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Understanding student viewpoints: sentiment and thematic insights from course feedback

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ABSTRACT

This study addresses the challenge of interpreting qualitative student feedback from the course experience surveys (CES). Traditional feedback analysis is labor-intensive and not easily scalable. We combine sentiment and thematic analysis to enhance the depth of qualitative insights, uncovering deeper perspectives in student comments. The obtain, scrub, explore, model, and interpret (OSEMN) framework guided data collection, cleaning, exploration, and modeling. The analysis showed that over 70% of student feedback was positive, reflecting high satisfaction with educational experiences. Key findings included a long-tailed distribution of comment lengths, with shorter comments more prevalent. Interestingly, longer comments showed a weak negative correlation with sentiment scores, indicating that length does not necessarily reflect more positive or negative sentiment. Nuanced feedback patterns emerged; higher counts of positive words sometimes decreased sentiment scores, while negative words correlated positively, suggesting complex sentiment expression. We identified five primary themes, they are: i) educational engagement; ii) classroom dynamics; iii) appreciative learning; iv) educational excellence; and v) instructional effectiveness. The study underscores the value of student feedback in driving educational improvements and offers actionable insights for administrators. It demonstrates the potential of automated analysis to transform qualitative data into strategic enhancements, ultimately improving student outcomes and institutional effectiveness. Future research should examine the long-term impacts of feedback-driven interventions and strategies to increase survey engagement.

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1. INTRODUCTION

In the fast-paced world of higher education, University of Saint La Salle is constantly working to make the student learning experience better and to create a culture of academic excellence. A huge part of that effort is requiring students in the higher education unit (HEU) to rate the quality of teaching, their course experiences, and to give comments or feedback at the end of each semester using the course experience survey (CES). By gathering the students' feedback, the university can get a clearer picture of how students feel about their professors and course structures [1]. Feedback plays a crucial role in motivating students toward the desired outcomes [2], and it facilitates idea-sharing, problem-solving, and flexibility in response to challenges [3].

Traditional methods of interpreting student feedback are often labor-intensive and time-consuming [4], [5]. As a result, numerous studies have explored approaches to streamline the processing of such data. Researchers have proposed methods ranging from coding techniques to the integration of data visualization tools, all aimed at improving the efficiency and accuracy of qualitative analysis [6]. Natural language processing (NLP) has become popular recently because it can automate text analysis without the intensive manual effort traditionally required [7]. The rapid advancements in NLP have revolutionized various industries, including business and education [8]. Within higher education, NLP has become a valuable tool for extracting meaningful insights from unstructured textual data, such as student feedback, surveys, and course evaluations, providing institutions with actionable information to improve their pedagogical approaches and course offerings [9], [10]. Common NLP techniques include topic modeling and sentiment analysis [11]. Sentiment and thematic analysis are used to extract meaningful insights from textual data, using NLP and deep learning models. Sentiment analysis focuses on determining the polarity of text, often complemented by thematic analysis that identifies recurring themes in data [12]–[14]. Despite the growing adoption of NLP techniques in educational research, there is a notable gap in the literature regarding their specific application to process, evaluate, and interpret student comments through combined sentiment and thematic analysis. Recent studies have primarily focused on broader applications of NLP, such as analysis of discussion forums or assessment of social media interactions, without specifically extracting the polarity of feedback and uncovering key themes related to students' overall course experience [15]–[18].

While University of Saint La Salle traditionally gathers student feedback through CES, the potential of this resource often goes unutilized due to the complexity and volume of qualitative feedback. This study introduces a novel approach by integrating sentiment analysis with thematic analysis using NLP, addressing the scalability limitations of manual coding while enhancing qualitative insights. Unlike prior research that applies either thematic or sentiment analysis separately, our method analyzes student feedback by identifying key themes and quantifying sentiment at the individual comment level, uncovering complex patterns such as the relationship between comment length and sentiment of each comment. This combined sentiment-thematic lens for course feedback provides a more comprehensive understanding of student experiences, supporting university administrators and educators to interpret not just overall sentiment trends but also the nuances in how students express their feedback [19], leading to richer and more actionable insights.

2. LITERATURE REVIEW

There are several crucial points in comprehensive analysis of student feedback. Plante *et al*. [20] talked about a shift from traditional course evaluations to the digital one, and some challenges, such as frequency of gathering the response, non-response bias as well as perspectives provided in comments. Khokhlova and Lamba [21] discussed biases typical of the existing higher education due to which gender and cultural stereotypes have been rooted into students' evaluation of teaching. Such results call for the urgent removal of biases which affect academic systems. Martinez *et al*. [22] concluded that integrating quantitative performance indicators with qualitative insights from student interviews produced feedback that was more specific, timely, and relevant. A few researchers in recent years have presented various approaches for sentiment analysis like Aryal [23] and Pinargote-Ortega *et al*. [18]. We investigated in-class feedback, sentiment scores from courses' feedback, and development of a sentiment analysis for online learning. The articles by Cozoğlu and Aslanargun [24], and Santoso *et al*. [25] are a testament to how thematic analysis has been established within the research of education using multiple NLP methods to determine latent themes and trends. Finally, Capra-Ribeiro [26] and Muharam *et al*. [27] had provided perspectives about data visualization.

3. METHOD

This study used the obtain, scrub, explore, model, and interpret (OSEMN) framework for the research processes and the data analysis procedures. The framework is a methodology in data science that helps to direct the analyses of data [28]. The framework has 5 sequential processes, as depicted in Figure 1.

Figure 1. The OSEMN framework

3.1. Obtain (data collection)

Data collection commenced upon obtaining ethics approval from the Research Ethics Review Committee (RERC) to comply with ethical requirements. The primary data for this study is the unstructured textual data from students' comments from the College of Engineering and Technology (CET) for academic years 2021-2022, 2022-2023, and 2023-2024. The study's limitations include potential biases in student comments and the ability of NLP to detect nuances like sarcasm and ambiguity [29]–[32]. The exclusion of non-English languages such as Hiligaynon and Filipino limits its comprehensiveness.

3.2. Scrub (data preparation and cleaning)

Data preparation and cleaning are essential in any data analysis process to ensure the data's accuracy, consistency, and reliability [33], [34]. We simplified the dataset by reading it into a data frame using Python and Pandas [35], and then identified and removed columns that lacked data. To prevent any potential bias and protect privacy, named entities recognized as "PERSON", "ORG", "GPE", and "MONEY" were removed from the student comments. All emojis, unicode errors, and line breaks were also removed to standardize the text format. We then converted the text to lowercase to ensure consistency throughout the dataset and streamline subsequent processing. We stripped URLs, email addresses, and phone numbers from the comments to concentrate solely on the textual content.

Data was further refined wherein common stop words and punctuation marks were removed in order to increase the relevance and accuracy of the textual analysis being done. Non-alphabetic characters were also removed to include only alphabets of meaning that could contribute toward a linguistic analysis. In the case of empty values in the comment's column, imputation methods had been used in order to maintain the integrity of the dataset. Lastly, duplicate comments were removed to ascertain that each piece of data contributed uniquely to the different insights that would be derived from the analysis that will be performed on the next stage.

3.3. Explore (data analysis)

We examined the cleaned data to gain insights and identify recurring patterns and trends by aggregating it based on specific features. Graphical representation of data allows us to explore and see things from another perspective which can be challenging when it is in a tabular form [36]. In exploratory data analysis, we found outliers, correlations, and other associations between variables [37]. We also counted the unique values across different variables to identify potential data duplications or missing values. We then used descriptive statistics to describe the data and insights about its distribution and central tendency [38].

3.4. Model

We further refined the data by converting it into a string data type and then segmented it into individual words or tokens. We then applied lemmatization to normalize the words to their base forms to reduce lexical variances and to improve the dataset's consistency [39]. We then employed sentiment analysis using spacytextblob to generate sentiment ratings for each comment and classify it as either positive, negative, or neutral. The next step was to compute the coherence scores to determine the optimal number of topics. Using a latent dirichlet allocation (LDA) model, each word in the students' comment is probabilistically assigned to a topic. The model then iterates over each word, reassigning it based on its prevalence and frequency until it reaches a steady state where it assigns words to topics accurately. The model also assigned a weight to each word in a topic, signifying its importance.

3.5. Interpret

The last stage of the OSEMN framework is significant for turning analysis results into practical recommendations. This entails conveying findings, formulating conclusions, and recognizing constraints. It also involves not only recognizing practical implications of the results but also providing insights that can guide strategic decisions.

4. RESULTS AND DISCUSSION

The dataset is a multivariate dataset formatted as a CSV file with 32,352 rows and 5 features: academic year, semester, year, program, and comment. The unique values for each feature are: 2021-2022, 2022-2023, and 2023-2024 for the academic year; 1 and 2 for the semester; 1, 2, 3, 4, and 5 for the year; Bachelor of Science in Computer Science (BSCS), Bachelor of Science in Entertainment and Multimedia Computing (BSEM), Bachelor of Science in Food Technology (BSFT), Bachelor of Science in Information Technology (BSIT), Bachelor of Science in Computer Engineering (ENCE), Bachelor of Science IN Chemical Engineering (ENCH), Bachelor of Science in Electronics Engineering (ENEC), Bachelor of Science in Electrical Engineering (ENEE), and Bachelor of Science in Materials Engineering (ENME) for the program. There are 11,884 unique values for the comment column. After extensive data cleansing, the overall number of comments was reduced to 11,598 or by 35.85%. The decrease in data can be mainly ascribed to the discovery and elimination of irrelevant columns, stop words, and instances of missing or invalid data [40], [41]. In particular, the cleaning process led to differences in the number of comments for each semester within an academic year.

Figure 2 illustrates the dispersion of distinct comment lengths and their corresponding relative frequencies, with a notable characteristic being its long-tailed distribution. There is a high relative frequency of very short comments, with the most instances (166 occurrences) found in comments consisting of only one word. As the length of the comment increases, the frequency reduces significantly, resulting in a long tail in the distribution [42]. The plot indicates that most comments are concise, with a notable drop in frequency after approximately 50 words. Nevertheless, there are still a few occurrences of far longer comments, with the longest comment consisting of 514 words, albeit only appearing once. The shape of the distribution indicates that although most comments are brief, a significant portion of comments are longer and more elaborate. This could be attributed to the students' communication styles or the context in which the comments were provided [43], [44]. It is important to note that these measures provide a quantitative overview of the comment lengths but do not reveal the qualitative aspects of the responses. Therefore, sentiment analysis and topic modeling will be conducted subsequently to gain deeper insights into the substance of the comments.

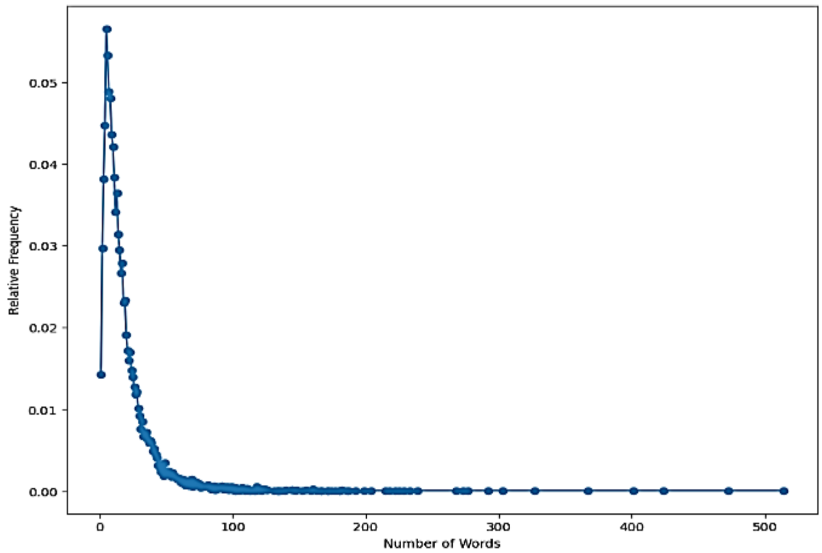

Figure 2. Relative frequency of unique comment word lengths

As shown in Figure 3, there is a notable inclination towards positive sentiment, with 8,159 comments classified as positive, or 70.348%. The vast majority of comments, which are favorable, optimistic, or satisfactory, indicate an overall positive tone and attitude [45] expressed by the students. In contrast, the proportion of negative sentiment is relatively minimal, just 975 out of the total comments, or 8.406%, suggesting a smaller quantity of comments expressing dissatisfaction, criticism, or negative sentiments. 2,464 of the comments, or 21.245%, are considered neutral, indicating that they do not have a distinct emotional tone or objective views [46]. Although most comments in CES are favorable, the inclusion of neutral and negative remarks suggests that a variety of opinions and experiences are being captured [47]. This provides a well-rounded view and significant insights.

Looking at Figure 4, it is apparent that the variability in the data, especially in programs with a wider interquartile range (IQR) like BSIT, underscores the presence of diverse student experiences and opinions within these programs. In general, students have a predominantly positive sentiment. The BSIT program is particularly noteworthy for having the highest median sentiment score of 0.25 and an IQR that extends to 0.5. This indicates a positive consensus and the most considerable difference in opinions among all the programs. In contrast, the ENEC demonstrates the lowest median sentiment, measuring at 0.18, indicating a more subdued expression of positive sentiment. Furthermore, except for BSFT and ENCH, all programs have their first quartile (Q1) anchored at 0, indicating a lack of significant negative sentiments.

The outliers observed in the BSCS, BSEM, BSIT, ENCE, and ENEC programs suggest extreme sentiments deviating from the general trend. However, these outliers are relatively few and do not significantly impact the overall positive sentiment.

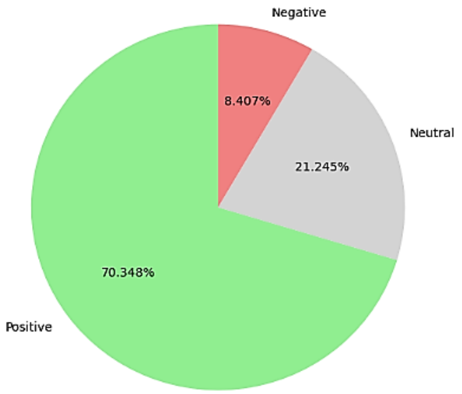

Figure 3. Overall sentiment distribution (%)

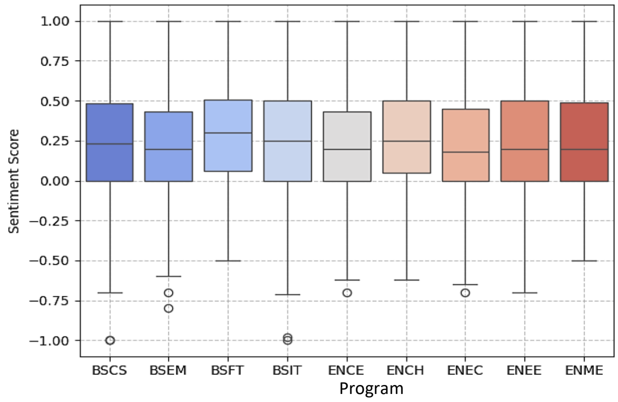

Figure 4. Distribution of sentiment scores per program

The frequency of the top ten positive words utilized in student comments is illustrated in Figure 5. The word "very" is the most prevalent, appearing 2,035 times. This indicates that students often emphasized positive statements. With 1,340 occurrences, "good" ranks second and may suggest a general sense of contentment with certain facets of the academic experience. The third most frequent word, "more", with 1,064 instances, may indicate that students are seeking a continuation of the positive attributes they have already experienced. The usage of "great" and "really" (631 and 718, respectively) reinforces the positive sentiment. The frequency of occurrences of "best", "fun", and "able", spanning from 496 to 356, indicates the positive perception of specific aspects of the student experience. Finally, "easy" and "clearly", which appear in 326 and 328 instances, may indicate that students have a favorable opinion of the clarity of the instruction and course material.

Figure 6 depicts the frequencies of the top ten negative words derived from student comments, which may indicate concerns or difficulties. The word "subject" is mentioned 857 times, suggesting frequent conversations about specific topics or curricular content. The words "hard" and "difficult" are mentioned 311 and 138 times, respectively, indicating that a significant number of the comments are related to the rigor or difficulty of the coursework. Occurrences of words such as "not", "due", and "little", ranging from 179 to 127, may be associated with different aspects of academic stress, such as meeting deadlines ("due") or inadequacy in specific contexts ("not" and "little"). The adverb "very" can intensify other adjectives, indicating a high level of intensity in the students' experiences [48], regardless of whether they are positive or negative. The words "late" and "less", with frequencies of 87 and 64, respectively, may indicate challenges related to time management or the quantity of coursework.

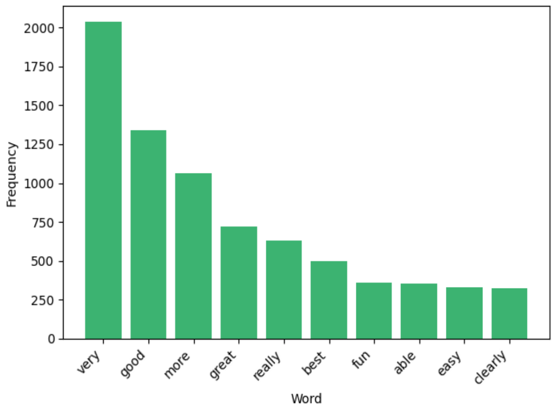

Figure 5. Top ten positive words

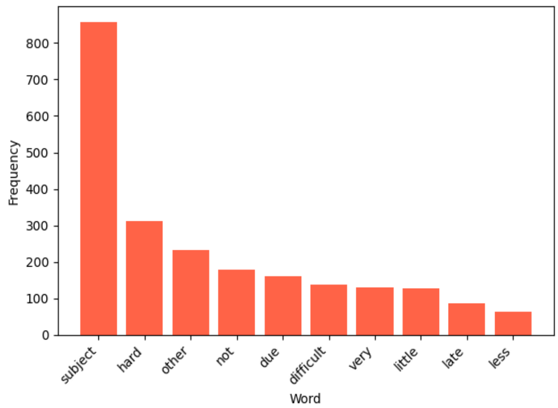

Figure 6. Top ten negative words

Figure 7 reveals the relationships among comment length, sentiment score, and the counts of positive and negative words in student comments. Comment length has a weak negative correlation with sentiment score (-0.12) and positive words (-0.14), suggesting that longer comments are not necessarily more positive [49]. Similarly, Guzsvinecz and Szűcs [50] observed that negative reviews tend to be longer than positive reviews. A stronger negative correlation (-0.48) between positive words and sentiment scores suggests that sentiment scores decrease as the count of positive words increases. This pattern may indicate that students often use more positive language to offset or balance comments that include criticism or mixed feelings. Contrary to typical expectations, negative words exhibit a positive correlation (0.36) with sentiment scores, suggesting their potential use in nuanced contexts that do not strictly convey negative sentiments. Additionally, a moderate negative correlation (-0.32) between negative words and comment length suggests that longer comments tend to have fewer negative words.

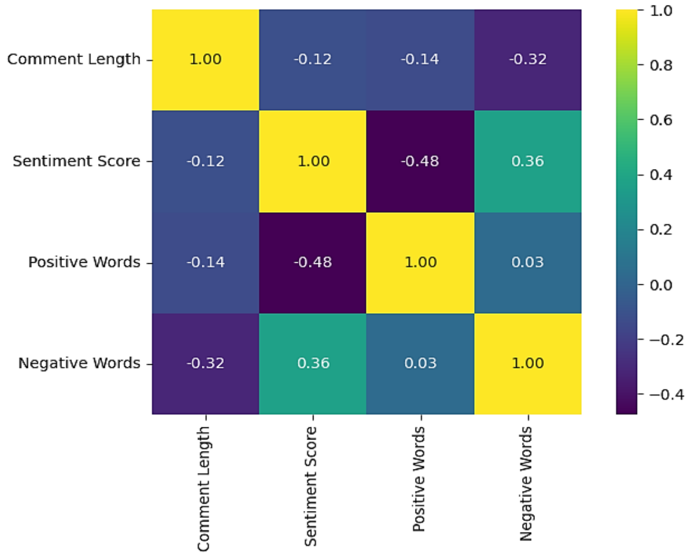

Figure 7. Correlation heatmap

Figure 8 illustrates the frequency of the top ten bigrams derived from student comments. The bigram "good teacher" is the most frequently occurring, with 452 instances. This suggests that students frequently provide favorable feedback regarding the high standard of teaching. The bigram "great teacher" appears 298 times, while "learned lot" appears 257 times. These frequent occurrences suggest that teaching is perceived as effective and that a significant amount of learning is taking place. The bigrams "understand lesson" and "thank sir" indicate that students appreciate their teachers and solidly comprehend the lessons. The recurring theme of satisfaction with lesson delivery is evident, with "lesson well" and "good teaching" also mentioned. The occurrence of the bigrams "best teacher" and "teacher good" strengthens the positive emotion toward teachers. Additionally, the bigram "easy understand" suggests the students appreciate the clarity of instruction. The bigrams demonstrate a favorable correlation between the teachers and the learning process, as evidenced by the students' comments.

Figure 9 presents the frequency of the top ten trigrams. The phrase "keep good work" has been identified 127 times, indicating high support and gratitude for the teachers' effort and performance. The trigram "one best teacher", appearing 60 times, and "sir good teacher", with 50 instances, indicate a strong admiration for teachers, potentially ascribing their expertise and admirable character traits. The phrases "explains lesson well" and "understands lesson well" were mentioned 40 and 36 times, respectively, highlighting the importance of explicit instruction and efficient communication in lessons. Expressions of appreciation such as "good work sir" and "sir great teacher" express admiration and esteem for teachers. The phrase "always make sure" suggests a commitment to thoroughness and consistency in the educational approach. In contrast, the phrase "teachers teach well" supports the positive emotion regarding the effectiveness of teaching methods. Finally, the fact that "learned a lot of subjects" is mentioned 34 times highlights a successful attainment of knowledge in particular areas. These trigrams emphasize a positive educational experience, with a distinct emphasis on the excellence of teaching and the achievements in learning as perceived by the students.

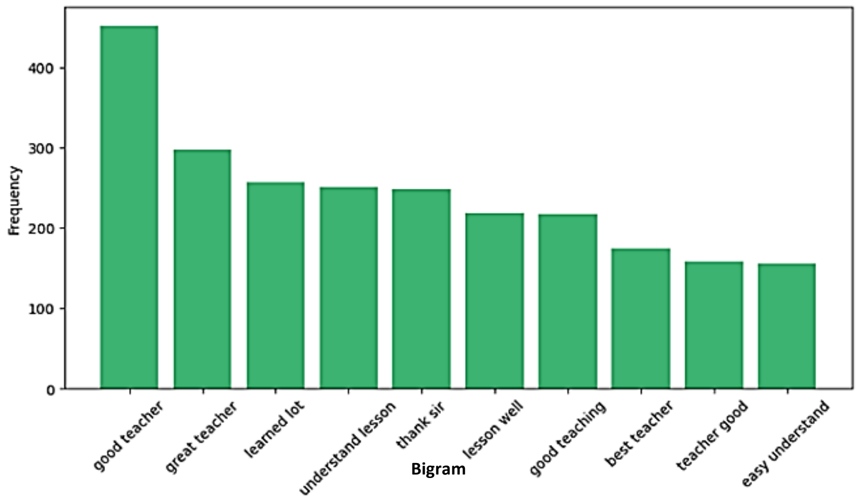

Figure 8. Top ten bigrams

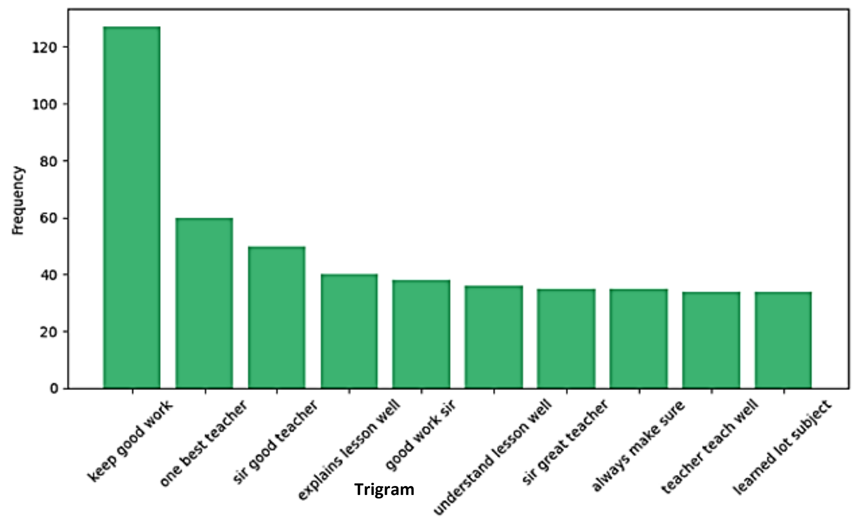

Figure 9. Top ten trigrams

The word cloud in Figure 10 identifies dominant themes by displaying frequently occurring terms in larger font sizes. This allows for an easy, at-a-glance summary of key terms [51] like “teacher”, “lesson”, and “student” indicate that these are the main themes in the comments. The terms “good” and “well” signifies positive sentiments, whereas the words “understand”, “learning”, and “teaching” underscore the emphasis on the educational process. Expressions of respect and appreciation, such as “sir” and “thank”, indicate a favorable relationship and gratitude towards teachers. Terms such as “hard”, “clearly”, “easy”, and “time” might indicate students’ subjective evaluations of the level of difficulty and comprehensibility of the course. The inclusion of terms such as “activity”, “discussion”, and “module” implies that particular elements of the curriculum are often covered.

The LDA model was employed to iteratively refine the allocation of words to topics, which serve as underlying themes in the student comments. The significance of each word to a topic is measured by its weight within that topic. To determine the optimal number of topics, we aimed to discover the highest coherence score among many potential topics. Coherence scores determine the degree of semantic similarity among the most significant terms within each topic, with higher scores suggesting more logically connected and cohesive topics [52]. Figure 11 reflects the coherence scores in C_v for different numbers of topics employed in LDA modeling. An initial increase in coherence can be observed as the number of topics increases from 2 to 5. This indicates that a more significant number of topics might be more effective in capturing the underlying structure of the data up to this point. Significantly, there is a prominent spike at 5 topics, where the coherence score reaches its highest point, indicating that this is the ideal number of topics for the model. Once 5 topics were surpassed, a significant decline in coherence at six topics can be seen, followed by a fluctuating drop. This drop indicates that the inclusion of more than 5 topics may result in separating semantically related words into distinct topics, hence diminishing the overall coherence of the model [53].

Figure 10. Word cloud

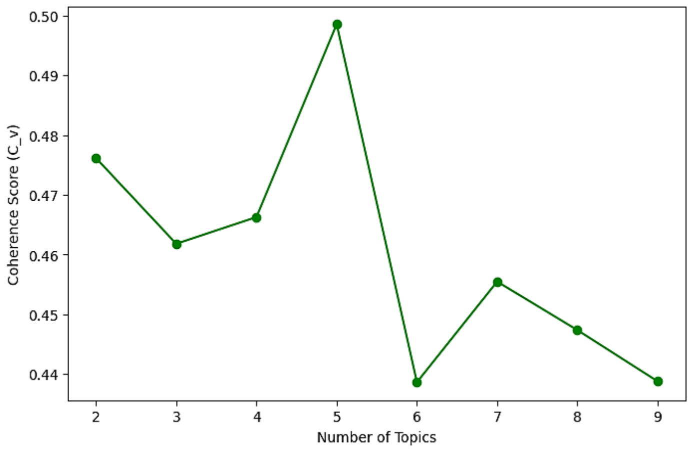

Figure 11. Coherence scores by number of topics

The provided words were categorized into groups based on their topic, considering their similarities and probabilities. An analysis was conducted on the words associated with each topic to identify and uncover hidden or latent themes. The 5 distinct latent themes associated with specific commonly occurring words were discovered are presented in Table 1, each reflecting different facets of the educational process. The first theme emphasizes the dynamic interactions between instructors and students, highlighting both the practical activities and the cognitive and emotional outcomes of education. The second theme focuses on the functional aspects of classroom settings, including the roles of teachers and students, operational elements like time management, and affective responses to teaching. Underscoring the depth of learning and the emphasis on specific subjects within the curriculum, the third theme explores respect and gratitude towards educators. The fourth theme advocates for high-quality education and continuous improvements in teaching and learning, emphasizing positive interactions and the need to address specific educational needs. Lastly, the fifth theme focuses on education delivery, teaching methods effectiveness, and educational assessment outcomes, highlighting a commitment to pedagogical excellence and improvement.

Table 1. Word distribution per topic with latent themes

Topic 1 Educational engagement	Topic 2 Classroom dynamics	Topic 3 Appreciative learning	Topic 4 Educational excellence	Topic 5 Instructional effectiveness
Teach	Class	Learn	Teacher	Teacher
Student	Time	Sir	Good	Lesson
Hope	Give	Understand	Student	Student
Class	Teacher	Lot	Subject	Teaching
Activity	Student	Make	Question	Think
Know	Lesson	Lesson	Time	Good
Lesson	Understand	Teacher	Need	Improve
Understand	Like	Thank	Great	Explain
Sir	Topic	Subject	Improvement	Give
Subject	Activity	Especially	Work	Grade

The significance of different words in each topic can be seen in Figure 12. A bar represents each word, with the height of the bar indicating the word's importance. The most prominent word in Topic 1 is "teach" which points to conversations regarding teaching strategies; in Topic 2, it is "class" which suggests that the topic is centered on classroom experiences or settings; in Topic 3, it is "learn" which strongly emphasize the learning process or outcomes; in Topic 4, it is "teacher" which indicates meaningful discussions on teacher performance or characteristics; and in Topic 5, it is once again "teacher" which highlights its significance in student feedback. The weights assigned to the words, such as 0.066 for "teach" in Topic 1 and 0.093 for “teacher” in Topic 4, represent the degree of correlation between the words and their respective topics. These numbers imply a substantial level of relevance [53]. The words with the lowest weights, such as “subject” in Topic 1 and “work” in Topic 4, indicate that they are less central despite being significant in the context of their respective topics.

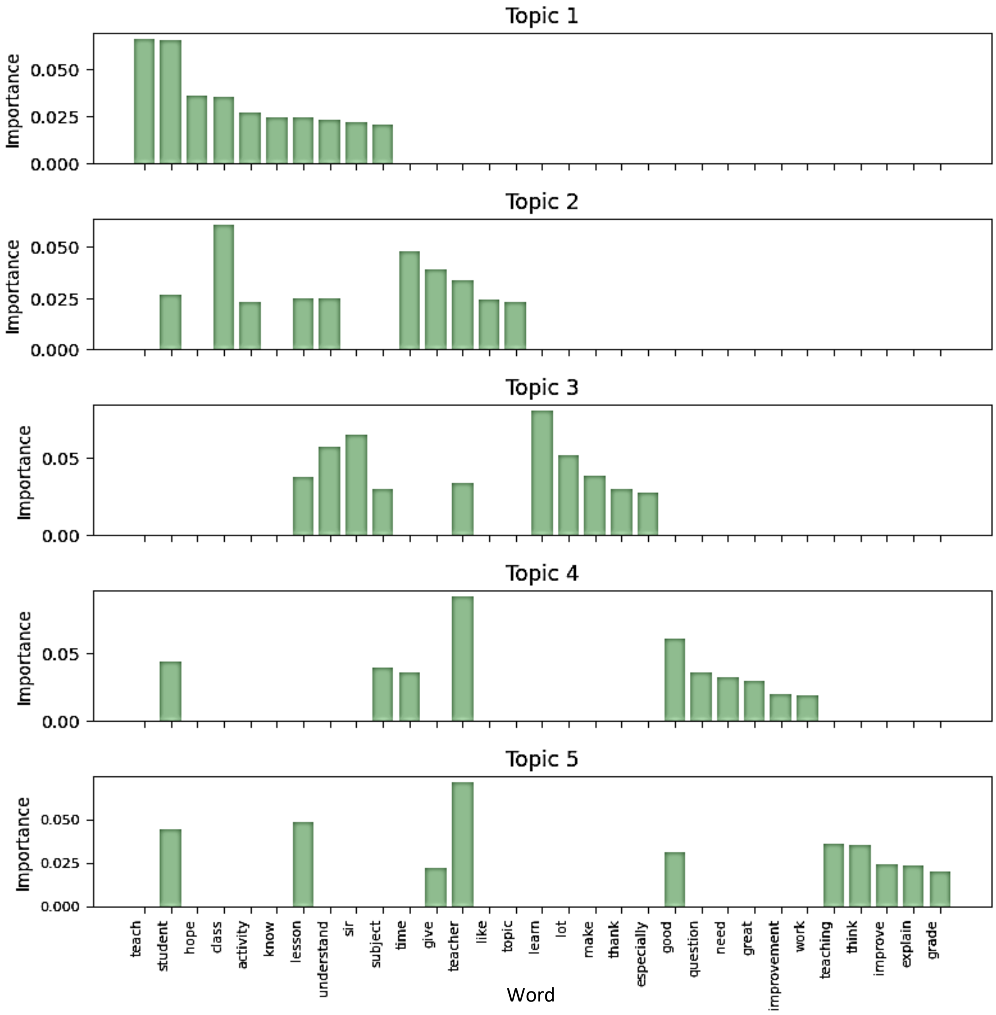

Figure 12. Word importance per topic

For each identified topic, there is a dominant comment that significantly embodies the theme. The contribution percentage of this comment is quite close to 100%, ranging from 99.67% to 99.78%. The high percentage indicates a good correlation between each comment and its respective topic, suggesting that the dominant comment is mainly representative of the topic’s content in the dataset. This implies that each topic in this analysis has a specific comment that effectively communicates the main sentiment.

According to the results reported here, sentiment analysis revealed that a substantial 70.348% of comments were positive, while 8.406% were negative, and 21.245% were neutral, capturing a broad spectrum of student opinions. Comment length showed a long-tailed distribution, with short comments being more common. Across different programs, positive sentiment was dominant, with variations indicating diverse student experiences; notably, the BSIT program had the highest median sentiment. Word frequency analysis highlighted that positive words such as “very”, “good”, and “more” suggested overall satisfaction, whereas negative terms like “subject” and “hard” pointed to challenges related to the curriculum. Correlation analysis found that longer comments did not necessarily align with higher positivity or negativity; in fact, there was a weak negative correlation between comment length and sentiment score. The count of positive words sometimes decreased sentiment scores, hinting at nuanced feedback from students, while negative words correlated positively with sentiment scores, indicating complex expressions of students’ sentiment.

Further insights were gleaned from LDA topic modeling, which uncovered 5 latent themes: educational engagement, classroom dynamics, appreciative learning, educational excellence, and instructional effectiveness. These themes emphasized the significance of teaching quality, classroom interactions, and efforts for continuous improvement. Visualizations, including word clouds, bigrams, and trigrams, underscored students' appreciation of teaching and the learning experience, frequently expressing respect and gratitude toward their professors. The analysis provided a comprehensive understanding of student feedback, highlighting both strengths and areas for enhancement in educational delivery.

5. CONCLUSION

The sentiment analysis revealed a predominantly positive tone within student comments, with a significant majority expressing favorable sentiments while only a tiny portion reflected negative sentiments. The higher volume of positive feedback reflects student satisfaction with various aspects of their course experience, which is a favorable indicator for the educational institution. The analysis of student comments has revealed significant relationships between commonly used words, pointing to interlinked themes of teaching quality, classroom engagement, and course content. Thematic analysis using LDA identified key themes. Interestingly, the analysis revealed an overwhelmingly dominant comment for each topic, nearly singular in representing the essence of that topic's content. This result points to a potential concentration of sentiment within a few articulate and pivotal pieces of feedback.

The findings suggest that students view their academic experience positively, particularly regarding teaching quality and classroom engagement. This can affect the university and its faculty by reinforcing the importance of interactive and engaging teaching methods and may influence future pedagogical strategies. For students, the findings validate the importance of their feedback in shaping their educational environment.

Drawing from the study's insights, it is recommended that the university should bolster support during the pivotal first semester and maintain feedback mechanisms throughout students' academic tenure, paying particular attention to courses flagged as challenging. Recognition programs for faculty receiving positive evaluations could incentivize high-quality teaching, while detailed scrutiny of negative feedback can guide improvements in the curriculum and support services. Programs with low engagement in CES require strategies to increase feedback. Future research should include longitudinal studies to monitor the impact of such interventions over time, continually adapting to enhance the educational landscape.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

We have carefully evaluated any potential conflicts whether financial, personal, or professional. We have also considered non-financial interests such as political, religious, ideological, academic, and intellectual factors. After thorough assessment, we declare that we have no known competing interests or personal relationships that might have influenced the research reported in this paper.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author, [NB], upon reasonable request. Because these data contain information that could compromise participant privacy, they are not publicly available. Any requests for access will be assessed on a case-by-case basis to uphold confidentiality.

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