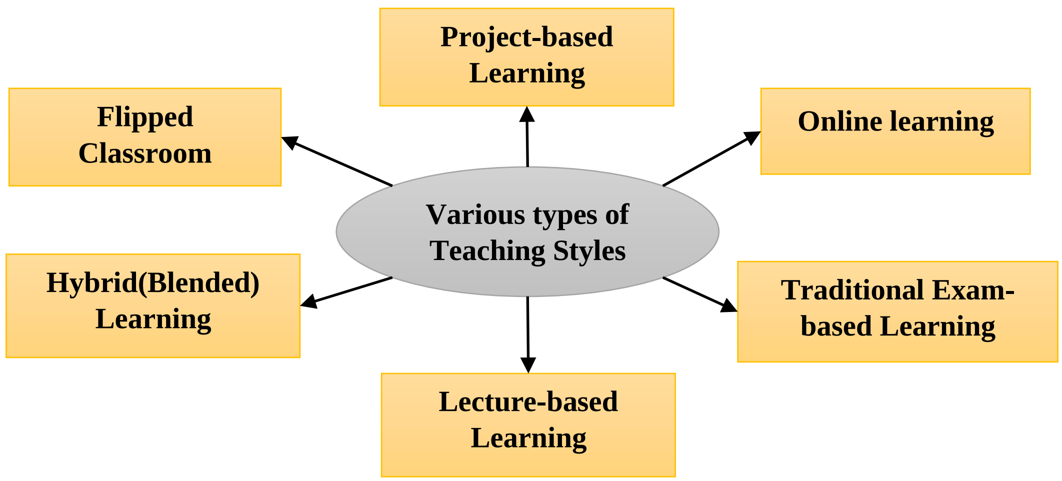

Figure 1. Various types of Teaching and Learning Styles

Different instructional strategies address learning modality and learning objectives as illustrated in the figure below. The teacher-centred approach in teaching entails the presentation of material to the students in a clear format, focusing on the coverage of the content material in the least time possible while at the same time hindering student interest [6]. Project-based learning (PBL) entails the practical solving of real-life problems, hence increasing problem-solving and teamwork. The flipped classroom model is the exact opposite of the traditional model where students learn content at home and use the classroom time for activities [7]. Online learning is convenient and can be accessed from anywhere at one's own time but it may be hard to grab the attention of the students. Hybrid or blended learning is the integration of face-to-face and online learning delivery modes that fosters individualized learning. The conventional forms of testing and evaluation are mainly based on examinations, which, despite their simplicity, do not assess other important skills such as problem-solving and innovation. Each of the methods has its strengths and drawbacks that determine the learning process as a whole [8].

The purpose of this research is to enhance the evaluation of teaching techniques by incorporating the large amount of unsolicited feedback that students share on social media, which is ignored when using official forms [9]. Standardized tests are good for checking students' achievements and knowledge, but they cannot capture all the aspects of student experience and attitude, which is why the researcher is concerned with this topic [10]. The opportunity to use this data to gain a deeper and more accurate understanding of how students see various instructional approaches in the context of using social media as an open discussion platform is possible. This project is intended to extend the current understanding of teaching effectiveness by incorporating formal evaluations with sentiment analysis of social media posts [11]. In this way, the researcher aims to create a framework that will assist teachers in responding to inputs from students faster, improving the teaching techniques, and making learning a more enjoyable process for the students [12-13]. The major contributions of this study are as follows:

- The research introduces the use of VADER sentiment analysis to capture informal, real-time feedback from social media, offering insights that traditional formal evaluations often miss. This method allows for the extraction of nuanced, dynamic student sentiments that reflect their immediate reactions and experiences with different teaching styles, beyond the structured and often limited scope of formal surveys.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

- The study tracks how student sentiments change throughout the academic semester, offering a temporal view of student satisfaction that is often missing in formal evaluations. This approach reveals how perceptions of teaching effectiveness evolve, providing a deeper understanding of how students respond to different teaching styles at various stages of the semester.
- The study compares social media feedback with formal evaluations, revealing where they align or differ, especially in teaching methods like online learning and flipped classrooms. This way of comparing makes it possible to obtain a broader picture of teaching effectiveness by using both formal and informal feedback sources.

The rest of the paper is organized as follows: In Section 2, we discuss the prior literature on traditional student evaluations, teaching styles and the more recent use of sentiment analysis in education research with a focus on social media data. Section 3 of the study describes the approach used in the research, the sentiment analysis using the VADER tool, the data collection techniques used in social media and formal assessments, and the particular teaching approaches under discussion. Section 4 offers the results of the sentiment analysis, the distribution of the sentiment, the keywords identification, and the trends over time, and finally, a comparison with the formal evaluation results. In Section 5, we share the implications of the study findings and demonstrate how the insights gathered from social media can improve the assessment of teaching performance and the development of instructional approaches. Section 6 provides the conclusion of this paper highlighting the major findings of this research.

2. Literature Review

2.1 Related Works on Teaching Styles and its evaluation

Table 1 summarizes key studies focused on teaching styles and their evaluation, detailing methods, findings, and limitations. Najla M. Alnaqbi (2023) [14] employed ChatGPT, social media, and Neutrosophic sets, finding that these tools enhance student feedback collection while addressing data uncertainties; however, challenges with indeterminate data and ethical concerns regarding chatbots remain. Ibtisam Al Kharusi (2023) [15] used the Students' Course Evaluation Questionnaire (SCEQ) and the Mann-Whitney test to reveal a significant correlation between teacher and student evaluations, though limitations included a small sample size and potential self-reporting bias.

C. Keerthigha (2023) [16] utilized social judgment measures and online chat interactions, concluding that relationship-oriented teachers received higher ratings, with motivation acting as a mediator of competence judgment. However, the study did not fully account for cultural differences. Mehwish Ajmal (2024) [17] used a mixed-methods approach, incorporating surveys and focus groups, to show that student feedback enhances clarity, motivation, and overall teaching effectiveness. The study, however, was time-intensive and featured a small sample size. Brittany Oletti (2024) [18] explored the alignment of learning styles through statistical correlation analysis, finding that closer alignment between teaching and student learning styles correlates with improved student grades, though the learning style categories used were considered oversimplified.

Sajeel Ahmed (2024) [19] focused on real-time feedback mechanisms and AI for grading, determining that AI-enhanced grading promotes fairness and equity in the evaluation process, though issues like AI bias and lack of transparency were identified. Skyler Neu (2023) [20] examined the use of Mosston's Spectrum of Teaching Styles and found that mixing multiple teaching styles can address diverse student needs, thus enhancing learning effectiveness. However, this method was difficult to apply in large, diverse classrooms. Nuala Byrne (2019) [21] compared electronic and paper-based methods for collecting feedback, finding that electronic methods resulted in higher response rates and better data for decision-makers, though response rates were still lower than those seen in paper-based collection. E. Dimitriadou (2023) [22] employed biometric analysis, including facial expressions and speech rate, to provide reliable automated feedback, outperforming human observers in certain areas but missing subjective aspects like emotional engagement.

Table 1: Summary of the reviewed literature on teaching styles and its evaluation

Author(s)	Year	Method Used	Findings	Limitations
Najla M. Alnaqbi [14]	2023	ChatGPT, social media, Neutrosophic sets	Enhanced feedback and data uncertainty addressed	Indeterminate data, ethical issues with chatbots
Ibtisam Al Kharusi [15]	2023	SCEQ, Mann-Whitney test	Correlation between teacher and student evaluations	Small sample, self-reporting bias
C. Keerthigha [16]	2023	Social judgment measures, online chat	Higher ratings for relationship-oriented teachers	Cultural differences not fully accounted for

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

Mehwish Ajmal [17]	2024	Mixed methods, surveys, focus groups	Improved clarity, motivation, teaching effectiveness	Time-intensive, small sample size
Brittany Oletti [18]	2024	Learning styles, statistical correlation	Learning style alignment improves grades	Oversimplified learning style categories
Sajeel Ahmed [19]	2024	Real-time feedback, AI grading	AI promotes fairness in grading	AI bias, lack of transparency
Skyler Neu [20]	2023	Spectrum of Teaching Styles, mixing styles	Diverse student needs met, enhanced learning	Hard to apply in large, diverse classrooms
Nuala Byrne [21]	2019	Electronic vs paper collection	Higher response rates, better data	Lower response rates than paper
E. Dimitriadou [22]	2023	Biometric analysis, speech rate, intonation	Reliable feedback is better than human observers	Misses subjective aspects like emotional engagement

2.2 Related Works on Sentiment Analysis in Education

In the education sector to enhance teaching efficacy, Betsy M. Rice [23] has used sentiment analysis to evaluate student comments. By using these analytical tools, educators can get a better understanding of the student's attitudes and feelings towards various approaches to teaching. This approach makes it possible to gain a more differentiated picture of students' satisfaction and learning processes to improve teaching activities to achieve better educational results.

Jefferson A. Peña-Torres [24] employed sentiment analysis using big language models to determine sentiments concerning instruction from students. His research aims at improving teaching quality and practice through coming up with better interpretations of students' feedback. The usage of these advanced models results in 93% of feedback classification, which will provide a more accurate insight into students' attitudes. In addition to that, Peña-Torres's work shows how large language models are useful in enhancing feedback in educational settings and proposes potential research avenues for enhancing sentiment analysis in the educational field.

As pointed out by Sweta Soni [25], the current sentiment analysis is revolutionising educational data mining and all its applications. Through the evaluation of the attitudes of the students, the educational institutions are in a better position to understand the learner involvement hence improving on the strategies that are used to address the learner's needs. It also improves the educational experience in general; this helps institutions devise better strategies for improving student interest, learning, teaching effectiveness and, thus, performance and satisfaction. This is why Sweta's work enlightens the possibilities of sentiment analysis for forming contemporary educational practices.

Using students' affective knowledge, sentiment analysis is used by Xu Fan et al. [26] to enhance curriculum design and teacher evaluation. Their work uses the CNN–SVM model to classify EEG signals and identify the students' emotional state while learning. As such, it offers a far greater insight into how students feel about their experiences and about what could be done to make learning more enjoyable and effective. This method of including emotional data in teaching evaluations can help make learning environments more effective for students.

An Android application developed by F. A. Casarin [27] analyses the sentiment of students on courses offered. It is an effective tool that will help to get information about the students' attitudes toward their learning process immediately and easily. The study conducted so far has revealed that the app yields a high level of accuracy in sentiment classification and users of the app have expressed satisfaction in regards to the ease and efficiency of the app. The results of this study indicate that this app could be used as a useful instrument for complementing the existing course review and advancing the quality of the pedagogy based on the student's feelings.

Another mobile application created by Sarah A. Alkhodair [28] analyzes the students' comments on courses using sentiment analysis. It makes it possible to gather and analyse students' opinions in real-time, so the assessment of teaching quality and course satisfaction is convenient and efficient. Initial results of the study show that the app is accurate in detecting positive and negative sentiments and the users also expressed satisfaction in the use of the app and its performance. Such findings imply that the app could be instrumental in enhancing course assessments and optimizing the pedagogy model according to the learners' feedback.

Qurbonov Doniyor Davlatovich's [29] work focuses on the application of sentiment analysis in the context of the educational area and is designed to assess the quality of the teaching process. His study focuses on the qualitative data

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

of students' views on teaching and learning activities with the help of sentiment analysis. Using these techniques, the research aims to give educators a better insight into student satisfaction to improve teaching practices to foster educational achievement.

In assessing different sentiment analysis techniques used on feedback from Indonesian higher learning institutions, Jimmy et al. [30]. It compares the performance and accuracy of three prominent classifiers: Some of the algorithms used in this study include Naive Bayes, Support Vector Machine (SVM) and the Decision Tree. The study identifies significant disparities in the efficiency of these models and offers a new approach to linking classifiers to improve the efficiency of sentiment analysis. It also outlined areas that may need further research and development about upgraded methodologies of sentiment analysis in the field of education with emphasis on the enhancement of the feedback appraisal procedures for enhancing the efficiency and quality benchmarks of teaching performance and student satisfaction.

Possible ethical dilemmas in emotional analysis are described by Soni Sweta [31] with a focus on sentiment analysis. The work discussed issues of privacy, data quality, and logical prejudices of understanding emotional data. As pointed out in the paper, as sentiment analysis tools are getting more and more involved in the learning environment, it is necessary to pay special attention to the personal information of students and be honest and unbiased when working with their data.

To identify the most efficient approaches for handling large amounts of feedback data, Nikolaos Spatiotis et al. [32] compared the performance of many sentiment analysis models on large datasets. Their work goes beyond the evaluation of the accuracy and performance of these models and also looks at the advancement of machine learning and data handling in the future, especially sentiment analysis. This way, the study is useful to address the limitations of sentiment analysis by pointing out issues such as scalability and the speed of processing to enhance the applicability of sentiment analysis in education and other sectors.

Sri Ramakrishna Chandrasekaran et al. [33] opine that the change that is currently being witnessed in the education system is a result of technological and data analysis advancements. Their work is on the use of machine learning methods for sentiment analysis of the comments made by students. Using such sophisticated techniques, the study intends to identify students' experience and satisfaction, which will in turn assist educators to change their teaching practices to suit the current education needs. Such an approach is indicative of the contemporary trends in the application of data solutions in the transformation of educational assessment and improvement of learning efficiency.

The new approach for sentiment analysis was designed for online learning by Fanjie Lin [34]. This approach is used to improve the knowledge of the student's feedback and provide more detailed information to the educators about students and their experience and views regarding the course quality. The present research employs the sophisticated sentiment analysis approach to offer a more precise and comprehensive assessment of online learning environments, and, therefore, facilitate the enhancement of the educational process. This work contributes to the methodological advancement in the use of data analytics to improve and enhance the quality of online learning.

A student feedback mining system developed by Gaurav Pandey et al. [35] uses sentiment analysis to automatically assess student input. This system is designed to provide educators with more efficient and accurate insights into student satisfaction and areas for improvement. By automating the feedback analysis process, the system offers real-time data that can be used to enhance teaching methods and the overall educational experience. This innovation holds the potential to significantly improve the way student feedback is processed, leading to more responsive and student-centered educational practices.

Xingyu Tian et al. [36] have proposed a real-time sentiment analysis system using the mini-Xception architecture that can recognize seven different types of sentiments of students with high accuracy. This system allows educators to get an instant view of the feelings of the learners when learning so that appropriate measures can be taken. The real-time feature of this model means that educators can track students' interaction and satisfaction levels at any time and therefore foster a more responsive learning environment. This high accuracy of the system suggests that the real-time feedback in the educational environment could be enhanced.

The main focus of T.O. Efuwape et al. [37] is the sentiment analysis of digital technologies by the academic stakeholders. Applying the method based on VADER, the study finds that people have both positive and negative attitudes towards collaborative tools. Some of the stakeholders have positive attitudes where they value the efficiency and connectivity of the tools while others have challenges such as technical issues and accessibility. Such a mixed

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

response points to the fact that academic stakeholders have had varying experiences with digital collaboration tools, and hence the need to continue to enhance the tools to cater for the positive and negative experiences as indicated above. The findings of the literature review are summarized in Table 2 below.

Table 2: Summary of the reviewed literature on sentiment analysis in education

Ref.	Method	Finding	Limitation
[23]	Various sentiment analysis techniques	Explores techniques for student feedback	Limited discussion on real-time techniques, lack of focus on specific educational subjects
[24]	Sentiment analysis with LLM	Achieves 93% accuracy in sentiment classification	Open-ended questions require more time, and subjective interpretation is needed.
[25]	Assessing learner's feedback	Enhances engagement and personalized learning	Challenges in leveraging Sentiment Analysis, need for unbiased consideration.
[26]	CNN and SVM models	Effectively analyzes sentiment from EEG signals	Accuracy and fairness of algorithms are crucial, potential biases must be considered.
[27]	Sentiment Analysis with Naive Bayes and VADER	Naïve Bayes: 68.8% accuracy, VADER: 72.12%	Challenges faced in application design, recommendations for improvements
[28]	Requirement elicitation	VADER outperforms Naive Bayes, with 100% user satisfaction	Small dataset size, difficulties in data collection
[29]	Various machine-learning techniques	Investigate sentiment analysis for feedback	Aims to improve teaching effectiveness through opinions
[30]	Naive Bayes, SVM, Decision Tree	SVM outperforms others	Incorrect classifications were identified, evaluation focused on Indonesian text.
[31]	Natural Language Processing algorithms	Key methodologies identified for sentiment analysis	Ethical considerations in emotional analysis challenges with tools
[32]	Supervised Machine Learning	Effectively classifies Greek texts	Social information enhances accuracy and future work for imbalanced data handling.
[33]	Sentiment analysis using lexicons	Reveals insights into teaching quality	Comparison of techniques conducted, no limitations mentioned
[34]	Structured framework design	Innovative methodology enhances understanding of student feedback	Complex language processing is needed, and privacy concerns
[35]	Sentiment analysis using NLP techniques	Automates feedback analysis	Provides actionable insights, low response rates, subjectivity in collection
[36]	Real-time identification of sentiment	Mini-Xception model: 76.71% accuracy	Improves understanding of engagement, incomplete feedback content, delayed analysis
[37]	VADER-based Sentiment Analysis	17.27% negative towards collaborative tools, 22.7% positive	Limited use in Nigerian institutions, negative sentiments reported

3. Materials and Methods

This figure illustrates the flowchart of how to analyse the teaching styles through social media data. The process starts with data extraction from different social media sites including, Facebook, Twitter, and Reddit. This data is then aggregated and preprocessed to filter out the noise and get it in a format ready for analysis. The pre-processing step comprises data cleaning, tokenization and removing the stop words. Afterwards, the preprocessed data is transformed into analysis with sentiment analysis using the VADER model to determine the sentiment of the data. The results of the sentiment analysis are categorized into three classes: positive, negative, and neutral. Lastly, these categorized sentiment scores are employed for teaching style identification; the correlation between various teaching styles and sentiments is then studied. This approach allows for the analysis of teaching styles using the vast amount of data available on social media platforms.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

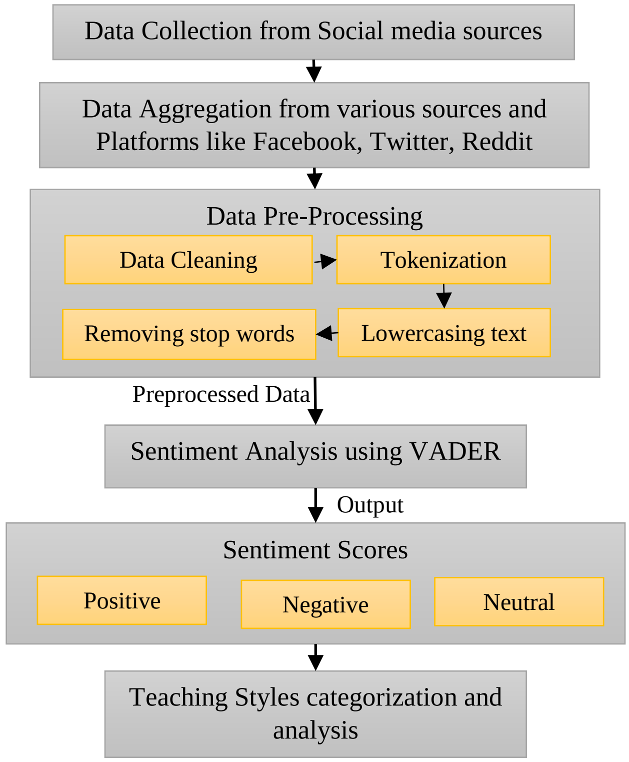

Figure 2. Overview of the proposed approach

3.1 Data Collection

The data used in this study was collected from social media sites; Twitter, Facebook and Reddit. The data gathering took four months, which covered an academic semester to capture students' feedback at various stages of teaching and learning. Since student-generated content is vast, it is essential to narrow down the posts to those that are relevant to teaching styles only for analysis; therefore, a set of keywords and hashtags was created to capture such posts. These teaching style-related keywords comprised phrases like "Lecture-based learning", "Flipped classroom", "Project-based learning", "Hybrid learning", and "Exam-based learning", there were other teaching-related tags like #flippedclassroom, #projectlearning, #hybridlearning, #onlinelearning, #exambased.

For ethical considerations, only posts that are accessible to the public domain were considered for the analysis and any information that could lead to the identification of the users was removed during the pre-processing stage. Requirements of data privacy policies of the platforms were maintained to the highest level and the data collected from the users were anonymised to avoid users' identification.

Institutional quantitative data was retrieved from questionnaires filled by students at the end of the academic semester. Teaching effectiveness across the various styles was assessed using a 5-point Likert scale in the surveys. These evaluative sessions offered a more formal assessment of teaching practices such as lecture-style, project-based, flipped classroom, online learning, blended learning, and examination-based teaching and learning. Both the Likert scale quantitative data and the qualitative comments were collected, making a clear comparison with the responses obtained from social media.

3.2 Data Pre-processing

3.2.1 Social Media Data Cleaning

When the data was obtained from social media, the text was preprocessed to make it suitable for analysis. Firstly, posts unrelated to the topic, advertisements and posts that are duplicates were removed. Prepositions, conjunctions, articles, and other non-significant words like "the," "and," and "is," were omitted. Also, URLs, special characters,

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

punctuations, and numbers were removed as they were not important to sentiment analysis. The abbreviations and acronyms commonly used on social media platforms were also maintained as they may hold sentiment.

Emoji were translated into textual descriptions by using a custom dictionary to prepare them for analysis. For instance, ☺ was interpreted as “happy,” and ☹ as “angry” so that the sentiment tool could include these symbols in the analysis.

3.2.2 Text Normalization and Tokenization

Preprocessing was done on the text to eliminate any unnecessary characters in the posts. This comprised of preprocessing the text in which all characters were lowercase, where an attempt was made to reduce the variations in forms of the words in a text through lemmatization and where common misspellings and informal abbreviations were addressed. For example, “u” was established as “you” “prof” was used as “professor”. Text tokenization was conducted at word level where each post was divided into words or tokens. This made easy the processing by the sentiment analysis tool and also made it easy to extract keywords and topics.

3.3 Sentiment Analysis

In the process of performing sentiment analysis on the preprocessed social media data, the VADER tool was used since it is designed to handle social media text. VADER employs rules to calculate sentiment scores, the intensity of words, punctuation, capitalization, and emoticons and therefore, is ideal for the informal tone normally seen in social media. Each post was given a compound sentiment score ranging from -1 to +1, in addition to the positive sentiment score, neutral and negative sentiment scores. These scores were then summed to obtain average sentiment scores for each of the teaching styles. When the compound scores were higher than 0.05, the post was considered positive, and if the compound scores were lower than -0.05, the post was considered negative; otherwise, the post was considered to be neutral.

3.3.1 VADER Sentiment Analysis Tool

VADER is a rule-based, lexicon-based SA tool that is developed to measure the sentiment of text data. Unlike many other approaches to SA that depend on machine learning algorithms to classify a text into positive, negative, or neutral based on training on large labelled data, VADER is a lexicon and rule-based approach that works based on a set of words (the lexicons) and their corresponding sentiment strengths. It is popular because it is fast and accurate especially when used with informal data, short text, and data from social media. Slangs, abbreviations, emoticons, and capitalized words are typical for social media and expressing emotions, so VADER was designed to recognize them. The tool can classify text into positive, negative, neutral and compound polarity scores. These features make VADER highly relevant for the analysis of social media data, such as student feedback on the teaching styles frequently containing informal language and abbreviations.

VADER has an extensive lexicon of over 7,500 words and symbols for which each is assigned a valence score that defines the intensity of the sentiment. The words with positive valence scores include ‘good’, ‘great’, and ‘excellent’ while the words with negative valence scores include ‘bad’, ‘terrible’, and ‘poor’. In the case of neutral words, words that do not have a positive or negative sentiment, are given a score of zero. Apart from individual words, VADER can analyze phrases, emoticons and even slang that is frequently used in the text of social networks. For example, terms like "lol" or emojis such as ":“:)” are identified as positive polarity while “:’(“ is considered as negative polarity.

The actual VADER-based sentiment analysis is represented in Figure 3. First, the input text is dissected into a tokenized manner, that is, the words or phrases (tokens) are separated from each other. Each token is then compared against a predefined lexicon in VADER such that positive negative or neutral sentiment values are assigned depending on the inherent sentiment of the word, for example, happy is positive while sad is negative. The system then uses rule-based adaptations to the developed model. These include changing the level of intensity in which Positivity by using intensifiers (for example, changing the comment from ‘happy’ to ‘very happy’) or the opposite, diminishers (for instance, altering the comment from ‘good’ to ‘somewhat good’) or using negation where necessary such as changing ‘good’ to ‘not good,’ or sentimental markers such as punctuation or emojis. After these changes, the sentiment is the compound score which ranges from -1, the most negative, to 1, the most positive with the middle values as neutral. Depending on the compound score, the text is categorised as positive, negative or neutral. In the end, the system provides the sentiment analysis results in terms of positive, neutral, negative and compound scores.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

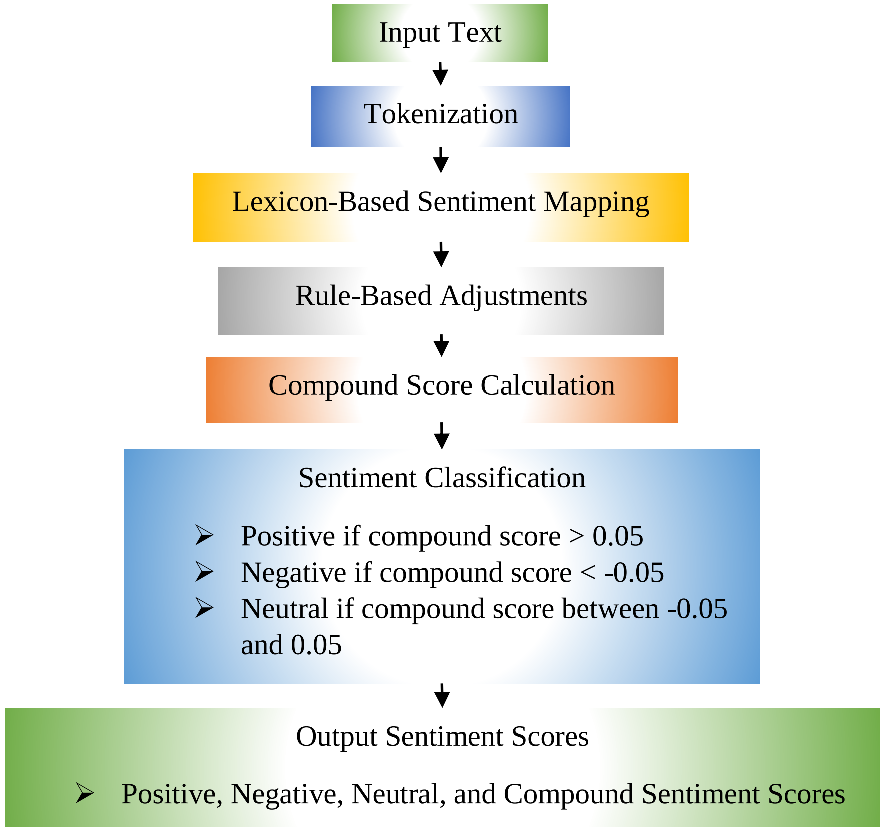

Figure 3. Overview of the VADAR-based sentiment analysis

3.3.2 Sentiment Classification

In this work, preliminary sentiment classification helps categorize the student feedback obtained from social media according to the particular teaching style in consideration. This process involves sorting the posts based on the occurrence of some keywords and phrases associated with some teaching methodologies. After categorization, each post gets its sentiment analyzed using the VADER sentiment analysis tool. To arrange the posts in the categories of teaching styles, we came up with a list of keywords and phrases associated with each of the methods. These keywords were identified from a study of the teaching practices literature and a preliminary analysis of the data sources to identify the words most frequently used by the students in their narratives. Table 3 below is a summary of the keywords and phrases associated with each teaching style.

Table 3: Keywords and Phrases for Teaching Style Classification

Teaching Style	**Keywords and Phrases**
Lecture-Based	lecture, slides, professor, classroom, notes, traditional, chalkboard, blackboard
Project-Based	project, group work, hands-on, real-world, collaboration, team, prototype, design
Flipped Classroom	flipped, videos, interactive, self-paced, watch at home, in-class activity, preparation
Online Learning	online, remote, Zoom, virtual, web-based, e-learning, video lecture, asynchronous
Hybrid Learning	hybrid, blended, mix of online and in-person, flexible, combination
Exam-Based	exam, test, midterm, final, multiple-choice, time pressure, grades

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

3.4 Teaching Style Categorization

The categorization of teaching styles in this study was done by identifying specific terms that are related to specific teaching techniques in the context of the posts on social media. For lecture-based teaching, the posts that contain the terms such as 'lecture', 'slides' and 'classroom' were classified under this label. The terms adopted within the context of the project-based learning posts referred to 'group projects' and 'hands-on learning' which spoke of team tasks as well as practical activities. The flipped classroom model was established from phrases like 'watch videos', and 'in-class discussions' that describe pre-class preparation and participation respectively. In the posts about online learning, the authors referred to virtual environments, for example, by the names of 'Zoom' and 'e-learning'. Face-to-face and online delivery modes were categorized as blended learning and flexible teaching methods. Last, exam-based teaching posts referred to "exams" "tests" "memorization" and emphasized traditional forms of assessment. These categorized posts allowed for improved analysis of sentiment since they provided a clearer picture of how students' experience and satisfaction vary with the type of teaching.

3.5 Data Analysis

The data analysis process involves a presentation of the findings of the social media sentiment analysis and a comparison of the findings of the formal student feedback to assess the effectiveness of various teaching strategies. Firstly, all the posts from all the social media platforms used in the study were preprocessed by the removal of all the text noise for example; special characters, URLs and stop words in order to ensure that only relevant content for analysis was included in the study. The collected preprocessed data were then classified into the teaching styles mentioned above by using keywords and phrases obtained during classification. To each post, the sentiment score was assigned with the help of the VADER, which is suitable for the analysis of the social media data because of the possibility of identifying positive and negative sentiments in the language. VADER assigns an overall sentiment polarity for each of the posts categorizing the post as either positive, negative or neutral. The data obtained was then totalled to give the overall sentiment for each of the teaching styles about the sentiment scores that were assigned. This made it possible to compare the students' attitudes towards different instructional methods with the comments they made on social media. After that, the sentiment data were preprocessed to identify the most frequent keywords and trends in the students' feedback. Chronological trend analysis was made to see how the sentiment changes over the semester and whether students' satisfaction or dissatisfaction with some teaching behaviours occurred. To confirm the findings captured by the social media sentiment analysis, the study also included the formal student assessment data that was collected using a Likert scale questionnaire. These assessments offered constructive feedback on the teaching performance and this was compared to the sentiments analysis findings. The level of association between the formal evaluations and the social media sentiments required the use of statistical measures to compare the two feedbacks. Furthermore, to compare and contrast the identified sentiment for certain styles of teaching, the differences and divergence in the sentiment related to specific styles were accentuated to show where social media sentiment provided more depth or an entirely different perspective than the standard assessments.

4. Results

Table 4 highlights the breakdown of sentiments about teaching style based on the feedback received from social media. The result of the analysis revealed that Flipped Classroom has the highest positive sentiment of 63.5% while the second highest sentiment is Project-Based Learning at 52.3% and the third is Hybrid Learning at 50.7%. This suggests that students indeed have a positive attitude towards such more engaging and flexible forms of teaching. On the other hand, Traditional Exam Based teaching received the lowest percentage of positive sentiment at 35.4 % which implies that the students may not be content with conventional teaching and learning methods. Lecture-Based Teaching and Online Learning had the lowest positive percentage sentiment scores at 45.6% and 40.2% respectively. Notably, the largest percentage of sentiments in the case of Online Learning was neutral (38.1%) and could be attributed to the fact that the students had positive feelings towards the flexibility of learning, but had negative sentiments concerning interaction. Among all the methods, Lecture-Based Teaching and Traditional Exam-Based methods recorded more negative sentiment where 24.2% and 19.6% respectively highlighted areas that were least satisfying to learners.

Table 4: Sentiment Distribution of Student Feedback

Teaching Style	Positive Sentiment (%)	Neutral Sentiment (%)	Negative Sentiment (%)	Total Posts Analyzed
Lecture-Based Teaching	45.6%	30.2%	24.2%	1,250
Project-Based Learning	52.3%	25.4%	22.3%	1,100

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

Flipped Classroom	63.5%	21.8%	14.7%	900
Online Learning	40.2%	38.1%	21.7%	950
Hybrid (Blended) Learning	50.7%	30.6%	18.7%	800
Traditional Exam-Based	35.4%	45.0%	19.6%	1,000

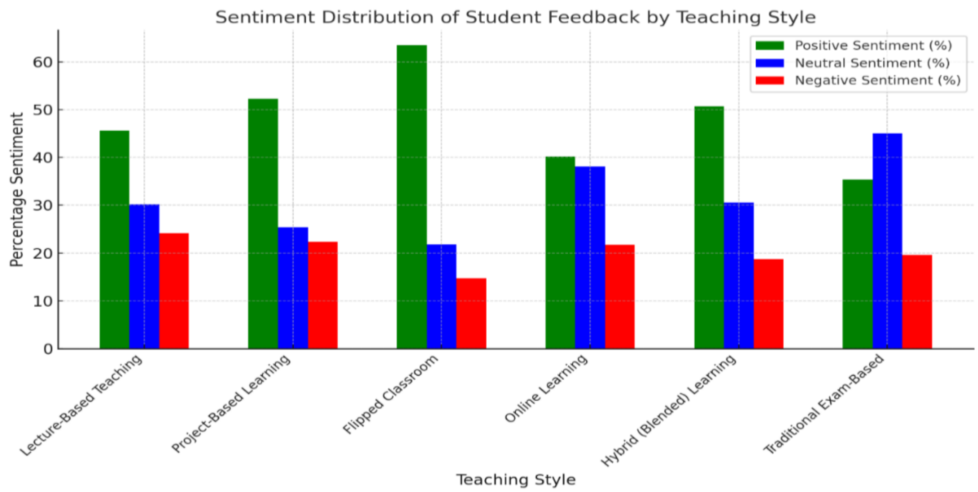

Figure 4. Sentiment Distribution of Student Feedback

Figure 4 presents the sentiment distribution of the teaching styles. The chart also shows that Flipped Classroom has the highest positive sentiment among the four types of classes and the lowest negative sentiment as well. On the other hand, Traditional Exam-Based teaching has the least skewed sentiment distribution with a great deal of neutral sentiments, although a slightly lower positive response.

Table 5 shows the analysis of positive and negative feedback words used by teachers with different teaching styles. In Lecture-Based Teaching, such words as “Clear”, “Organized” and “Helpful” show that students appreciate order and clarity. But words like ‘Boring’, and ‘Monotonous’ express dissatisfaction with the level of engagement. Project-based learning is described by positive adjectives such as “Hands-on” and “Practical,” while negative words like “Confusing” and “Chaotic” refer to difficulties in organization and direction. The terms used in Flipped Classroom are positive and its name suggests that students are active participants; Interactive, Empowering but the negative feedback are overwhelming and stressful. For Online Learning, words that reflect its nature include ‘convenient’ and ‘flexible’ while ‘isolated’ and ‘disconnected’ are from students’ experiences. Hybrid Learning is positively termed as “Balanced” and “Collaborative” but students express difficulties in clarity and interaction through terms like “Complicated” and “Lack of interaction.”

Table 5: Top 5 Most Common Words Associated with Positive and Negative Feedback

Teaching Style	Top 5 Positive Words	Top 5 Negative Words
Lecture-Based Teaching	"Clear", "Organized", "Helpful", "Structured", "Informative"	"Boring", "Monotonous", "Dry", "Dull", "Unengaging"
Project-Based Learning	"Hands-on", "Practical", "Engaging", "Real-world", "Collaborative"	"Confusing", "Lack of guidance", "Chaotic", "Stressful", "Time-consuming"
Flipped Classroom	"Interactive", "Engaging", "Self-paced", "Empowering", "Dynamic"	"Unprepared", "Difficult", "Overwhelming", "Stressful", "Confusing"
Online Learning	"Convenient", "Flexible", "Accessible", "Efficient", "Comfortable"	"Isolation", "Unclear instructions", "Disconnection", "Boring", "Difficult to concentrate"
Hybrid (Blended) Learning	"Balanced", "Flexible", "Collaborative", "Interactive", "Supportive"	"Complicated", "Unclear expectations", "Confusing", "Overwhelming", "Lack of interaction"

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

The overall average compound sentiment score of each teaching style is presented in Table 6 using the VADER sentiment analysis tool. The Flipped Classroom was the most positively viewed model of implementation, with an average score of 0.47. There was also positive feedback on Hybrid Learning (0.35) and Project-Based Learning (0.31). Lecture-Based Teaching (0.23) and Online Learning (0.18) received lower values indicating that the students have more neutral or mixed attitudes towards these methods. Traditional Exam-Based teaching, with a score of 0.10, is the lowest sentiment as is expected given its high negative sentiment and low satisfaction ratings in other tables.

Table 6: Average Sentiment Scores by Teaching Style

Teaching Style	Average Compound Sentiment Score
Lecture-Based Teaching	0.23
Project-Based Learning	0.31
Flipped Classroom	0.47
Online Learning	0.18
Hybrid (Blended) Learning	0.35
Traditional Exam-Based	0.10

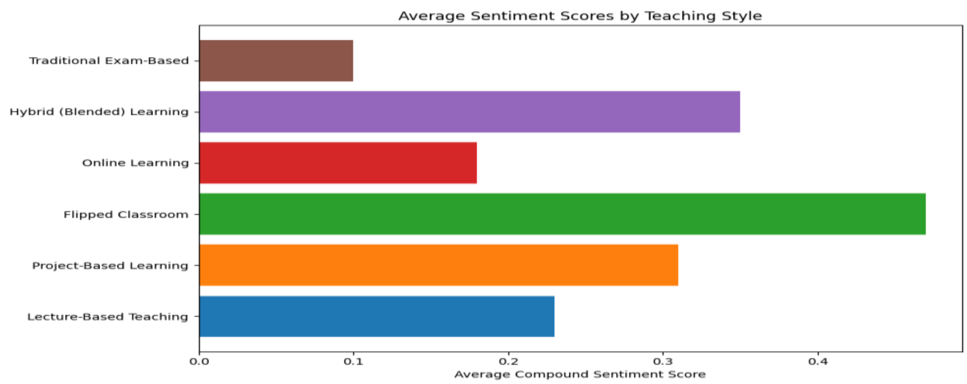

Figure 5. Average Sentiment Scores by Teaching Style

Figure 5 illustrates the average of the sentiment scores. As for the students' preferences, the Flipped Classroom is the most effective, and Hybrid Learning and Project-Based Learning are also more effective than Traditional Classroom Learning. At the same time, the Traditional Exam-Based approach occupies the lowest position, which indicates that students are less satisfied with this approach, which is more formal and focused on testing knowledge. Lecture-based and Online Learning methods have a relatively lower sentiment score which implies the need to enhance the students' satisfaction and engagement in the Lecture-Based and Online Learning methods.

Table 7 compares the sentiment collected from social media with the more structured feedback on teaching styles using the Likert scale. The Flipped Classroom is the least polarized in terms of social media sentiment (0.47) and formal assessment (4.2), with a difference of 0.3 per cent. The same is true for Project-Based Learning where there is a small difference between the social media sentiment score (0.31) and the formal assessment score (3.8) which is -1.2% different. On the other hand, Online Learning was comparatively high at 6.0% and shows that students have a formal evaluation of 3.0 on it as compared to what they posted on social media at 0.18. This may mean that students like the format of the formal surveys, but they are more detailed and even potentially more negative on social media. Hybrid Learning also had a 3.0% positive difference, which means that while having a higher score in the formal evaluation (4.0), it was slightly lower in social media feedback (0.35). Lecture-Based Teaching and Traditional Exam-Based methods show marginal negative differences of -2.8% and -4.0% respectively, which implies that these methods are considered less positive in formal assessment than on social media.

Table 7: Comparative Analysis of Formal Evaluation vs. Social Media Evaluation

Teaching Style	Social Media Sentiment (Avg. Compound Score)	Formal Evaluation Score (Likert Scale 1-5)	Difference (%)
Lecture-Based Teaching	0.23	3.2 (Neutral)	-2.8%
Project-Based Learning	0.31	3.8 (Positive)	-1.2%

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

Flipped Classroom	0.47	4.2 (Very Positive)	-0.3%
Online Learning	0.18	3.0 (Neutral)	+6.0%
Hybrid (Blended) Learning	0.35	4.0 (Positive)	+3.0%
Traditional Exam-Based	0.10	2.5 (Negative)	+4.0%

The results for the student satisfaction for each of the teaching styles are provided in Table 8 and Figure 6. The teaching method that got the highest satisfaction was Flipped Classroom with 68.0% satisfaction and 9.5% dissatisfaction proving why it is a preferred method of teaching. The level of satisfaction on Project-Based Learning and Hybrid Learning was also high with 55.3% and 53.5% of the students expressing satisfaction. However, both methods also received moderately positive responses with 25.1% for Project-Based Learning and 29.5% for Hybrid Learning, thus there is still a lot of room for improvement. Lecture-Based Teaching has 40.5% satisfaction level and 29.0% dissatisfaction level which shows that students have mixed feelings about the method. Online Learning is the least preferred teaching method with a 38.0% satisfaction level and a very high 42.0% neutrality. The worst effects are felt in the Traditional Exam-Based teaching method where 25.0% of the students had a positive attitude towards the teaching method, 25.0% had a negative attitude and 50.0% had a neutral attitude towards the teaching method.

Table 8: Comparison of Teaching Styles by Student Satisfaction

Teaching Style	**Satisfied (%)**	**Neutral (%)**	**Dissatisfied (%)**
Lecture-Based Teaching	40.5%	30.5%	29.0%
Project-Based Learning	55.3%	25.1%	19.6%
Flipped Classroom	68.0%	22.5%	9.5%
Online Learning	38.0%	42.0%	20.0%
Hybrid (Blended) Learning	53.5%	29.5%	17.0%
Traditional Exam-Based	25.0%	50.0%	25.0%

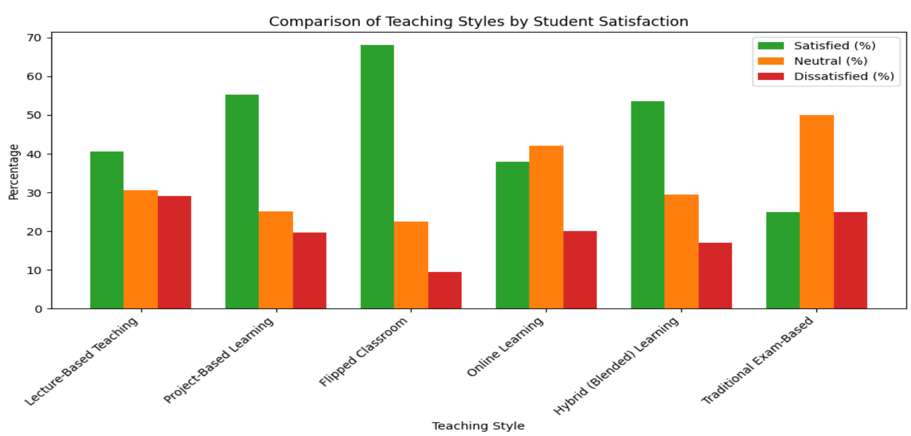

Figure 6. Comparison of Teaching Styles by Student Satisfaction

Figure 6 illustrates a comparative analysis of various teaching styles based on student satisfaction levels. The data represented in the figure highlights how different pedagogical approaches impact student engagement and contentment. Teaching styles such as lecture-based instruction, project-based learning, flipped classrooms, online learning, hybrid learning, and traditional exam-based methods are prominently featured.

Table 9 analyses monthly sentiment changes for various teaching methods from January to June. Flipped Classroom has the highest sentiment scores throughout the year, beginning with 0.44 in January and increasing to 0.50 in March. Project-based learning also exhibits consistent sentiment over time; it is at 0.28 in January and rises to 0.35 in March before slightly dropping in the following months. Hybrid Learning is also on the same trend, with the highest score of 0.40 in March and slightly declining in the following months. Lecture-based teaching also increases from 0.12 in January to 0.25 in March but still is one of the lowest-scoring approaches. Online Learning sentiment remains fairly constant and overall low, with a high of 0.19 in March. Traditional Exam-Based teaching is the least popular method throughout the period, as it always has the lowest score, rising only slightly from 0.07 in January to 0.12 in March.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

Table 9: Sentiment Trends Over Time (Monthly Analysis)

Month	Lecture-Based Teaching	Project-Based Learning	Flipped Classroom	Online Learning	Hybrid Learning	Traditional Exam-Based
January	0.12	0.28	0.44	0.15	0.32	0.07
February	0.20	0.32	0.48	0.18	0.36	0.10
March	0.25	0.35	0.50	0.19	0.40	0.12
April	0.23	0.33	0.45	0.17	0.37	0.09
May	0.18	0.31	0.46	0.19	0.34	0.08
June	0.21	0.30	0.42	0.16	0.35	0.10

Figure 7 represents the changes in student sentiment regarding each of the teaching styles presented in Table 9 over six months. The Flipped Classroom is again the most positively perceived teaching strategy having the highest sentiment value throughout the study. The sentiment of Project-Based Learning and Hybrid Learning also remains positive and is at its high in March, whereas Lecture-Based Teaching and Online Learning show less consistent sentiment, which indicates the level of satisfaction of the students. Traditional Exam-Based teaching continues to record the lowest sentiments throughout the entire six-month period. This figure underlines the shift of student attitude and at the same time, stresses the continuous popularity of the interactive and flexible teaching methodologies such as Flipped Classroom and Project-Based Learning.

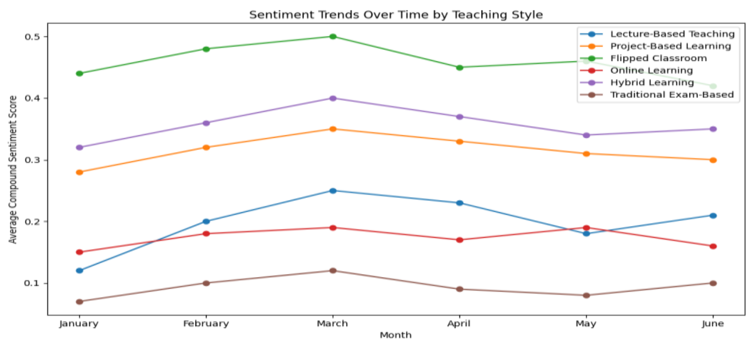

Figure 7. Sentiment Trends Over Time (Monthly Analysis)

Table 10 reveals an evaluation of the teaching style contrasted between the social media sentiment analysis and the formal feedback rating, which is determined by the effectiveness score (range 1-10). The Flipped Classroom method is the most effective with an efficiency score of 8.5, average social media sentiment of 0.47 and an average formal feedback of 4.2. This proves its high popularity and efficiency based on students' oral and written feedback. Hybrid Learning also has a high effectiveness score of 7.5; a moderate social media sentiment score of 0.35 and a formal feedback score of 4.0 showing that it is viewed as a moderate approach. Next on the list is Project-Based Learning with an effectiveness score of 7.0 The correlation between positive social media sentiment and the formal feedback rating is 0.31 and 3.8 respectively. Lecture-Based Teaching has been rated 5.5 and Online Learning has been rated 4.0 which indicates that these two modes of teaching have moderate to low effectiveness in terms of the gap between social media sentiment and formal feedback. Traditional Exam-Based teaching receives the lowest effectiveness rating, 3.5, with corresponding low social media sentiment, 0.10, and a negative formal feedback rating of 2.5.

Table 10: Teaching Style Effectiveness Based on Social Media Sentiment vs. Formal Feedback

Teaching Style	Social Media Sentiment (Avg.)	Formal Feedback Rating (1-5)	Effectiveness (Score 1-10)
Lecture-Based Teaching	0.23	3.2	5.5
Project-Based Learning	0.31	3.8	7.0
Flipped Classroom	0.47	4.2	8.5
Online Learning	0.18	3.0	4.0
Hybrid (Blended) Learning	0.35	4.0	7.5
Traditional Exam-Based	0.10	2.5	3.5

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

Table 11 shows the positive and negative feedback themes for each teaching style in order of frequency. In Lecture-Based Teaching, positive feedback incorporates characteristics like “clear” “structure” and “informative” and such formation conveys students’ appreciation of well-donor structure knowledge. Nevertheless, the negative aspects are characterized by ‘boring’, ‘monotonous’ and ‘unengaging’ suggesting the inertness of this method. Interesting asides of Project-Based Learning include the following as it is an effective practice, which is practical, creative, hands-on, collaborative, and real-life oriented. Nonetheless, negative perceptions such as ‘chaotic,’ ‘stressful,’ and ‘lacking direction’ can be problematic in as much as they speak of order and management. As is the case with all methods that allow the students to be involved in the learning process actively, Flipped Classroom is highly appreciated for being ‘self-paced’, ‘empowering’ and ‘interactive’. However, it can be “confusing,” “overwhelming,” and can even be “underprepared.” Online Learning gets appreciation for being “convenient,” “flexible,” and “easy to access,” but the complaints of “isolation,” “disconnection,” and “no engagement” show that lack of face-to-face interaction is an issue. Hybrid Learning is considered to be ‘moderate’, ‘engaging’ and ‘helpful’ while it can be ‘muddled’ and ‘overwhelming’ due to the vagueness of expectations. Finally, in the analysis of Traditional Exam-Based teaching, there is no notable positive feedback and thus only percentages of negativity were calculated as the main negative feedbacks were “unfair,” “stressful,” and “uninspired,” which focused on the inefficacy of this type of teaching and students’ discontent.

Table 11: Detailed Breakdown of Common Positive and Negative Feedback Themes

Teaching Style	Positive Feedback Themes	Negative Feedback Themes
Lecture-Based Teaching	Clear, structured, informative, organized	Boring, monotonous, unengaging
Project-Based Learning	Hands-on, collaborative, real-world, practical	Chaotic, stressful, lack of guidance
Flipped Classroom	Self-paced, empowering, interactive, dynamic	Confusing, overwhelming, lack of preparation
Online Learning	Convenient, flexible, accessible, efficient	Isolation, disconnection, lack of engagement
Hybrid (Blended) Learning	Balanced, interactive, supportive	Confusing, overwhelming, lack of clarity
Traditional Exam-Based	N/A	Unfair, stressful, uninspiring

5. Discussion

The results of the current study reveal an interesting tendency of students to embrace more active and participatory forms of learning delivery, with the Flipped Classroom approach being deemed highly positive with a sentiment score of 63.5%. Project-Based Learning ranked second while Hybrid Learning was ranked third with positive sentiment scores of 52.3 % and 50.7% respectively. At the bottom of the list was Traditional Exam-Based teaching which recorded only 35.4% positive sentiment. This comparison indicates that students may find less traditional approaches less satisfying, a situation seen in the current approaches to teaching. In addition, it is also realized that the sentiment score for the Online Learning and Lecture-Based Teaching paradigms are also relatively low, which indicates that these paradigms are not very effective and attractive to students, and thus require improvement. The qualitative analysis complemented these findings, and students adopted positive adjectives such as ‘Interactive’ and ‘Hands-on’ about the innovative teaching methods but negative emotions to the traditional teaching methods.

The implication of the result of this research is vital to educators and institutions that wish to enhance students’ interest and satisfaction. The more positive attitude towards the Flipped Classroom and Project-Based Learning models implies that these models could be more suitable for addressing the multiple needs of students. These methodologies might help institutions adopt active learning into their curricula, which may be of advantage to the institutions. Moreover, the study shows the need to solve the dissatisfaction problem of Lecture-Based Teaching and Traditional Exam-Based methods. Thus, the incorporation of the more student-centred approach which focuses on interactiveness and collaboration will improve learning processes and their results. The findings of this research may also inform further curriculum planning and teacher training initiatives to help prepare teachers for the use of best practices in teaching.

However, there are some limitations in this study which need to be noted down, Firstly, this study gives an understanding of the perception of students towards various teaching methodologies. The use of social media feedback may also bring some kind of bias, as the feedback provided is normally expressed online and may not express the

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

opinions of many students. Furthermore, while quantitative data obtained from sentiment analysis might provide a means to sampling the students' emotional states, the qualitative findings from those analyses might not be enough to support an analysis of the student's experience. Another weakness is the failure to take sex, age, major, or academic performance which are likely to affect perception and attitudes towards them into consideration. Further research should therefore be made to sample data from a larger group of students and from a broad cross-section to gain a broader perspective of students' views and experiences.

This research could be followed up in the future by further investigation of the factors that led to the generation of student sentiments towards different approaches to teaching. Just like in the current study, looking into demographic variables like age, the field of study, and prior experiences with various teaching methods would probably offer a clearer picture of sentiment. In addition, where student attitudes are the focus of research, then longitudinal research could follow changes in such attitudes over time, especially after some form of predisposing change like altering the teaching strategies or curriculum. It might also be useful to examine the extent to which the combined teaching–learning strategies can be adopted in various settings. Last, more elaborate research could encompass the results of quantitative learning outcomes in students together with the analysis of sentiments to fully understand the extent of the effects various teaching and mentoring styles have on academic performance. Such a multidimensional approach could shed light on best practices in didactics and could contribute to the further development of educational practices that focus on students' satisfaction.

6. Conclusion

This research systematically investigated students' attitudes toward different approaches to teaching using quantitative and qualitative assessments of social media comments. The results show that students have a rather positive perception of active and participative methods of learning, including the Flipped Classroom which scored the highest positive sentiment of 63.5%. The two methods that received the next closest positive sentiment scores were Project-Based Learning with 52.3% and Hybrid Learning with 50.7%. On the other hand, Traditional Exam-Based teaching was described negatively and the percentage of positive sentiment recorded was as low as 35.4 % which was an implication of a high level of dissatisfaction with traditional learning paradigms. The quantitative analysis, backed by the average compound sentiment scores, showed that the Flipped Classroom had the highest score of 0.47 while Traditional Exam-Based teaching had the lowest score of 0.10 only. These numerical metrics support the call for new teaching approaches which help capture students' attention and incorporate them into the learning process. On the same note, Online Learning and Lecture-Based Teaching were also rated lower in sentiment score (0.18 and 0.23, respectively), therefore, suggesting that there is room for improvement in these modes of teaching to contribute to student satisfaction. From the standpoint of sentiment analysis, the significance of words that are associated with sentiment analysis provided a qualitative understanding of the perception of students of the two teaching styles. Positive adjectives like "Interactive," "Hands-on," and "Empowering" were often used by students to describe the Flipped Classroom and Project-Based Learning, which demonstrated students' positive attitude towards the mentioned approaches. On the other hand, negative feedback was associated with loneliness and isolation in Online Learning as well as perceptions of boredom in Lecture-Based Teaching. This qualitative feedback helps to understand what aspects of these methodologies are interesting for students, and which ones need to be improved.

References

[1] Whiteside, A.L., Dikkers, A.G. and Swan, K. eds., 2023. Social presence in online learning: Multiple perspectives on practice and research. Taylor & Francis.

[2] Tess, P.A., 2013. The role of social media in higher education classes (real and virtual)–A literature review. Computers in human behavior, 29(5), pp. A60-A68.

[3] Elbagir, S. and Yang, J., 2019, March. Twitter sentiment analysis using natural language toolkit and VADER sentiment. In Proceedings of the international multiconference of engineers and computer scientists (Vol. 122, No. 16). sn.

[4] Cone, L., Brøgger, K., Berghmans, M., Decuypere, M., Förschler, A., Grimaldi, E., Hartong, S., Hillman, T., Ideland, M., Landri, P. and van de Oudeweetering, K., 2022. Pandemic Acceleration: Covid-19 and the emergency digitalization of European education. European Educational Research Journal, 21(5), pp.845-868.

[5] Daly, A.J., Moolenaar, N.M., Bolivar, J.M. and Burke, P., 2010. Relationships in reform: The role of teachers' social networks. Journal of educational administration, 48(3), pp.359-391.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

[6] Marzano, R.J., Pickering, D. and McTighe, J., 1993. Assessing student outcomes: Performance assessment using the dimensions of learning model. Association for Supervision and Curriculum Development, 1250 N. Pitt St., Alexandria, VA 22314 (Stock Number 611-93179, $13.95).

[7] Mujahid, M., Lee, E., Rustam, F., Washington, P.B., Ullah, S., Reshi, A.A. and Ashraf, I., 2021. Sentiment analysis and topic modeling on tweets about online education during COVID-19. Applied Sciences, 11(18), p.8438.

[8] Darling-Hammond, L., Friedlaender, D. and Snyder, J., 2014. Student-centered schools: Policy supports for closing the opportunity gap. Stanford Center for Opportunity Policy in Education, pp.1-12.

[9] Marshall, K., 2013. Rethinking teacher supervision and evaluation: How to work smart, build collaboration, and close the achievement gap. John Wiley & Sons.

[10] Bennett, R.E., 2011. Formative assessment: A critical review. Assessment in education: principles, policy & practice, 18(1), pp.5-25.

[11] Ortigosa, A., Martín, J.M. and Carro, R.M., 2014. Sentiment analysis in Facebook and its application to e-learning. Computers in human behavior, 31, pp.527-541.

[12] Doyle, T., 2023. Helping students learn in a learner-centered environment: A guide to facilitating learning in higher education. Taylor & Francis.

[13] Tishkovskaya, S. and Lancaster, G.A., 2012. Statistical education in the 21st century: A review of challenges, teaching innovations and strategies for reform. Journal of Statistics Education, 20(2).

[14] Alnaqbi NM, Fouda W. Exploring the role of ChatGPT and social media in enhancing student evaluation of teaching styles in higher education using neutrosophic sets. International Journal of Neutrosophic Science. 2023;20(4):181-90.

[15] Al Kharusi I. Students' Evaluation of Teaching (SET) for Improving Learning and Teaching Quality in HE: Students' and Teachers' Perspectives. Journal of World Englishes and Educational Practices. 2023 Dec 4;5(3):93-103.

[16] Keerthigha C, Singh S. The effect of teaching style and academic motivation on student evaluation of teaching: Insights from social cognition. Frontiers in Psychology. 2023 Jan 19;13:1107375.

[17] Ajmal M, Basit I, Sadaf S. Evaluating the Role of Students' Feedback in Enhancing Teaching Effectiveness. Pakistan Journal of Humanities and Social Sciences. 2024 May 27;12(2):1492-9.

[18] Oletti BL. Board 79: Leveraging Learning Styles for Enhanced Student Outcomes: A Study at a New York University. In2024 ASEE Annual Conference & Exposition 2024 Jun 23.

[19] Ahmed S, Zaki A, Bentley Y. Automated Evaluation Techniques and AI-Enhanced Methods. InUtilizing AI for Assessment, Grading, and Feedback in Higher Education 2024 (pp. 1-27). IGI Global.

[20] Neu S, Liu J. Utilizing Multiple Teaching Styles to Enhance Student Learning. Strategies. 2023 Nov 2;36(6):30-3.

[21] Byrne N, Cowley H, Speight S. How in-class electronic collection of student evaluations is providing teachers and managers with better information for the development of teaching. InEDULEARN19 Proceedings 2019 (pp. 755-764). IATED.

[22] Dimitriadou E, Lanitis A. An integrated framework for developing and evaluating an automated lecture style assessment system. arXiv preprint arXiv:2312.00201. 2023 Nov 30.

[23] Bhagat BP, Dhande-Dandge SS. A Literature Review on Sentiment Analysis Using Machine Learning in Education Domain. InProceedings of 3rd International Conference on Artificial Intelligence: Advances and Applications: ICAIAA 2022 2023 Apr 15 (pp. 191-207). Singapore: Springer Nature Singapore.

[24] Peña-Torres JA. Towards an improved of teaching practice using Sentiment Analysis in Student Evaluation. Ingeniería y Competitividad. 2024 Jun 20;26(2).

[25] Sweta S. The Transformative Role of Sentiment Analysis in Education. InSentiment Analysis and its Application in Educational Data Mining 2024 Apr 21 (pp. 47-60). Singapore: Springer Nature Singapore.

[26] Fan X, Zhang J, Yang M. A sentiment analysis model for electroencephalogram signals of students in universities using a convolutional neural network and support vector machine models. Journal of Mechanics in Medicine and Biology. 2023 Nov 13;23(09):2340086.

[27] Alkhodair SA. A SENTIMENT ANALYSIS-BASED SMARTPHONE APPLICATION TO CONTINUOUSLY ASSESS STUDENTS'FEEDBACK AND MONITOR THE QUALITY OF COURSES AND THE LEARNING EXPERIENCE IN EDUCATIONAL INSTITUTIONS. IJAEDU-International E-Journal of Advances in Education. 2023 May 4;9(25):15-26.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024

[28] Alkhodair SA. A SENTIMENT ANALYSIS-BASED SMARTPHONE APPLICATION TO CONTINUOUSLY ASSESS STUDENTS'FEEDBACK AND MONITOR THE QUALITY OF COURSES AND THE LEARNING EXPERIENCE IN EDUCATIONAL INSTITUTIONS. IJAEDU-International E-Journal of Advances in Education. 2023 May 4;9(25):15-26.

[29] Bhagat BP, Dhande-Dandge SS. A Comparison of Different Machine Learning Techniques for Sentiment Analysis in Education Domain. InInternational Conference on Communications and Cyber Physical Engineering 2018 2023 Mar 10 (pp. 441-450). Singapore: Springer Nature Singapore.

[30] Jimmy J, Prasetyo VR. Sentiment analysis on feedback of higher education teaching conduct: An empirical evaluation of methods. InAIP Conference Proceedings 2022 Apr 25 (Vol. 2470, No. 1). AIP Publishing.

[31] Sweta S. Sentiment Tech: Exploring the Tools Shaping Emotional Analysis. InSentiment Analysis and its Application in Educational Data Mining 2024 Apr 21 (pp. 61-78). Singapore: Springer Nature Singapore.

[32] Spatiotis N, Perikos I, Mporas I, Paraskevas M. Sentiment analysis of teachers using social information in educational platform environments. International Journal on Artificial Intelligence Tools. 2020 Mar 31;29(02):2040004.

[33] Chandrasekaran S, Dutt V, Vyas N, Kumar R. Student Sentiment Analysis Using Various Machine Learning Techniques. In2023 International Conference on Artificial Intelligence and Smart Communication (AISC) 2023 Jan 27 (pp. 104-107). IEEE.

[34] Mite-Baidal K, Delgado-Vera C, Solís-Avilés E, Espinoza AH, Ortiz-Zambrano J, Varela-Tapia E. Sentiment analysis in education domain: A systematic literature review. InInternational conference on technologies and innovation 2018 Oct 2 (pp. 285-297). Cham: Springer International Publishing.

[35] Menaha R, Dhanaranjani R, Rajalakshmi T, Yogarubini R. Student feedback mining system using sentiment analysis. IJCATR. 2017; 6:1-69.

[36] Tian X, Tang S, Zhu H, Xia D. Real-time sentiment analysis of students based on mini-Xception architecture for wisdom classroom. Concurrency and Computation: Practice and Experience. 2022 Sep 25;34(21): e7059.

[37] Efuwape TO, Abioye TE, Abdullah AK. Text Analytics of Opinion-Poll On Adoption of Digital Collaborative Tools for Academic Planning using Vader-Based Lexicon Sentiment Analysis. FUDMA JOURNAL OF SCIENCES. 2022 Mar 31;6(1):152-9.

DOI: https://doi.org/10.54216/FPA.170218
Received: February 04, 2024 Revised: May 05, 2024 Accepted: October 02, 2024