Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #48539

Natural Language Processing Models to Detect Affective Fluctuations of Engineering Faculty and Students Responding to a Hidden Curriculum Survey

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Abstract

This empirical research full paper considers a validated mixed-methods vignette UPHEME (**U**ncovering **P**reviously **H**idden **E**ngineering **M**essages for **E**mpowerment) survey (2018-2019). For this study, 961 participants who belonged to a diverse population of engineering students and faculty were surveyed in Spring 2019. The survey was divided into four categories including hidden curriculum awareness, emotions, self-efficacy, and self-advocacy. The participants answered a few questions on hidden curriculum (HC) before they watched the video, then responded to some more questions on HC, self-identified their own emotion from 14 emotion categories and classified it as a positive or negative emotion on a 5-point Likert scale as they transitioned to later sections of the survey. This study uses Natural Language Processing (NLP) to analyze the responses of participants for one open-ended question in the 'emotions' category using four different pre-trained models from HuggingFace platform, an open-source platform for machine learning and data science, for detection of at least six emotions (sadness, joy, anger, surprise, fear, love and/or neutral). This study provides a contrast of the emotions experienced by engineering participants for all four models, explores the identified emotions across the demographics (primary discipline, self-identified age range, self-identified gender identity, self-identified race/ethnicity) of participants and compares the models with each other. The findings reflect a range of emotions as identified by four models and the need for an intersectional approach in developing inclusive strategies with a cultural and emotional awareness to empower individuals in navigating academic and professional settings. There are several implications of the study including how the participants' awareness of hidden curriculum affects their emotions which in turn affects their self-efficacy and self-advocacy, and their demographic correlations. It gives us insights to utilize NLP techniques for qualitative data within a mixed-methods survey to extract meaningful information for educational research in engineering education.

Keywords—NLP, Hidden Curriculum, Survey, Affect, Sentiment Analysis, Engineering, Engineering Education

Introduction

Hidden curriculum (HC) refers to unwritten or unacknowledged messages, values or perspectives that are often not communicated or conveyed directly which significantly affects learning experiences of students [1]. The exploration and identification of mechanistic HC pathways in engineering are tied to emotions, self-advocacy, and self-efficacy [1]. Within the HC pathways model, emotions are believed to be an igniter of decisions that spark action [2]. These emotions can vary from happiness, excitement, sadness, fear, and anger [3], [4] and depending on the perspectives of the individual, each emotion can be classified as being positive, negative or neutral to them [5]. Within Natural Language Processing (NLP), sentiment analysis is used to detect emotional intonation (valence, dominance, arousal) within textual data while emotion detection and analysis investigates specific types of emotions [6]. These techniques can be used to examine the impact of HC on emotional arousal, which is an underexplored field as there is limited literature in which NLP techniques are applied to hidden curriculum data [7].

Background

It is pertinent to utilize affective computing methods to identify students' emotions to better understand student learning and behavior of students within their learning environments to support their learning [8]. There are different ways to classify emotions including Ekman's Basic Emotions Model [4] that considers 6 emotions (anger, disgust, fear, happiness, sadness, surprise) while Plutchik's Wheel of Emotions brings into account other complex emotions along with the 8 primary emotions (anger, fear, sadness, disgust, surprise, anticipation, trust, joy) [3]. Identifying accurate emotions is difficult because of the complexities, contextual information and subtleties in human language [9]. Hence, hybrid methods are used to detect and validate its accuracy [9], [10], [11]. Traditional methods rely on rule-based systems, keyword spotting, and lexicon-based approaches [12], [13], [14] while machine learning (ML) approaches use supervised and unsupervised ML models [15], [16], [17], [18], [19], deep learning models [20], [21], [22], [23], and transfer learning with transformer models [24]. Supervised ML models have used Support Vector Machines (SVM), Decision Trees, Linear Regression, Naïve Bayes, and K-Nearest Neighbor [25], [26], [27], [28], [29] to detect emotions as they are robust and efficient. These methods are not scalable due to reliance on labeled datasets. Other unsupervised ML approaches include K-Means clustering, Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) [30], [31]. Other studies have use Deep Learning models particularly Convolutional Neural networks (CNNs), Long Short-Term Memory (LSTM) networks [20], [21], [22], [23], [24], and Recurrent Neural Network (RNNs) [32] that make use of emotion cues in textual data for accurate classification within the data.

Natural Language Processing (NLP), a subset of machine learning, has gained much attention in text preprocessing, feature extraction and emotion classification in textual data. Pre-trained models including BERT, DistilBERT, RoBERTA have also become widely adopted in NLP for sentiment analysis. A pre-trained model has undergone both pre-training and fine-tuning, encapsulating the learned parameters and architecture. This approach significantly reduces computational resource requirements, minimizes the need for high-performance computing infrastructure, and saves time on parameter optimization during fine-tuning [33].

Among various pre-trained models, BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based model pre-trained to generate deep bidirectional representations from unlabeled text by simultaneously considering both left and right context across all layers. DistilBERT is a distilled version of BERT while RoBERTa (Robustly Optimized BERT Pretraining Approach) shares a similar architecture to BERT but differs by using dynamic masking and being exclusively trained with a larger dataset and extended training time [34]. HuggingFace is an open-source ML platform which consists of about 900k models, 200k datasets, and 300k demos which are publicly available for users to explore and experiment with for machine learning and data science applications [35]. There is a need to combine different methods to create effective solutions that can understand the syntactic and semantic intricacies of human language by preprocessing and correctly classifying simultaneously.

Motivation & Aim of the Study

The motivation of this study is to understand the emotions experienced and expressed by engineering students and faculty members about their responses to the UPHEME instrument following a video showcasing a fictitious story framing hidden curriculum in engineering [1]. This study aims to apply NLP models on the data extracted from the UPHEME survey for the questions on emotions and present findings that convey how NLP techniques can be integrated into engineering education research. This study will additionally serve to validate an earlier study [7] in which a different question from the same survey was analyzed to see if there are any patterns or trends in emotion recognition that can be observed in responses. Moreover, another study used the same question from this survey to understand active and passive perceptions of hidden curriculum affecting students' emotions [36].

Research Questions

- RQ1: What are the emotions expressed by engineering students and professors to the questions on emotions in UPHEME?
- RQ2: How do the emotions of participants as identified by a pretrained NLP model vary in terms of demographics (primary discipline, self-identified age range, self-identified gender identity, self-identified race/ethnicity)?
- RQ3: How do different pre-trained NLP models differ in identifying participants' emotions expressed in UPHEME?

UPHEME Survey & Dataset

The UPHEME (**U**ncovering **P**reviously **H**idden **E**ngineering **M**essages for **E**mpowerment) survey (2018-2019) is a validated mixed-methods survey that has been used to understand the nuances of hidden curriculum. It is divided into different sections. The participants for UPHEME initially answered hidden curriculum (HC) open questions (Part 1), were introduced to the concept of HC and responded to a question (Part 2), watched the video on HC visualization and responded to a few questions (Part 3), and later responded to questions on emotions (Part 4), self-efficacy (Part 5), self-advocacy (Part 6), HC wrap-up (Part 7) followed by demographics (Part 8). For this paper, the researchers used the gathered data from 961 participants in Spring 2019 and focused on the textual data from different sections of the survey. The main idea is to recognize emotions in the data for those individuals. The dataset for this research study was the responses collected from the UPHEME survey. The focus of this study was on Q.5.2 only which was "***Can you think about an example of hidden curriculum you experienced in engineering? Briefly explain the situation and the emotions you had in that situation***". The total number of responses to the survey was 961 out of which 859 participants responded to Q.5.2. After data cleaning, the final number of emotional responses for Q.5.2. in UPHEME was 582.

Methodology & Methods

This study uses a pragmatist research paradigm by using NLP models to quantify participants' emotions [37]. For this study, the data collected from UPHEME survey was extracted. Data cleaning included removing null responses or responses with 'Not applicable', 'NA', 'na', 'N/A', etc. and non-English responses. After data cleaning, the qualitative responses were fed to four different pre-trained models from HuggingFace platform. Three out of four models had already incorporated the preprocessing steps (tokenization, stop word removal, stemming, lemmatization) as it utilized the HuggingFace pipeline component. The four models have been carefully selected to recognize at least six emotions. The models that recognized more than six emotions were categorized under the six basic emotions including anger, fear, joy, sadness, surprise, and love/neutral.

For this categorization purpose, the researchers manually classified the emotions into bigger categories. ChatGPT-4 was used as a secondary resource to categorize different emotions under a bigger umbrella of emotion. For example, in model 4, the emotions like anger, remorse, annoyance, disapproval, and disgust were all categorized as 'Anger' to be able to compare it with results from other models. This categorization is shown in Appendix A. For this study, students (474, 81.4%) include all undergraduate and graduate students while professors (84, 14.4%) include full professors, associate professors, assistant professors, adjunct professors, academic advisors, and lecturers. Out of the remaining 24 participants, 2 had already graduated and the others did not identify their role in the survey. The frequency counts of identified emotions in section A were normalized. Lastly, the emotions identified by the four pre-trained models were put together for comparison purposes.

Natural Language Processing (NLP) Models

There are four different NLP models used in this study. The rationale for using these models is because these models have been trained on a diverse range of datasets mainly focusing on conversational data from diverse sources. The details about the models are described below:

1. ***Model 1 (ahmetyaylalioglu/text-emotion-classifier)*** [38]

The first model is a refined version of the *bert-base-uncased* model that utilizes the low-rank adaptation (LoRA) for efficient finetuning. This model has been trained on 'dair-ai/emotion' dataset and identifies six emotions including sadness, joy, love, anger, fear, and surprise.

2. ***Model 2 (michellejieli/emotion_text_classifier)*** [39]

The second model used a *DistilRoBERTa-base* transformer model for sentiment analysis in textual data and refined it using the transcripts of Friends show. This model identifies seven emotions including anger, disgust, fear, joy, neutral, sadness, and surprise.

3. ***Model 3 (bhadresh-savani/albert-base-v2-emotion-labels)*** [40]

The third model used the *Albert-base-v2* model trained and refined on Twitter sentiment analysis dataset using the HuggingFace trainer. Some of the hyperparameters mentioned on the HuggingFace website for this model include learning rate=2e-5, batch size=64, and num_train_epochs=8. The emotions identified by this model include sadness, joy, love, anger, fear, and surprise.

4. ***Model 4 (SamLowe/roberta-base-go_emotions)*** [41]

The fourth model is a pre-trained model that used *roberta-base* text classification model based on the go_emotions dataset for classification of multi-labeled emotion groups. Some of the hyperparameters mentioned on the HuggingFace website for this model include learning rate=2e-5, weight decay=0.01, and num_train_epochs=3. The emotions identified by this model include admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, neutral, optimism, pride, realization, relief, remorse, sadness, and surprise.

Results & Discussion

This section presents the findings for all the research questions. Section A refers to the first research question about the emotions expressed by engineering students and professors to the emotion questions in UPHEME. Section B discusses the second research question on how the emotions of participants vary in terms of demographics (primary discipline, self-identified age range, self-identified gender identity, self-identified race/ethnicity) and Section C shows the findings for the third research question and gives a comparison of four pre-trained NLP models in identifying participants' emotions expressed in UPHEME.

A. Emotions expressed by Engineering Students and Professors in UPHEME (RQ1)

There were four pre-trained models that were applied to the cleaned data (582 out of 859 responses to the question) extracted from the survey. The identified emotions for all participants (students, professors, others) as frequency counts have been normalized are shown in Figure 1 to Figure 4. Also, the findings are represented as tables in Appendix B. The 'Others' category included 2 students who had already graduated but were not working in an academic position, and 13 participants did not identify their role, making a total of 24 participants.

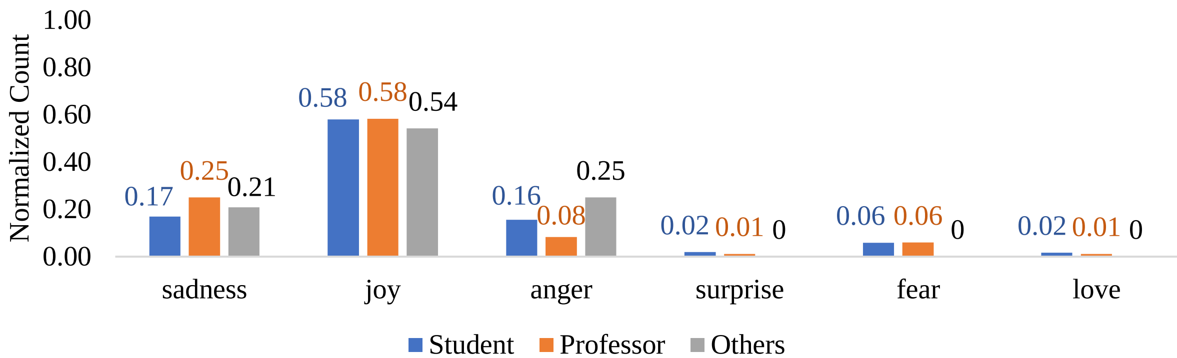

Figure 1: Normalized frequency counts of emotions for participants by Model 1

As shown in Figure 1, the normalized frequency counts of emotions recognized by Model 1 are presented for engineering students, professors, or others. This model did not include 'neutral' as an emotion category. 'Joy' is the highest emotion (0.58) reflected by engineering students and professors when asked about an example of hidden curriculum they experienced in engineering.

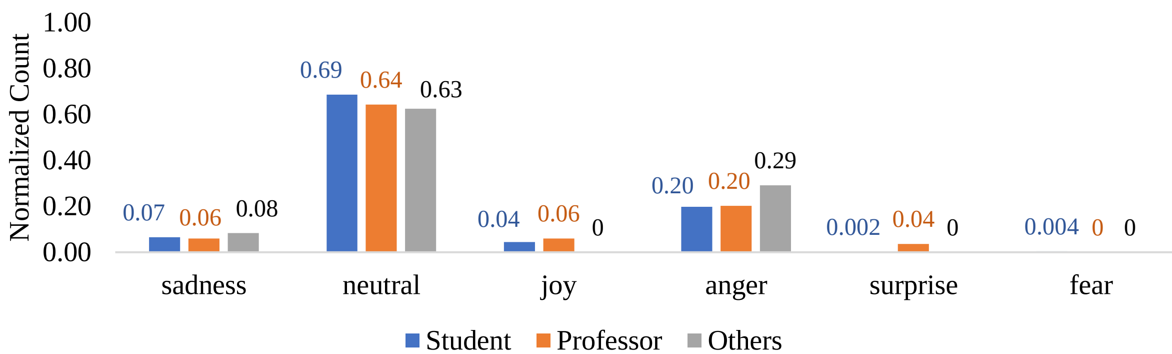

Figure 2: Normalized frequency counts of emotions for participants by Model 2

According to Figure 2, the normalized frequency counts of emotions recognized by Model 2 are shown for engineering students, professors, or other participants. This model did not include 'love' as an emotion category. 'Neutral' is the highest emotion (0.69 and 0.64) reflected by engineering students and professors respectively about their hidden curriculum experiences in engineering.

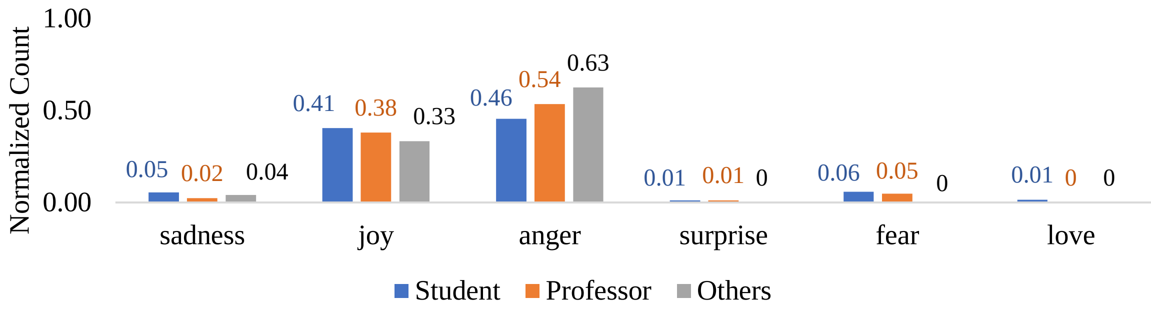

Figure 3: Normalized frequency counts of emotions for participants by Model 3

As illustrated by Figure 3, the normalized frequency counts of emotions detected by Model 3 across engineering students, professors or other participants are demonstrated. This model did not include 'neutral' as an emotion category. It is interesting to note that 'joy' and 'anger' were the highest emotions reflected by engineering students (0.41 and 0.46 respectively) and professors (0.38 and 0.54 respectively) when asked about an example of hidden curriculum they experienced in engineering.

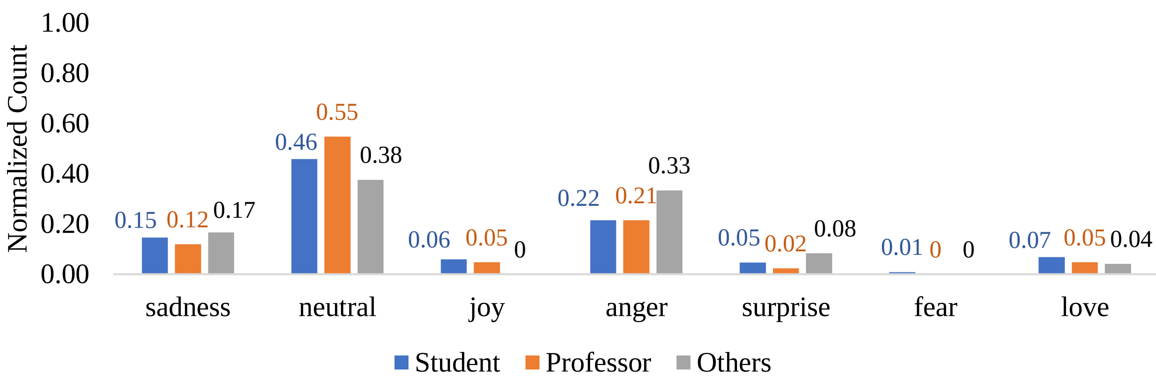

Figure 4: Normalized frequency counts of emotions for participants by Model 4

As reflected in Figure 4, the normalized frequency counts of emotions recognized by Model 4 are displayed for engineering students, professors, and other participants. This model showed 'neutral' and 'anger' as the highest emotions reflected by engineering students (0.46 and 0.22 respectively) and professors (0.55 and 0.21 respectively) when asked about an example of hidden curriculum they experienced in engineering.

B. *Identified Emotions of Participants by Demographics (RQ2)*

The fourth model is the most widely used (1,009,309 in December 2024) [41] for multi-label classification research and experimentation as it captures the subtleties in emotions experienced by individuals. Hence, the identified emotions of participants by demographics in this section of the research study shows the normalized frequency counts for the fourth model only. The values before the normalized frequency counts are shown in Appendix D. The demographics for each participant considered are primary discipline, self-identified age range, self-identified gender identity, and self-identified race/ethnicity. The results are shown in Table 1 to Table 4 respectively. For Table 1, the primary disciplines identified by participants were 41. The researchers manually collapsed these disciplines together into five main categories and used

ChatGPT-4 as an additional tool to verify the categories. This categorization is shown in Appendix C.

Table 1: Normalized emotions frequency counts for participants (by primary discipline) as identified by Model 4

Participant	Primary Discipline	sadness	neutral	joy	anger	surprise	fear	love
Student	Electrical, Electronics & Computer Engineering	0.114	0.193	0.094	0.099	0.080	0.250	0.139
	Mechanical & Manufacturing Engineering	0.304	0.246	0.281	0.248	0.240	0.000	0.278
	Civil, Structural & Environmental Engineering	0.291	0.284	0.313	0.314	0.400	0.000	0.333
	Chemical, Materials & Energy Engineering	0.076	0.042	0.156	0.107	0.040	0.500	0.028
	Specialized & Interdisciplinary Engineering	0.089	0.057	0.031	0.074	0.120	0.250	0.111
Professor	Electrical, Electronics & Computer Engineering	0.013	0.042	0.000	0.033	0.040	0.000	0.000
	Mechanical & Manufacturing Engineering	0.013	0.027	0.000	0.025	0.000	0.000	0.056
	Civil, Structural & Environmental Engineering	0.038	0.072	0.094	0.008	0.040	0.000	0.000
	Chemical, Materials & Energy Engineering	0.025	0.004	0.000	0.050	0.000	0.000	0.000
	Specialized & Interdisciplinary Engineering	0.038	0.027	0.031	0.033	0.000	0.000	0.056
Missing/ Other	Electrical, Electronics & Computer Engineering	0.000	0.004	0.000	0.000	0.040	0.000	0.000
	Mechanical & Manufacturing Engineering	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Civil, Structural & Environmental Engineering	0.000	0.004	0.000	0.008	0.000	0.000	0.000
	Chemical, Materials & Energy Engineering	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Specialized & Interdisciplinary Engineering	0.000	0.000	0.000	0.000	0.000	0.000	0.000

The distribution of engineering students, professors, or other participants' emotion recognition by primary engineering disciplines is listed in Table 1. Model 4 recognizes that 264 participants had 'neutral' emotions in comparison to other emotions (as shown in Appendix D). This number is reflected in the form of normalized frequency counts in Table 1. Within these 264 participants that had 'neutral' emotions, there were a majority of students (0.284) and professors (0.072) from the disciplines of Civil, Structural & Environmental Engineering. The second highest identified emotion by Model 4 is 'anger' with a total of 121 participants in which the majority of students were from the disciplines of Civil, Structural & Environmental Engineering (0.314), and most of the professors were from the disciplines of Chemical, Materials & Energy Engineering (0.050). It can be assumed that most participants had feelings of 'neutral', 'anger' and 'sadness' because at the time of the study HC was not widely understood and prior research indicates that individuals negatively react to unfamiliar concepts [42]. However, since a short video of HC was shown right before they answered the question considered for this study, either the participants did not completely understand the concept of HC, or it may have triggered memories about their experience of HC within engineering.

Table 2: Normalized emotions frequency counts for participants' self-identified age range as identified by Model 4

Participant	Age Range	sadness	neutral	joy	anger	surprise	fear	love
Student	18-29 years of age	0.785	0.649	0.719	0.727	0.720	1.000	0.806
	30-39 years of age	0.025	0.087	0.125	0.066	0.120	0.000	0.056
	40-49 years of age	0.038	0.079	0.031	0.033	0.040	0.000	0.028
	50-59 years of age	0.013	0.004	0.000	0.017	0.000	0.000	0.000
	60 years of age or older	0.013	0.000	0.000	0.000	0.000	0.000	0.000
Professor	18-29 years of age	0.013	0.030	0.000	0.017	0.000	0.000	0.000
	30-39 years of age	0.038	0.034	0.000	0.066	0.040	0.000	0.028
	40-49 years of age	0.038	0.087	0.125	0.041	0.040	0.000	0.056
	50-59 years of age	0.025	0.019	0.000	0.017	0.000	0.000	0.028
	60 years of age or older	0.013	0.004	0.000	0.008	0.000	0.000	0.000
Other	18-29 years of age	0.000	0.004	0.000	0.008	0.040	0.000	0.000
	30-39 years of age	0.000	0.004	0.000	0.000	0.000	0.000	0.000
	40-49 years of age	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	50-59 years of age	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	60 years of age or older	0.000	0.000	0.000	0.000	0.000	0.000	0.000

The distribution of different types of emotions of participants emotions recognized by model 4 across multiple age ranges is listed in Table 2. The students with an age range between 18-29 years had 'neutral' as the most identified emotion (0.649). Similarly, the professors with age range between 40-49 had 'neutral' as the most identified emotion (0.087) followed by the 'anger' emotion.

Table 3: Normalized emotions frequency counts for participants' self-identified gender as identified by Model 4

Participant	Gender	sadness	neutral	joy	anger	surprise	fear	love
Student	Male	0.554	0.506	0.500	0.414	0.577	0.500	0.432
	Female	0.265	0.288	0.375	0.375	0.231	0.500	0.432
	Other	0.012	0.004	0.000	0.008	0.038	0.000	0.000
Professor	Male	0.060	0.125	0.063	0.055	0.038	0.000	0.081
	Female	0.060	0.044	0.063	0.086	0.038	0.000	0.027
	Other	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Missing/ Other	Male	0.000	0.004	0.000	0.000	0.000	0.000	0.000
	Female	0.000	0.004	0.000	0.008	0.038	0.000	0.000
	Other	0.048	0.026	0.000	0.055	0.038	0.000	0.027

The distribution of various types of recognized emotions of participants with their self-identified genders is listed in Table 3. For all engineering participants, the highest emotion identified by Model 4 was 'neutral' with 271 participants (as shown in Appendix D). However, for both male and female students, the second highest identified emotion group is 'anger' followed by 'sadness'. In the case of professors, Table 3 indicates that for both male and female professors, Model 4 detected ‘neutral’ as the highest identified emotion followed by ‘anger’ and ‘sadness’ emotion on their thoughts about the hidden curriculum.

Table 4: Normalized emotions frequency counts for participants’ self-identified race/ethnicity as identified by Model 4

Participant	Ethnicity	sadness	neutral	joy	anger	surprise	fear	love
Student	American Indian or Alaska Native	0.011	0.014	0.000	0.016	0.000	0.000	0.000
	Asian	0.091	0.043	0.086	0.063	0.111	0.000	0.075
	Black or African American	0.068	0.061	0.057	0.016	0.000	0.000	0.050
	Hispanic, Latina/o, Chicana/o	0.375	0.288	0.286	0.273	0.407	0.500	0.275
	Native Hawaiian or Pacific Islander	0.000	0.004	0.029	0.008	0.000	0.000	0.000
	White	0.307	0.414	0.429	0.461	0.333	0.500	0.500
	Other	0.023	0.007	0.000	0.031	0.000	0.000	0.000
Professor	American Indian or Alaska Native	0.000	0.014	0.000	0.000	0.000	0.000	0.000
	Asian	0.000	0.004	0.000	0.000	0.000	0.000	0.000
	Black or African American	0.000	0.018	0.000	0.016	0.000	0.000	0.000
	Hispanic, Latina/o, Chicana/o	0.011	0.025	0.029	0.023	0.037	0.000	0.075
	Native Hawaiian or Pacific Islander	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	White	0.114	0.101	0.086	0.086	0.074	0.000	0.025
	Other	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Missing/ Other	Hispanic, Latina/o, Chicana/o	0.000	0.007	0.000	0.008	0.037	0.000	0.000

The distribution of detected emotions of survey participants among various ethnicities is shown in Table 4. By checking the number of people who participated in the survey, Hispanic, Latina/o, Chicana/o (198) and White (302) engineering people took a large proportion in this survey. Both engineering students and professors (total of 276) have ‘neutral’ as the highest detected emotion among various ethnicities (as shown in Appendix D). Specifically, among students, both ‘Hispanic, Latina/o, Chicana/o’ and ‘White’ engineering students were identified with ‘neutral’ emotions on their responses about the hidden curriculum followed by ‘anger’ and ‘sadness’ emotions. It is also important to note that white engineering students have an extremely higher number of ‘anger’ emotions. For professors, white engineering professors showed a similar trend.

Model 4 is the most salient emotion model as it captures the specific emotions in the textual responses. These identified emotions reflect the potential disparities within training datasets but show the variety of detected emotions while also highlighting underrepresented emotions which was also shown by another study [36]. The breakdown of demographics for participants’ identified emotional responses across factors including their ages, genders, and ethnicities reveal notable patterns. The younger students (18-29 years) showed higher sadness and anger sentiments than older participants (30 or above), indicating their naivety in navigating their educational and institutional expectations. The female participants collectively expressed stronger emotional responses such as sadness and love which indicates emotional experiences that may have impacted their engineering experiences. The Hispanic, Latina/o, and Chicana/o engineering community appear to have higher sadness and anger levels, possibly suggesting structural inequities or challenges which they may have experienced. To unpack these challenges on a deeper level and to offer support, training programs on the hidden curriculum should employ an intersectional approach that factors the participants cultural and emotional experiences as also shown in prior research while also exploring the influence of engineering epistemologies on behavior, knowledge and success in engineering education [43], [44].

C. *Comparison of pretrained models by identified emotions (RQ3)*

All the four models had identified the emotions differently based on their training data. The difference in the identified emotions can be seen in Table 5.

Table 5: Comparison of models by identified emotions

Model #	sadness	neutral	joy	anger	surprise	fear	love
Model 1	0.182	-	0.579	0.149	0.017	0.057	0.015
Model 2	0.065	0.677	0.045	0.203	0.007	0.003	-
Model 3	0.050	-	0.399	0.474	0.010	0.055	0.012
Model 4	0.143	0.467	0.055	0.220	0.045	0.007	0.064

The results from Model 1 and Model 3 had common identified emotions (305, 52%) while Model 2 and Model 4 had common identified emotions (348, 60%). This similarity is possible as Models 1 and 3 did not include 'neutral' as an emotion category while Model 2 did not include 'love' as an emotion category. However, it can be clearly seen that Model 1 showed 'joy' as the highest emotion (58%) when participants were asked to talk about hidden curriculum within engineering while Model 3 showed 'joy' as the second highest emotion identified by participants (40%). Both models 2 and 4 had 'neutral' as the highest emotion experienced by engineering participants (68% and 47% respectively).

Limitations

This study only used data from one question in the UPHEME survey to detect emotions of participants to understand their experience with HC in engineering. The participants' responses that were written in a language other than English were not considered in the study. While deleting the responses, two researchers discussed the responses that were to be deleted but there could have been potential bias introduced. In categorizing specific emotions into a broader category, the researchers discussed the categorization and verified it via ChatGPT-4, however, no psychologist or subject matter expert was consulted, which is a potential limitation of this study. This study only used pre-trained NLP models for emotion detection; however, these models may have inherent biases and limitations (differences in preprocessing steps and training datasets). Although we recommend Model 4 as it can identify specific emotions, another limitation of this study is that there is no conclusive result to decide on a reliable pretrained model as there were differences in identified emotions that could be observed between different models. Lastly, a Chi-square test was run in IBM SPSS Statistics 30.0 [45] to determine any correlation between demographics and model results, but no significant results were found; however, more specific analysis was not conducted.

Implications

Detecting emotions in engineering education is crucial as it highlights the emotional impact of unpopular topics, like hidden curriculum, on students influencing their learning, performance, and well-being. Negative emotions like stress and fear can hinder academic success while positive emotions can foster engagement and belonging. NLP models enable scholars and researchers to analyze emotions on a large scale, providing objective and nuanced insights and uncovering subtle cues and patterns that inform data-driven interventions and policy changes. Differences in emotional experiences across demographics reveal disparities in inclusion and equity leading to targeted interventions to improve support and create inclusive environments.

Conclusions & Future Work

This research study utilized the UPHEME survey to extract responses from a single open-ended question on the hidden curriculum in engineering. The emotions of 582 engineering participants were classified using four NLP pre-trained models from HuggingFace website. These models identified at least six emotion groups. This study compared the emotions of engineering participants for each model, investigated how the identified emotions of participants varied across the demographics of participants, and compared the identification of emotions for all four models. Based on the results, it is recommended to use Model 4 for future research purposes as it identifies specific emotions within the textual data. The findings reflect a variety in emotions experienced by the engineering participants and the need to develop inclusive strategies acknowledging the distinct challenges faced by various demographic groups to empower individuals with a cultural and emotional awareness to better navigate academic and professional settings.

In future work, an ML model can manually be designed by using a custom training dataset, pre-processing techniques, fine-tuning the model to identify emotions, and comparing it with the results from the pre-trained models. The responses in different languages can also be incorporated by using Google Translate and applying ML model to it. The intensity and valence (polarity) of emotions can be used to validate the results. The correlation between participant type corresponding to a specific demographic (age, gender, ethnicity, discipline) and the associated model result can be calculated as well. The results of this paper can be used as a foundation to create emotionally aware learning spaces by considering their institutional contexts and other demographics. Lastly, the responses from the selected question on the survey could be compared with the participant responses on the other questions in the survey.

Acknowledgements

This material is based upon work supported by the National Science Foundation (NSF) No. EEC-1653140 given to the third author. Any opinions, findings, and conclusions or recommendations expressed in this material do not necessarily reflect those of the NSF.

Author Contributions

GA: Conceptualization, Project Administration, Data Curation, Formal Analysis, Software, Visualization, Writing – Original Draft Preparation, **YW:** Conceptualization, Data Curation, Formal Analysis, Software, Visualization, Writing – Original Draft Preparation, **IVA**: Conceptualization, Resources, Supervision, Writing – Review & Editing, **EZM:** Conceptualization, Resources, Supervision, Writing – Review & Editing.

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Appendix A

Table 6: Mapping of emotions for all four models

<table>
<tr><th>Model 1</th><th>Model 2</th><th>Model 3</th><th>Model 4</th></tr>
<tr><td rowspan="5">Anger</td><td rowspan="3">Anger</td><td rowspan="5">Anger</td><td>Anger</td></tr>
<tr><td>Remorse</td></tr>
<tr><td>Annoyance</td></tr>
<tr><td rowspan="2">Disgust</td><td>Disapproval</td></tr>
<tr><td>Disgust</td></tr>
<tr><td rowspan="2">Fear</td><td rowspan="2">Fear</td><td rowspan="2">Fear</td><td>Fear</td></tr>
<tr><td>Nervousness</td></tr>
<tr><td rowspan="7">Joy</td><td rowspan="7">Joy</td><td rowspan="7">Joy</td><td>Amusement</td></tr>
<tr><td>Excitement</td></tr>
<tr><td>Gratitude</td></tr>
<tr><td>Joy</td></tr>
<tr><td>Optimism</td></tr>
<tr><td>Pride</td></tr>
<tr><td>Relief</td></tr>
<tr><td rowspan="5">Love</td><td rowspan="5">-</td><td rowspan="5">Love</td><td>Love</td></tr>
<tr><td>Admiration</td></tr>
<tr><td>Approval</td></tr>
<tr><td>Caring</td></tr>
<tr><td>Desire</td></tr>
<tr><td>-</td><td>Neutral</td><td>-</td><td>Neutral</td></tr>
<tr><td rowspan="4">Sadness</td><td rowspan="4">Sadness</td><td rowspan="4">Sadness</td><td>Sadness</td></tr>
<tr><td>Disappointment</td></tr>
<tr><td>Embarrassment</td></tr>
<tr><td>Grief</td></tr>
<tr><td rowspan="4">Surprise</td><td rowspan="4">Surprise</td><td rowspan="4">Surprise</td><td>Surprise</td></tr>
<tr><td>Confusion</td></tr>
<tr><td>Curiosity</td></tr>
<tr><td>Realization</td></tr>
</table>

Appendix B

Table 7: Breakdown of emotions for participants in Model 1

Emotion	Student	Professor	Other	Total	% (out of 582)
Sadness	80	21	5	106	18%
Neutral	-	-	-	-	-
Joy	275	49	13	337	58%
Anger	74	7	6	87	15%
Surprise	9	1	0	10	2%
Fear	28	5	0	33	6%
Love	8	1	0	9	2%
Total	**474**	**84**	**24**	**582**	**100%**

Note: This model did not include 'neutral' as an emotion category.

Table 8: Breakdown of emotions for participants in Model 2

Emotion	Student	Professor	Other	Total	% (out of 582)
Sadness	31	5	2	38	7%
Neutral	325	54	15	394	68%
Joy	21	5	0	26	4%
Anger	94	17	7	118	20%
Surprise	1	3	0	4	1%
Fear	2	0	0	2	0%
Love	-	-	-	-	-
Total	**474**	**84**	**24**	**582**	**100%**

Note: This model did not include 'love' as an emotion category.

Table 9: Breakdown of emotions for participants in Model 3

Emotion	Student	Professor	Other	Total	% (out of 582)
Sadness	26	2	1	29	5%
Neutral	-	-	-	-	-
Joy	192	32	8	232	40%
Anger	216	45	15	276	47%
Surprise	5	1	0	6	1%
Fear	28	4	0	32	5%
Love	7	0	0	7	1%
Total	**474**	**84**	**24**	**582**	**100%**

Note: This model did not include 'neutral' as an emotion category.

Table 10: Breakdown of emotions for participants in Model 4

Emotion	Student	Professor	Other	Total	% (out of 582)
Sadness	69	10	4	83	14%
Neutral	217	46	9	272	47%
Joy	28	4	0	32	5%
Anger	102	18	8	128	22%
Surprise	22	2	2	26	4%
Fear	4	0	0	4	1%
Love	32	4	1	37	6%
Total	**474**	**84**	**24**	**582**	**100%**

Appendix C

Table 11: Mapping of primary disciplines into main categories

Primary Discipline	Combined Category
Chemical Engineering, Materials Engineering, Packaging Engineering, Nuclear Engineering, Paper Engineering, Ceramic Engineering, Energy Engineering	Chemical, Materials & Energy Engineering
Civil Engineering, Environmental Engineering, Architectural Engineering, Construction Engineering, Geotechnical Engineering, Hydraulic Engineering, Highway Engineering, Green Engineering	Civil, Structural & Environmental Engineering
Computer Engineering, Electrical Engineering, Power Engineering, Computer Architecture, Audio Engineering, Electronics Engineering, Instrumentation Engineering, Control Engineering	Electrical, Electronics & Computer Engineering
Mechanical Engineering, Aerospace Engineering, Industrial Engineering, Manufacturing Engineering, Automotive Engineering, Production Engineering, Electromechanical Engineering	Mechanical & Manufacturing Engineering
Biomedical Engineering, Biological Engineering, Process Engineering, Engineering Education, Marine Engineering, Financial Engineering, Acoustic Engineering, Agricultural Engineering, Food Engineering, Pharmaceutical Engineering, Petroleum Engineering	Specialized & Interdisciplinary Engineering

Appendix D

Table 12: Breakdown of emotions for participants as identified by Model 4 by primary discipline

Participant	Primary Discipline	sadness	neutral	joy	anger	surprise	fear	love
Student	Electrical, Electronics & Computer Engineering	9	51	3	12	2	1	5
	Mechanical & Manufacturing Engineering	24	65	9	30	6	0	10
	Civil, Structural & Environmental Engineering	23	75	10	38	10	0	12
	Chemical, Materials & Energy Engineering	6	11	5	13	1	2	1
	Specialized & Interdisciplinary Engineering	7	15	1	9	3	1	4
Professor	Electrical, Electronics & Computer Engineering	1	11	0	4	1	0	0
	Mechanical & Manufacturing Engineering	1	7	0	3	0	0	2

	Civil, Structural & Environmental Engineering	3	19	3	1	1	0	0
	Chemical, Materials & Energy Engineering	2	1	0	6	0	0	0
	Specialized & Interdisciplinary Engineering	3	7	1	4	0	0	2
Missing/ Other	Electrical, Electronics & Computer Engineering	0	1	0	0	1	0	0
	Mechanical & Manufacturing Engineering	0	0	0	0	0	0	0
	Civil, Structural & Environmental Engineering	0	1	0	1	0	0	0
	Chemical, Materials & Energy Engineering	0	0	0	0	0	0	0
	Specialized & Interdisciplinary Engineering	0	0	0	0	0	0	0
Total		**79**	**264**	**32**	**121**	**25**	**4**	**36**

Table 13: Breakdown of emotions for participants as identified by Model 4 by self-identified age range

Participant	Age Range	sadness	neutral	joy	anger	surprise	fear	love
Student	18-29 years of age	62	172	23	88	18	4	29
	30-39 years of age	2	23	4	8	3	0	2
	40-49 years of age	3	21	1	4	1	0	1
	50-59 years of age	1	1	0	2	0	0	0
	60 years of age or older	1	0	0	0	0	0	0
Professor	18-29 years of age	1	8	0	2	0	0	0
	30-39 years of age	3	9	0	8	1	0	1
	40-49 years of age	3	23	4	5	1	0	2
	50-59 years of age	2	5	0	2	0	0	1
	60 years of age or older	1	1	0	1	0	0	0
Missing/ Other	18-29 years of age	0	1	0	1	1	0	0
	30-39 years of age	0	1	0	0	0	0	0
	40-49 years of age	0	0	0	0	0	0	0
	50-59 years of age	0	0	0	0	0	0	0
	60 years of age or older	0	0	0	0	0	0	0
Total		**79**	**265**	**32**	**121**	**25**	**4**	**36**

Table 14: Breakdown of emotions for participants as identified by Model 4 by self-identified gender

Participant	Gender	sadness	neutral	joy	anger	surprise	fear	love
Student	Male	46	137	16	53	15	2	16

	Female	22	78	12	48	6	2	16
	Missing/Other	1	1	0	1	1	0	0
Professor	Male	5	34	2	7	1	0	3
	Female	5	12	2	11	1	0	1
	Missing/Other	0	0	0	0	0	0	0
Missing/ Other	Male	0	1	0	0	0	0	0
	Female	0	1	0	1	1	0	0
	Missing/Other	4	7	0	7	1	0	1
Total		**83**	**271**	**32**	**128**	**26**	**4**	**37**

Table 15: Breakdown of emotions for participants as identified by Model 4 by self-identified race/ethnicity

Participant	Ethnicity	sadness	neutral	joy	anger	surprise	fear	love
Student	American Indian or Alaska Native	1	4	0	2	0	0	0
	Asian	8	12	3	8	3	0	3
	Black or African American	6	17	2	2	0	0	2
	Hispanic, Latina/o, Chicana/o	33	80	10	35	11	2	11
	Native Hawaiian or Pacific Islander	0	1	1	1	0	0	0
	White	27	115	15	59	9	2	20
	Other	2	2	0	4	0	0	0
Professor	American Indian or Alaska Native	0	4	0	0	0	0	0
	Asian	0	1	0	0	0	0	0
	Black or African American	0	5	0	2	0	0	0
	Hispanic, Latina/o, Chicana/o	1	7	1	3	1	0	3
	Native Hawaiian or Pacific Islander	0	0	0	0	0	0	0
	White	10	28	3	11	2	0	1
	Other	0	0	0	0	0	0	0
Missing/ Other	Hispanic, Latina/o, Chicana/o	0	2	0	1	1	0	0
Total		**88**	**278**	**35**	**128**	**27**	**4**	**40**