Revealing the Hidden Curriculum: Analyzing Emotional Responses Using Advanced Computational Sentiment Analysis Techniques

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Abstract— **This innovative practice full paper analyzed over 900 responses related to awareness of the hidden curriculum to explore the relationships between expressed emotions among students and faculty members. The hidden curriculum refers to the implicit values, behaviors, and norms that are not formally included in educational programs but are learned through the social and cultural environment of an institution. Using both emotional and demographic data collected from a larger national survey of engineering educators and students across the U.S., we examined correlations between participants' responses and the sentiment classifications observed.**

Our analysis employed two distinct tools: VADER for sentiment analysis and a pre-trained Recurrent Neural Network (RNN) model capable of classifying six specific emotions. Through detailed analysis and comparison, we uncovered significant insights into the emotional dynamics within engineering education. Overall, we found a predominance of positive sentiment, with "joy" emerging as the most frequently expressed emotion among both students and faculty. However, we also identified nuanced variations in emotional expression, influenced by factors such as gender, engineering disciplines, and the sentiment analysis methods employed.

These findings contribute to the ongoing discourse on the hidden curriculum's impact on emotional experiences, emphasizing the importance of considering both sentiment and distinct emotional states in educational research and practice. By providing a deeper understanding of emotional patterns, this research offers valuable perspectives on how emotions shape the educational experience in engineering.

Keywords—NLP, Hidden Curriculum, Sentiment analysis, Data Correlation, Survey, Emotion, Faculty Attitudes.

I. INTRODUCTION

the concealed aspects of knowledge acquisition [1]. At its core, education is often portrayed through formal instruction, characterized by meticulously crafted lesson plans, standardized assessments, and clearly defined learning objectives [1] , [2]. These elements constitute the overt curriculum, which educators and students engage with directly. However, beneath this seemingly straightforward educational façade lies a clandestine world of subtleties, intricacies, and unspoken lessons that quietly but profoundly shape the educational experience. This concealed realm, often referred to as the "hidden curriculum", comprises a complex web of unwritten rules, cultural norms, and implicit values that operate as the unseen forces guiding the educational voyage [1] , [2] .

Emotions have long played an integral role in the learning process, subtly weaving their threads into the tapestry of educational experiences [3], [4], [5]. As individuals engage with academic content, their emotional states can oscillate from curiosity and enthusiasm to frustration and confusion [4] . These emotions, often transient and ephemeral, are not mere byproducts of learning but are intrinsically intertwined with cognitive processes, memory formation, and overall engagement with educational materials [3], [4]. Understanding these emotional nuances is critical, as they can profoundly impact the effectiveness of pedagogical strategies and the ultimate success of learners. Hence, in our investigation, we delve into the emotional spectrum of those traversing the landscape of the hidden curriculum (HC), uncovering the sentiments that may be stirred by this enigmatic realm.

This paper embarks on an exploration that transcends traditional pedagogical boundaries. In our pursuit, we venture into the intersection of emotional states and the hidden curriculum, wielding the power of cutting-edge computational sentiment analysis techniques to unearth the sentiments that lie beneath the surface. Our research seeks to reveal the emotional responses provoked by the hidden curriculum, providing a unique perspective that can enhance our comprehension of its impact on learners, educators, and the broader educational community. In doing so, the idea is to not only decipher the emotional terrain of education but also to shed light on the often-concealed aspects of the educational landscape, fostering a deeper understanding that can drive positive change in pedagogical practices and curricular design

A. Traditional methods to explore emotion

In the ever-evolving landscape of education, the study of emotions has been guided by a diverse array of traditional methods, each offering unique insights into the intricate tapestry of emotional experiences within educational settings. From the familiar territory of surveys and questionnaires that tease out self-reported feelings to the keen eye of observational techniques that decipher non-verbal cues, such as body language and facial expressions, researchers have embarked on journeys into the emotional realm of learners. Qualitative interviews have delved deeper into the complexities of emotions, allowing for rich narratives and nuances to emerge, while content analysis has dissected the language students use to express their feelings. Even physiological measures, though less common due to their invasive nature, have probed the physiological responses underpinning emotions. Behavioral assessments and diary studies have painted real-time portraits of emotional evolution, while focus groups have facilitated collective exploration, revealing shared emotional themes. Standardized tools have honed in on specific emotional constructs, while controlled experiments have illuminated the impact of variables on students' emotional responses. These time-tested methods, supplemented by modern technological advances, continue to illuminate the profound role of emotions in shaping the educational experience, offering a deeper understanding of the human dimension of learning.

B. Computational Sentiment Analysis

Computational sentiment analysis, a subset of Natural Language Processing (NLP) [6], [7], plays a vital role in various fields, including marketing, customer service, social media analysis, and education [8]. Its primary function is to automatically assess and understand the sentiment or emotional tone expressed in text data, such as reviews, comments, or social media posts [6], [8]. In recent years, the utilization of NLP has surged to the forefront of technological advancements, fundamentally transforming the way we process and derive meaningful insights from text data. NLP [8], a branch of artificial intelligence, focuses on the interaction between computers and human language, enabling machines to understand, interpret, and generate human language in a way that is both valuable and contextually relevant [7], [8], [9].

Implementing sentiment analysis with NLP involves a range of approaches and techniques tailored to the complexity of language and the nuances of human emotions [7]. Sentiment labels can be binary (positive/negative), multi-class (e.g., positive/neutral/negative), or fine-grained (e.g., very positive, slightly positive) [10]. Among some of the primary approaches used in sentiment analysis, the two most popular ones are Lexicon-based and Machine Learning approaches [8], [11].

C. Lexicon-based methods

Lexicon-based methods rely on sentiment lexicons or dictionaries containing pre-defined sentiment scores for words or phrases [6]. These scores typically range from highly negative to highly positive. The sentiment of a text is determined by aggregating the sentiment scores of its constituent words or phrases. Popular lexicons include the Valence Aware Dictionary sEntiment Reasoner (VADER) and the AFINN lexicon [12]. VADER analyzes text and provides a positive, negative, and neutral valence value for the text under observation [10]. AFINN lexicon provides valence to English words ranging from negative (-5) to positive (+5) with 0 being neutral [13]. These methods provide many possibilities for applications such as social media monitoring, product and service reviews, and brand reputation management among many other possible applications.

D. Machine Learning Methods

Machine Learning (ML) techniques involve training models on labeled data to predict sentiment in unseen text. Common ML algorithms for sentiment analysis include Naïve Bayes, Support Vector Machines (SVM), Random Forests, Neural Networks, and Recurrent Neural Networks [14], [15]. Machine learning algorithms can be used for several different purposes. These algorithms are classified as supervised and unsupervised machine learning algorithms [6]. Supervised learning algorithms create a function model from labeled input data, which is then used to make decisions on how to map future data to the appropriate output. Unsupervised learning algorithms attempt to identify underlying structures within input data, which are then used to map unlabeled data to emotional classes [6].

E. Other popular methods

Other popular tools worth mentioning are Syuzhet and Flair which are two valuable tools in the field of NLP, each with their unique features and applications. Syuzhet primarily focuses on sentiment analysis of literary texts and relies on lexicons like Syuzhet, Bing, AFINN, and NRC [16]. Flair, on the other hand, is an NLP library developed by Zalando Research [9], primarily designed for sentiment analysis tasks. It employs sequence labeling, a deep learning method, to predict sentiment labels for individual words or tokens within a text [9]. In summary, Syuzhet specializes in sentiment analysis of literary texts while Flair excels in fine-grained sentiment analysis with pre-trained models and adaptability for domain-specific tasks. Both tools cater to different NLP needs, making them valuable assets in their respective domains.

F. NLP for Sentiment Analysis on Hidden Curriculum Survey Responses

NLP techniques can be employed to perform a much faster sentiment analysis of hidden curriculum survey responses than using traditional qualitative methods. Using NLP techniques involves assessing the emotional tone of the text and categorizing it as positive, negative, or neutral text [11], [12]. When applying sentiment analysis to open-ended survey questions about the hidden curriculum, the prevailing emotional sentiments associated with it could be identified. For example, one might discover that students often express frustration or confusion when discussing implicit norms or unwritten rules in the survey responses. NLP can potentially be a powerful tool for extracting and analyzing emotions from survey responses not only limited to hidden curriculum. It could enable educators and researchers to gain a deeper understanding of how students perceive and experience the unspoken aspects of education, ultimately leading to more informed decision-making and potentially improved educational practices.

II. AIM OF THE STUDY

This study aims to investigate the relationship between qualitative and quantitative emotional responses to the hidden curriculum among engineering students and faculty. Using a vignette survey instrument, we'll capture a broad spectrum of emotional reactions. We'll then employ sentiment analysis and NLP to analyze these responses and understand how they relate to demographic variables. By exploring these connections, we hope to uncover patterns and disparities in emotional reactions across different groups. Additionally, we aim to evaluate the effectiveness of sentiment analysis and NLP in extracting emotional content from the survey data. Ultimately, this research aims to deepen our understanding of the emotional dimensions of the hidden curriculum in engineering education and inform strategies for creating a supportive learning environment.

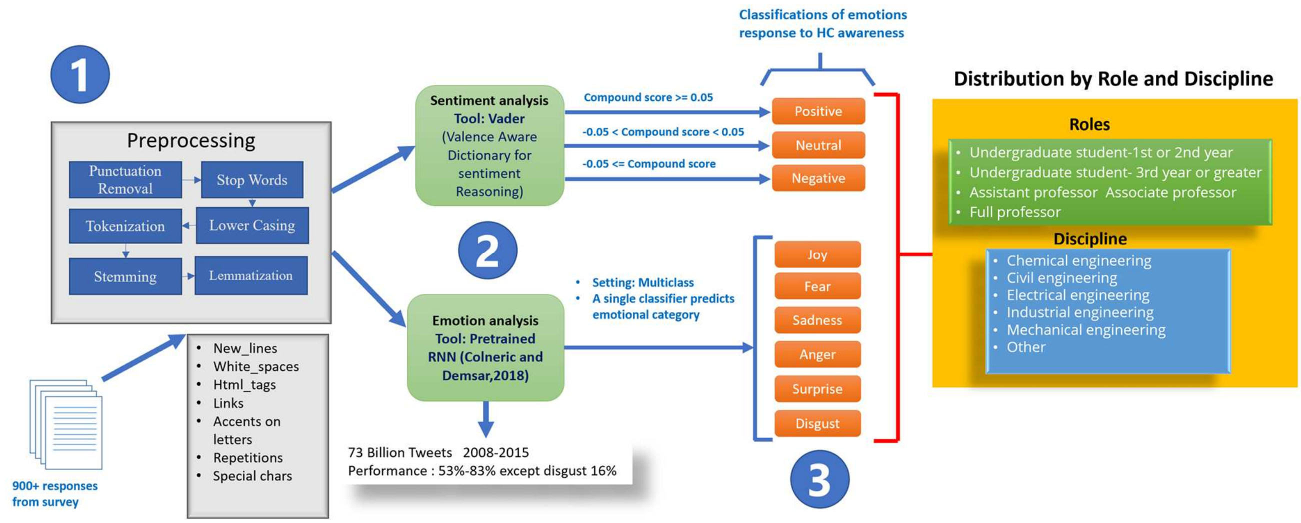

Figure 1. Three-Stage Model for Analysis: 1) Preprocessing, 2) Sentiment Analysis, 3) Emotion Classification and Qualitative Analysis

A. Research Question.

This research project delves into the intricate realm of hidden curriculum awareness within the educational landscape, with a primary focus on unveiling the sentiments and emotions conveyed by engineering students and faculty. The central research question driving this investigation is: What sentiments and emotions are articulated by engineering students and faculty members concerning their awareness of the hidden curriculum?

In addition to this primary inquiry, a supplementary research question adds depth to the study: Are there discernible differences among various NLP tools when employed to extract sentiment from hidden curriculum-related questions? This secondary question aims to scrutinize and compare different NLP tools, exploring their efficacy in discerning sentiments related to hidden curriculum awareness. By examining potential variations in NLP tool performance, we seek to gain insights into the nuances of sentiment analysis in the context of hidden curriculum discussions.

B. Hypothesis.

Our hypothesis posits that faculty members will exhibit more positive sentiments and emotions when discussing hidden curriculum awareness compared to engineering students. This conjecture draws inspiration from previous research [17] that yielded similar outcomes in a different context. Specifically, the study found that during exams, instructors consistently underestimated the difficulty of questions relative to students. We believe that a similar pattern might emerge in the context of hidden curriculum discussions, where faculty members are expected to express more favorable sentiments and emotions compared to students.

The gap addressed in this study lies in the exploration of the relationship between qualitative and quantitative emotional responses elicited by the hidden curriculum among engineering students and faculty. While the hidden curriculum remains a significant aspect of educational discourse, understanding the nuanced sentiments and emotions it evokes remains relatively uncharted territory. By employing sentiment analysis and natural language processing (NLP), this study aims to bridge this gap by deciphering the emotions expressed by engineering stakeholders regarding their awareness of the hidden curriculum.

III. MATERIAL AND METHODS

This work used a dataset gathered from [1] and [18], consisting of ten types of questions ranging from raw engineering belief to demographic data. The Data from [18] introduces the development and assessment of the quantitative portion of a mixed-methods vignette survey instrument designed to explore students' and faculties' responses to hidden curriculum. The data from this study represent more than 900 responses from engineering students and faculty from across the United States (US) and Puerto Rico (PR). Only the responses from HC awareness demographics and emotions were used for this project. 849 responses from engineering students and faculties from across the US and Puerto Rico were provided.

A. Analysis Framework or Plan

The proposed framework for this project consists of three steps as outlined in Figure 1. The first step is the pre-processing, the second use of sentiment analysis tools, and the third is quantitative analysis for finding distribution across demographics. Preprocessing has a six-part sub-stage process while the sentiment analysis classification uses a two-model configuration [19].

B. Preprocessing Steps

1. Removing Punctuations: Punctuation marks such as commas, periods, and exclamation points do not carry significant semantic meaning for sentiment analysis and can introduce noise into the data [6]. Therefore, the first step involves removing punctuation using the Python string module.
2. Removing Stop Words: Stop words are commonly occurring words in a language (e.g., "the," "is," "and") that do not contribute much to the overall meaning of a sentence. Removing stop words helps reduce the dimensionality of the data and focuses on content-bearing words, improving the efficiency of sentiment analysis algorithms [6], [7]. The NLTK (Natural Language Toolkit) library was employed for stop words removal.
3. Lowercasing: Standardizing the case of words by converting all text to lowercase ensures consistency in word representation. This step prevents redundancy in the analysis caused by treating the same word in different cases (e.g., "Engineer" and "engineer") as distinct entities [6], [8].
4. Tokenization: Tokenization involves splitting the text into individual words or tokens, facilitating further analysis at the word level [6], [8]. The NLTK library was utilized for tokenization. Tokenization ensures that each word is processed independently, allowing for a more granular analysis of sentiment within the text.
5. Stemming: Stemming is a process of reducing words to their root form or stem, which helps consolidate variations of words with the same root [6], [8]. For example, words like "running," "run," and "ran" are stemmed from their common root "run." The NLTK library was also used for this purpose.
6. Lemmatization: Unlike stemming, which simply chops off word endings to obtain the root form, lemmatization aims to reduce words to their base or dictionary form, known as the lemma [6], [8]. The NLTK library was used for this process which ensures that the transformed word exists in the language's dictionary, preserving semantic meaning.

C. Training and Classification

For Training two models are going to be used: Valence Aware Dictionary for sentiment Reasoning (Vader) for sentiment Analysis and a pre-trained emotion analysis tool [9]. Vader will provide a compound score that will range between negative and positive numbers to classify the sentiment from the response as positive, negative, or neutral. For the emotion analysis tool,[10] used 73 billion tweets to train a recurrent neural network proving six types of emotion for classification (Joy, Fear, Sadness, Anger, surprise, and disgust). Results from this classifier provide a performance that ranges between 54% and 83% for each emotion.

IV. RESULTS

A. Sentiment analysis using Vader

Results from applying NLP and Vader sentiment analysis are shown in Table 1. Evaluations were performed on individual professors and students, as well as overall evaluations, based on the subject and gender. The sentiment analysis was conducted using a compound value, which ranges from -1 to 1, with higher scores indicating more positive sentiment.

Looking at Table 1, we can see that for both male and female professors and students, the mean sentiment analysis score is generally around 0.1, indicating slightly positive sentiment. Among the subjects, the mean sentiment analysis score for Biological/Chemical and Civil/Environmental subjects is slightly higher than the other subjects for both male and female professors and students.

It is worth noting that the mean sentiment analysis score for female Electrical/Computer professors and students is slightly negative (-0.1), suggesting a modestly negative sentiment. However, the sample size for this group is relatively small, comprising only 9 professors and 35 students, which may limit the generalizability of these findings.

Overall, the sentiment analysis scores are relatively consistent across gender and subject, with a slightly positive sentiment for both professors and students. However, it is important to note that sentiment analysis is not a perfect measure of evaluation, and other factors such as course difficulty, workload, and teaching style may also impact overall evaluations.

Similarly, Figure 2 shows the compound mean value of the sentiment analysis for the professor and student classes, classified as positive, negative, or neutral. The compound score represents the overall sentiment, ranging from -1 (most negative) to 1 (most positive), with 0 being neutral.

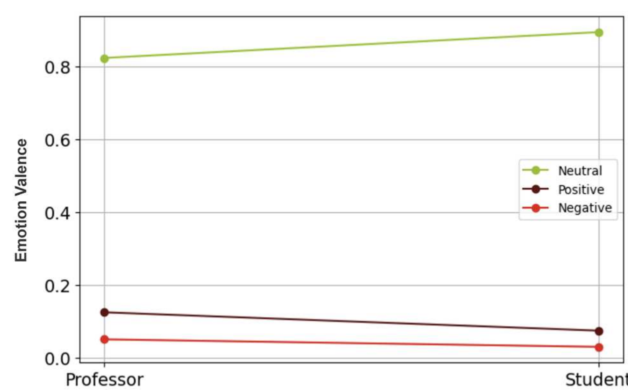

Figure 2. Resulting Vader Analysis: Mean Emotion Valence by Engineering Role

From the plot, we can see that for both the professor and student classes the positive sentiment mean values are larger than the negative or neutral ranges although the neutral values seats at even larger values. The positive sentiment range for the professor class is slightly higher than that of the student class. However, both classes have similar patterns indicating that the majority of the comments or texts analyzed have positive sentiments. There are still a significant number of data points in the neutral range, which suggests that some comments or texts may not have a clear sentiment or could be perceived as neutral. Overall, this plot provides insights into the sentiment of the texts analyzed and shows that the majority of the texts tend to have positive sentiments towards the professor and student classes.

Furthermore, a sentiment analysis based on gender classification was conducted, Figure 3. The plot shows that both male and female genders have a predominantly positive compound score, with males having a slightly higher mean value than females. This implies that both male and female genders expressed more positive sentiments than negative ones.

The plot also shows that both male and female genders have a similar distribution of sentiment scores across positive, and negative mean values. The plot suggests that gender classification does not play a significant role in determining the sentiment expressed. However, it does show that males tend to express slightly more positive sentiments than females.

Table 1. Emotion Resulting from Vader and RNN Model Analysis

			compound	Anger	Disgust	Fear	Joy	Sadness	Surprise
Professor	**Biological/Chemical**	**Female**	0.178	0.069	0.025	0.0173	0.478	0.070	0.186
		Male	0.146	0.036	0.010	0.151	0.572	0.061	0.169
	Civil/Environmental	**Female**	0.175	0.043	0.023	0.217	0.385	0.106	0.226
		Male	0.123	0.047	0.014	0.162	0.312	0.118	0.347
	Electrical/Computer	**Female**	-0.128	0.040	0.018	0.212	0.363	0.082	0.284
		Male	0.137	0.046	0.025	0.205	0.377	0.116	0.231
	Industrial/Manufacturing	**Female**	0.104	0.063	0.011	0.075	0.303	0.213	0.335
		Male	0.153	0.059	0.013	0.156	0.525	0.034	0.214
	Mechanical/Aerospace	**Female**	0.114	0.065	0.010	0.202	0.402	0.041	0.281
		Male	0.030	0.029	0.036	0.109	0.341	0.092	0.394
Student	**Biological/Chemical**	**Female**	0.108	0.054	0.031	0.125	0.383	0.077	0.329
		Male	0.105	0.048	0.036	0.214	0.292	0.101	0.310
	Civil/Environmental	**Female**	0.091	0.062	0.028	0.174	0.401	0.096	0.238
		Male	0.061	0.065	0.028	0.151	0.344	0.080	0.331
	Electrical/Computer	**Female**	0.040	0.082	0.031	0.191	0.368	0.078	0.249
		Male	0.139	0.062	0.021	0.159	0.366	0.090	0.301
	Industrial/Manufacturing	**Female**	0.055	0.060	0.020	0.254	0.335	0.089	0.241
		Male	0.111	0.087	0.072	0.175	0.410	0.067	0.188
	Mechanical/Aerospace	**Female**	0.150	0.045	0.015	0.087	0.473	0.082	0.297
		Male	0.094	0.063	0.028	0.148	0.396	0.093	0.271

Similarly results from sentiment analysis scores by engineering fields categories using Vader is presented in Figure 4. From the figure, we can observe that some engineering fields have a higher average positive score than others. For example, Biological/chemical and Industrial/Manufacturing engineering have the highest average positive scores, while Civil/Environmental has the lowest average positive scores. On the other hand, fields such as Electrical/Computer engineering have relatively balanced positive and negative scores.

It is important to note that sentiment analysis is a subjective analysis, and the results may vary based on the dataset used and the context of the text being analyzed. Therefore, the interpretation of the results should be taken with caution and may require further analysis to determine the factors contributing to the sentiment scores of different engineering fields.

B. *Sentiment analysis using the pre-trained RNN Model*

Results from sentiment analysis conducted using the pre-trained RNN model are also shown in Table 1. Table 1 shows the emotions expressed by professors and students against different engineering fields. These emotions are Anger, Fear, Joy, Sadness, and Surprise. Also in Table 1, the emotions expressed by females and males in the two groups of professors and students are shown.

When looking at Table 1 closely, it can be seen that professors express more joy than any other emotion towards engineering fields, with 45.2% of their total emotional expressions being classified as joy. Students, on the other hand, express more joy than any other emotion as well, with 43.4% of their total emotional expressions being classified as joy.

Among professors Engineering Field, Biological/Chemical Engineering was the engineering field that expressed the most joy emotions in its response with 66.7% while for students was Mechanical/Aerospace engineering with 50.0%.

Table 2 Results of sentiment analysis performed using the pre-trained RNN model by field.

		Biological/Chemical	**Civil/Environmental**	**Electrical/Computer**	**Industrial/Manufacturing**	**Mechanical/Aerospace**	**Total**
Anger	**neg**		2 (40.0%)	2 (28.6%)	1 (100.0%)	2 (66.7%)	7 (36.8%)
	pos	3 (100.0%)	3 (60.0%)	5 (71.4%)		1 (33.3%)	12 (63.2%)
	Subtotal	3 (100.0%)	5 (100.0%)	7 (100.0%)	1 (100.0%)	3 (100.0%)	19 (100.0%)
Disgust	**neg**	1 (50.0%)				1 (100.0%)	2 (33.3%)
	pos	1 (50.0%)	1 (100.0%)	1 (100.0%)	1 (100.0%)		4 (66.7%)
	Subtotal	2 (100.0%)	1 (100.0%)	1 (100.0%)	1 (100.0%)	1 (100.0%)	6 (100.0%)
Fear	**neg**	4 (17.4%)	6 (13.0%)	2 (10.0%)	5 (41.7%)	6 (31.6%)	23 (19.2%)
	pos	19 (82.6%)	40 (87.0%)	18 (90.0%)	7 (58.3%)	13 (68.4%)	97 (80.8%)
	Subtotal	23 (100.0%)	46 (100.0%)	20 (100.0%)	12 (100.0%)	19 (100.0%)	120 (100.0%)
Joy	**neg**	9 (13.2%)	7 (6.0%)	6 (9.2%)	2 (9.5%)	9 (9.0%)	33 (8.9%)
	pos	59 (86.8%)	110 (94.0%)	59 (90.8%)	19 (90.5%)	91 (91.0%)	338 (91.1%)
	Subtotal	68 (100.0%)	117 (100.0%)	65 (100.0%)	21 (100.0%)	100 (100.0%)	371 (100.0%)
Sadness	**neg**		5 (41.7%)	1 (16.7%)		1 (11.1%)	7 (19.4%)
	pos	7 (100.0%)	7 (58.3%)	5 (83.3%)	2 (100.0%)	8 (88.9%)	29 (80.6%)
	Subtotal	7 (100.0%)	12 (100.0%)	6 (100.0%)	2 (100.0%)	9 (100.0%)	36 (100.0%)
Surprise	**neg**	5 (10.2%)	20 (17.7%)	7 (14.6%)		2 (2.8%)	34 (11.4%)
	pos	44 (89.8%)	93 (82.3%)	41 (85.4%)	15 (100.0%)	70 (97.2%)	263 (88.6%)
	Subtotal	49 (100.0%)	113 (100.0%)	48 (100.0%)	15 (100.0%)	72 (100.0%)	297 (100.0%)
Total		152 (100.0%)	294 (100.0%)	147 (100.0%)	52 (100.0%)	204 (100.0%)	849 (100.0%)

Surprise is the second most expressed emotion by both groups, with students expressing a slightly higher percentage of surprise than professors. Mechanical/Aerospace engineering for professors was the field with a higher percentage of surprise at 50.0% and Civil/Environmental with 38.5% for students. Surprisingly, professors express more Fear than students, with 15.8% of their total emotional expressions being anger compared to 13.8% for students.

Results in Table 1 show that both female and male professors express more joy than any other emotion towards engineering fields, with females expressing a slightly higher percentage of joy than males, 48.1% against 43.5% for professors and 46.6% against 41.5% for students. Males express more surprise than Females for both categories, while for fear Females express more fear than females for professors 16.7% against 15.2%. For students, the results are the opposite, Male students express higher fear in their responses than Female students, 18.8% against 12.1%.

Overall, the results suggest that joy is the most common emotion expressed in engineering fields, with surprise being the second most expressed emotion. The results also show some differences in emotional expressions between professors and students, as well as between females and males in both groups.

C. *Comparing results among models*

Results of sentiment analysis performed using the two different methods, Vader sentiment analysis, and the pre-trained RNN model, are presented in Table 1 and Table 2. The sentiment analysis is applied to the six different field domains. The sentiment analysis from the pre-trained RNN model measures six different emotions: anger, disgust, fear, joy, sadness, and surprise. The table presents the number and percentage of sentences classified as either positive or negative, as classified by Vader Sentiment analysis. for each emotion and field domain, as well as the subtotal and total.

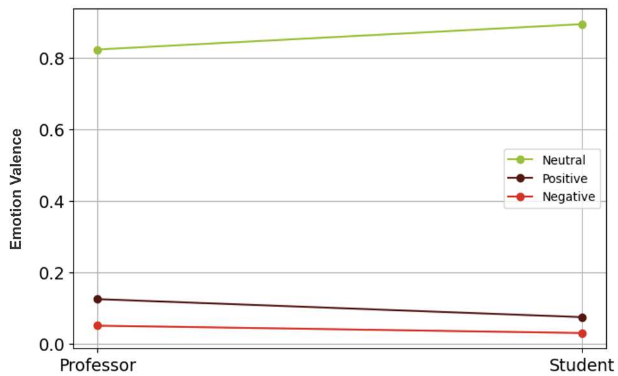

Figure 3. Resulting Vader Analysis: Mean Emotion Value by Gender

In general, the results show that the majority of sentences in each field domain are classified as positive for joy and surprise, while the number of negative sentences is higher for fear and anger. The results also suggest that the sentiment analysis methods used in the study provide consistent results, as the percentages of positive and negative sentences for each emotion are generally similar between Vader and the RNN model.

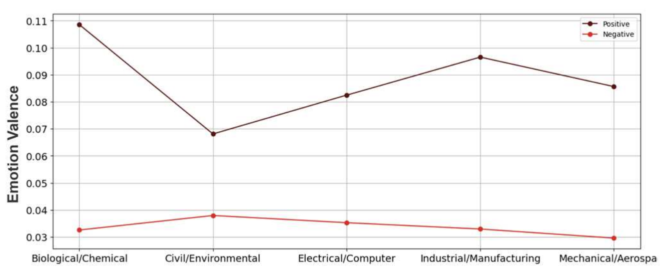

Figure 4. Resulting Vader Analysis: Mean Emotion Valence by Field.

However, there are some notable differences between the two methods. For example, the percentage of negative sentences for fear in the Biological/Chemical domain is much higher with Vader (82.6%) compared to RNN (13.0%). Additionally, the percentage of positive sentences for disgust in the Mechanical/Aerospace domain is higher with RNN (100.0%) compared to Vader (66.7%).

The same analyses were presented in terms of positive and negative emotions, broken down by role (Professor and Student) and emotion (Anger, Disgust, Fear, Joy, Sadness, and Surprise), Table 3. Looking at the table, we can see that both methods generally classify most of the emotions as positive. Joy is the most prevalent emotion in both methods, with a high percentage of positive sentiment. Fear is the second most prevalent emotion, and both methods classified the vast majority of fear as positive.

In terms of differences between the methods, we can see that the RNN model classified more instances of anger and disgust as positive compared to Vader. For example, the RNN model classified 100% of anger instances among professors as positive, while Vader classified 38.9% of these instances as negative.

Similarly, the RNN model classified all instances of disgust as positive, while Vader classified 33.3% of these instances as negative.

Overall, the results suggest that both methods perform well in identifying positive emotions, but there are some differences in the classification of negative emotions. Further analysis and comparison of the two methods may be necessary to understand these differences and their implications.

V. DISCUSSION

The results of sentiment analysis provide valuable insights into the emotional landscape within engineering education, with implications for both teaching and learning environments. When using Vader sentiment analysis, it's evident that overall sentiments, reflected in the mean sentiment analysis scores, tend to be slightly positive across gender and subject categories. Notable nuances emerge in the data, such as the slightly negative sentiment exhibited by female Electrical/Computer professors and students, highlighting potential areas for further investigation. While most of the texts analyzed reflect positive sentiment towards both professors and students, there is also a significant presence of neutral sentiment, indicating varying levels of emotional expression. These findings emphasize the importance of cultivating a positive emotional climate in engineering education to enhance student engagement and overall satisfaction.

Similarly, sentiment analysis using the pre-trained RNN model reveals intriguing patterns in emotional expressions among professors and students across engineering fields. Joy emerges as the predominant emotion, followed by surprise, indicating an overall positive disposition toward engineering education. However, variations exist between genders and engineering fields, with differences in the prevalence of specific emotions. For instance, females tend to express slightly higher levels of joy than males, while males exhibit greater surprise and fear in their responses. Such insights into gender-specific emotional expressions highlight the need for tailored approaches to address diverse emotional needs within engineering education.

Comparing results between Vader sentiment analysis and the pre-trained RNN model unveils consistent trends in the predominance of positive emotions, particularly joy, across both methods. However, discrepancies emerge in the classification of negative emotions, with notable differences in the percentage of negative sentences for fear and disgust across engineering domains. These disparities underscore the importance of employing multiple sentiment analysis methods to gain a comprehensive understanding of emotional dynamics within engineering education. Further investigation is warranted to elucidate the factors contributing to these differences and their implications for instructional design and student support initiatives.

The implications drawn from the results in engineering education pave the way for several avenues of future research and practical applications:

Tailored Support Strategies: Understanding the emotional landscape of engineering education allows for the development of tailored support strategies for both students and faculty. Future research could explore the effectiveness of targeted interventions, such as mentoring programs or emotional resilience workshops, in addressing specific emotional needs identified through sentiment analysis.

Curriculum Design and Pedagogy: Insights from sentiment analysis can inform curriculum design and pedagogical approaches to enhance student engagement and satisfaction. Future studies might investigate the impact of emotion-aware instructional strategies, such as incorporating emotionally engaging content or implementing adaptive feedback mechanisms, on learning outcomes and retention rates in engineering education.

Inclusive Learning Environments: By uncovering patterns of emotional expression across gender and engineering fields, future research can inform efforts to create more inclusive learning environments. Investigating the influence of classroom climate, instructor-student interactions, and peer dynamics on emotional experiences could provide valuable insights into promoting diversity and equity within engineering education.

Technological Innovations: Advances in natural language processing and sentiment analysis techniques offer opportunities for the development of innovative educational technologies. Future research could explore the integration of sentiment analysis tools into learning management systems or virtual learning environments to provide real-time feedback on students' emotional states and personalize learning experiences accordingly.

Cross-Cultural Perspectives: Exploring cross-cultural variations in emotional experiences within engineering education can deepen our understanding of the cultural factors shaping learning environments. Comparative studies across different cultural contexts could elucidate cultural norms and values influencing emotional expression and inform culturally responsive teaching practices.

Longitudinal Studies: Conducting longitudinal studies to track changes in emotional experiences over time can provide insights into the dynamic nature of engineering education. Longitudinal research could examine how emotional responses evolve throughout a course or program, as well as the impact of life events or external factors on students' emotional well-being and academic performance.

Interdisciplinary Collaboration: Collaboration between engineering education researchers, psychologists, computer scientists, and educational technologists can enrich our understanding of the emotional dimensions of learning and teaching. Future research initiatives could leverage interdisciplinary approaches to integrate psychological theories, computational methods, and educational interventions in addressing emotional challenges within engineering education.

Table 3. Results of sentiment analysis performed using the pre-trained RNN model by roles.

		Professor	**Student**	**Total**
Anger	**neg**		7 (38.9%)	7 (36.8%)
	pos	1 (100.0%)	11 (61.1%)	12 (63.2%)
	Subtotal	1 (100.0%)	18 (100.0%)	19 (100.0%)
Disgust	**neg**		2 (33.3%)	2 (33.3%)
	pos		4 (66.7%)	4 (66.7%)
	Subtotal		6 (100.0%)	6 (100.0%)
Fear	**neg**	4 (17.4%)	19 (19.6%)	23 (19.2%)
	pos	19 (82.6%)	78 (80.4%)	97 (80.8%)
	Subtotal	23 (100.0%)	97 (100.0%)	120 (100.0%)
Joy	**neg**	6 (9.1%)	27 (8.9%)	33 (8.9%)
	pos	60 (90.9%)	278 (91.1%)	338 (91.1%)
	Subtotal	66 (100.0%)	305 (100.0%)	371 (100.0%)
Sadness	**neg**	2 (33.3%)	5 (16.7%)	7 (19.4%)
	pos	4 (66.7%)	25 (83.3%)	29 (80.6%)
	Subtotal	6 (100.0%)	30 (100.0%)	36 (100.0%)
Surprise	**neg**	7 (14.0%)	27 (10.9%)	34 (11.4%)
	pos	43 (86.0%)	220 (89.1%)	263 (88.6%)
	Subtotal	50 (100.0%)	247 (100.0%)	297 (100.0%)
Total		146 (100.0%)	703 (100.0%)	849 (100.0%)

VI. CONCLUSIONS

In conclusion, the findings from this study shed light on the intricate emotional landscape of engineering education, offering valuable insights into the sentiments and experiences of both students and faculty members. Through the application of sentiment analysis techniques, we have uncovered patterns, trends, and disparities in emotional expressions across gender, subject areas, and sentiment analysis methodologies.

Our analysis reveals a generally positive sentiment prevailing within engineering education, with joy emerging as the predominant emotion expressed by both students and faculty members. However, nuanced variations exist, with differences observed in emotional expressions based on gender, engineering fields, and sentiment analysis methods employed.

These findings carry significant implications for the design of inclusive learning environments, the development of tailored support strategies, and the advancement of pedagogical practices within engineering education. By understanding and addressing the emotional dimensions of learning and teaching, educators can cultivate supportive ecosystems that foster student engagement, satisfaction, and success.

In summary, future research endeavors should continue to explore the implications of sentiment analysis in engineering education, with a focus on informing evidence-based interventions, promoting inclusivity, leveraging technological innovations, and advancing our understanding of the complex interplay between emotions, learning, and teaching in the engineering domain.

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