Does Self-Efficacy Correlate with Positive Emotion and Academic Performance in Collaborative Learning?

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***Abstract*— This full research paper studies the correlation of self-efficacy in computer science as well as learning and social skills with students' academic performance and their emotions in collaborative learning environments. Self-efficacy is an essential part of social cognitive theory and provides the foundation for analyzing human thoughts, motivations, and actions. Studies show that students' successful performance and accomplishment are directly affected by the level of self-efficacy. Therefore, analyzing self-efficacy in engineering education is important since it can impact the learning process in academic settings as well as provide a metric to track for improvement. Social cognitive theories also emphasize that students' interaction with each other affects their learning process and how they perform in educational settings. In previous work [5], we analyzed students' conversations in low-stake teams in an introductory programming course (CS1) and observed a strong positive correlation between students' positive emotions while interacting with each other with their performance in the course. In this study, we focus on the correlation of self-efficacy with learner's emotion and performance. We measure students' self-efficacy with a standard instrument called "Student Attitudes Toward STEM (S-STEM) Survey". For this purpose, we asked the participants to self-report on a 5-point Likert-scaled survey including 20 questions. These 20 questions are grouped into 2 main categories of computer science and learning/social skills. Students' emotions were extracted from their speeches in teams by applying natural language processing (NLP) methods. The result of data analysis shows a statistically significant correlation between overall self-efficacy and performance in the course and positive emotions during the teamwork. We further investigate which category of self-efficacy questions most correlate with students' performance. The result shows self-efficacy in interpersonal skills and learning ability most impact students' performance.**

Keywords—self-efficacy, social skill, computer science, emotion mining, sentiment analysis, NLP, collaborative active learning

I. Introduction

Attitude is a complex subject that has several dimensions such as affect, cognition, and behavior [1, 2]. It is defined as a tendency to have certain beliefs and feelings about a given context and involves behavioral aspects to accomplish a task and achieve the goal [2]. Attitude is a key element in students' learning in the academic setting and is observable through students' behavior in class and how they engage in class activities and teams [2]. Students' attitude impacts their success in the given domain, as well as their interpersonal relationships [1,3,4].

Emotion and affective states are important aspects of attitude. According to research, positive emotions like joy, happiness, and satisfaction about the given subject positively influence students' learning experience [5] while emotional obstacles such as anger, anxiety, etc. can hinder their cognition process [6].

Self-efficacy is one other construct of the attitudinal domain which is defined as how individuals judge and perceive their ability to perform a specific task [2,7]. Self-efficacy is the perception that one can successfully accomplish a given task and the motivation to apply learned skills [7]. It has its roots in self-regulation and is an integral part of social cognitive theory [33, 7, 8]. It is believed that self-efficacy has a positive impact on students' academic performance and has drawn the attention of researchers in engineering education for the past several years [7, 8, 9]. Identifying the factors that contribute to self-efficacy can help educators apply required interventions to improve students' learning experiences [7]. According to research students,' academic success and accomplishment are results of higher self-efficacy, which in turn boosts self-efficacy [7, 8].

Different factors like various background experiences, interpersonal skills, as well as physical and emotional states can impact self-efficacy, which makes it a dynamic attribute that can change over time [7]. This dynamic aspect of self-efficacy makes it difficult to measure and analyze, especially in the educational setting.

While the tone of existing research emphasizes the key role of self-efficacy in students' academic success [7, 8], some researchers witness a lack of correlation between self-efficacy and academic performance in some populations of students and in different situations [10]. Our observation from the existing literature is that the correlation of self-efficacy and performance depends on different factors, like the background of students, their age, major, and the learning environment and class setting.

In this study, we investigate the correlation of self-efficacy with emotion and students' performance in an introductory computer science class (CS1) which is conducted in a collaborative active learning setting. We further analyze which components of self-efficacy most correlate with students' performance. Our finding shows that students' self-efficacy in their interpersonal and learning skills is strongly correlated with how they perform in the course. Our analysis also shows a positive correlation between self-efficacy and positive emotion in this study group.

The rest of this paper is organized as follows; we review the literature on attitude constructs and their impact on students' performance, next we present our research methodology, the study design, and data collection protocol, we present the result of data analysis and test the hypotheses followed by the conclusion and plan for the future work.

II. Background

The impact of self-efficacy and affective states on students' performance makes them important concepts to focus on in engineering education. Such concepts help instructors to identify the students who experience emotional difficulties or have lower levels of self-conception during the early stages of the course and to provide them appropriate feedback [11].

The relationship between self-efficacy and academic performance at the college level has been widely studied by researchers in the field [12]. In [13] the authors found that, in the context of a CS1 course, in particular, self-efficacy affected students' performance in learning programming and that this skillset can be used to predict students' performance [9, 8]. In engineering education research, self-efficacy is considered as a bridge to connect the past experience with the future performance outcome [12]. This applies to both high school and college-level students [21].

In addition to the impact of self-efficacy on students' performance, research shows self-efficacy also impacts students' major and future career choices [22, 20]. It is shown that higher-level self-efficacy and social support play a big role in orienting students to computing careers [23].

Literature suggests that other factors like gender [18], age [14,15,16], and prior experience [17,13,18] impact the correlation between self-efficacy and performance in college-level students. Furthermore, the combinations of self-efficacy and gender result in different patterns in learning programming [8]. For example, in [18] the researchers found that female and male students with no prior background in programming performed at the same level while the females with prior experience had higher performance than males with prior experience in programming. In another study [19] the authors examined the correlation of self-efficacy and goal orientation with performance. The result showed the connection of self-efficacy with performance among female students is different from that of male peers [19].

In another study, the authors analyze the correlation among the triangle of computer self-efficacy, learning performance, and learning engagement. They apply the General Self-Efficacy Scale developed by Schwarzer, et.al. [28] in adults who seek computing as their second job. The result of their study shows that computer self-efficacy is positively correlated with learning performance and learning engagement. They also found that learning engagement is positively related to learning performance [29].

Different methods and standard instruments have been developed to measure self-efficacy in educational settings. Some of the common ones are the "Student Attitudes Toward STEM (S-STEM) Survey" [27], Motivated Strategies for Learning Questionnaire (MSLQ) [25], and General Self-Efficacy Scale (GSE) [24].

One of the most common approaches to measure self-efficacy is having students fill out surveys such as the Motivated Strategies for Learning Questionnaire (MSLQ) self-report tool [8]. It is a common self-report tool to measure student motivation and learning strategies in a given context [8].

One of the studies that applied the Motivated Strategies for Learning Questionnaire (MSLQ) [25] measured the self-efficacy of 39 students in a CS1 class. The result of this study showed a strong positive correlation between motivational and learning strategy scales with students' performance in the course [25]. Again, in another study [26], the authors identify MSLQ scores to be highly correlated with students' performance.

"Student Attitudes Toward STEM (S-STEM) Survey" [27] is a widely used instrument to measure the self-efficacy of students in the STEM field. This tool asks participants about their confidence level and attitude disposition about STEM subjects and career areas as well as the required skills for the 21st century. The result of this test can be applied by administrators and program directors to adjust the curriculum accordingly [35].

In this work, we adapt the S-STEM tool to measure students' self-efficacy in learning computer science as well as their self-efficacy about social skills in a CS1 collaborative active learning class. In particular, we study if students' self-efficacy about their learning and interpersonal skills correlate with their performance and their positive emotions. In the following section, we present our research hypotheses and the methodology.

III. Research Method

The main goal of this study is to identify the correlation of self-efficacy with positive emotions and performance. We conduct the case study on the population of mixed female and male students with diverse backgrounds in a programming class (CS1).

In order to measure students' self-efficacy, we apply the Student Attitudes Toward STEM (S-STEM) tool. Students' emotions are extracted by Natural Language Processing (NLP) methods from their collaborative speech in low-stake teams [5] in which the emphasis is on building communication skills and learning from peers rather than a group grade for the outcome. The students' individual grade in the course is considered as the performance metric. In this study, we want to identify the association between self-efficacy and performance as well as students' emotional disposition in teams. We further identify the self-efficacy factors that impact students' programming performance.

To answer the research question, we formulate the following Null hypotheses:

$H1_0$. There is a correlation between students' self-efficacy and individual performance.

$H2_0$. There is a correlation between students' self-efficacy and positive sentiments (frequency and intensity of compound values) in low-stake teams.

The research methodology is categorized into three main phases: 1) identify a standard tool to measure self-efficacy, 2) describe an emotion mining algorithm to measure the positive sentiments, 3) present a study design for data collection. The high-level visualization of the tools and methods we applied for data collection from the beginning to the end of a semester is presented in Fig. 1. We elaborate on these tools and methods in the remainder of this section.

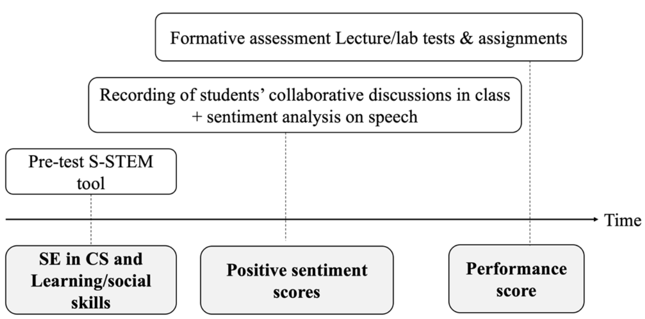

Fig. 1. Study design for data collection in one semester

A. Self-efficacy

For measuring students' self-efficacy, we applied the "Student Attitudes Toward STEM (S-STEM) Survey" which is a standard self-report tool [27]. S-STEM is a five-point Likert Scale tool that measures students' self-efficacy in five categories of 'Math', 'Science', 'engineering and technology, '21st-century learning', and 'about yourself'. The category of '21st-century learning' focuses on soft skills like collaboration and social skills and the 'about yourself' section measures how the individuals expect themselves to perform in the given domain.

In this study, we focus on the 'science' (CS) and 'the 21st-century learning' (L&S) components of the self-efficacy tool to be applied in a CS1 class. The questions in each category are presented in Table 1.

A self-efficacy test was conducted at the beginning of the semester to measure the level of self-efficacy in students. The response rate to this survey was 100% which enabled us to use this as a metric and analyze its correlation with students' performance and positive sentiments.

TABLE 1. S-STEM QUESTIONS [27]

ID	Description
CS1	I am sure of myself when I do computer science.
CS2	I would consider a career in computer science.
CS3	I expect to use computer science when I get out of College.
CS4	Knowing computer science will help me earn a living.
CS5	I will need computer science for my future work.
CS6	I know I can do well in computer science.
CS7	Computer science will be important to me in my life's work.
CS8	I can handle most subjects well, but I cannot do a good job with computer science.
CS9	I am sure I could do advanced work in computer science
L&S1	I am confident I can lead others to accomplish a goal.
L&S2	I am confident I can encourage others to do their best.
L&S3	I am confident I can produce high-quality work.
L&S4	I am confident I can respect the differences of my peers.
L&S5	I am confident I can help my peers.
L&S6	I am confident I can include others' perspectives when making decisions.
L&S7	I am confident I can make changes when things do not go as planned.
L&S8	I am confident I can set my own learning goals.
L&S9	I am confident I can manage my time wisely when working on my own.
L&S10	When I have many assignments, I can choose which ones need to be done first.
L&S11	I am confident I can work well with students from different backgrounds.

B. Sentiments

For operationalizing students' positive emotions, we recorded their speech while they worked in teams in class during the semester. NLP methods (i.e., NLTK, VADER) were adopted to extract the polarity of students' sentiments. The recording process in the classroom had some challenges, the main one being the environmental noise level as all crosstalk during class time. To improve the quality of recorded audios for analysis we applied voice filtering and noise reduction methods on them. Next, we cleaned the data by assigning a unique ID to each speaker based on a voice recognition mechanism.

The algorithm for text mining and sentiment analysis from speech corpora is presented in our previous work [5]. This algorithm took the transcribed speech tokens as input and classified the sentiments in three classes of positive, negative, and neutral emotion as well as the compound value which is a unique metric calculated based on the three classes of emotion.

In order to analyze the positive sentiments, we measure both the intensity and frequency of sentiments by applying NLTK and VADER algorithms on the tokenized speech vectors. The output feature vectors are sentiment classes of positive, neutral, and negative as well as compound scores as shown in Fig. 2.

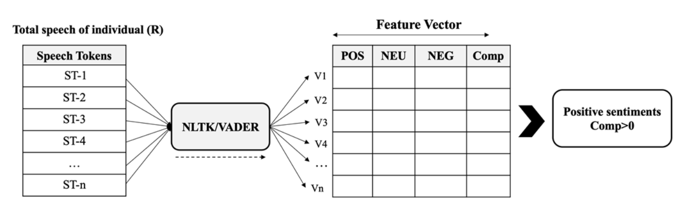

Fig.2. The process of extracting positive sentiments (com>0) from speech

Here R is the total recorded speech dataset of each participant during the semester and ST is speech segmentation based on the initiation of talks, and V is the feature vector consisting of four features of Pos, Neu, Neg, and Comp.

To extract the positive emotions, we considered the vectors with compound values greater than zero (comp >0). We normalize the intensity and frequency of positive sentiments based on the number of speech segments (n) in each dataset (R). Frequency refers to the number of vectors that have positive compound values (comp>0) and intensity refers to the actual value of compound scores in each vector.

Equations (1) and (2) shows how the mean frequency and intensity values of positive sentiments are calculated [5]:

$$Frequency = \frac{m}{n} \quad (1)$$

$$Intensity = \frac{\sum_{x=1}^{m}(comp\_value_x)}{n} \quad (2)$$

Where:
n= total number of vectors in each dataset
Vectors with positive comp_value= {1,2, …m}

The result presented in our previous study [5] showed a strong positive correlation between students' positive emotions as they communicated in teams with their performance in the course. In this study, we use the same result of sentiment analysis to identify the correlation of positive emotions with self-efficacy.

C. Data collection

We collected data from a CS1 active learning class with 63 students. From the total number of students, 48 students participated in the study. The study design was such that students were assigned to work in pairs during the class activity. Using a collaborative active learning approach to teaching this course, the class time was divided into three parts: 1) a low-stake poll quiz from the previous content followed by a Q/A discussion to resolve students' misconceptions, 2) a mini-lecture on the prep work that students were supposed to study before attending the class, and 3) teamwork class activity. The class duration was 75 minutes for two sessions per week and about 40 minutes of each session was dedicated to low-stake teamwork and class activity. We recorded students' conversations as they talked in teams to solve given problems. The recording was done in every session of the class, however, if one team member didn't attend a class we excluded that team from recording for that session. This resulted in dropping the teams that missed more than two sessions of recording for our analysis. As a result, we could collect data from 28 students consistently throughout the semester. Accordingly, we only considered the self-efficacy and performance scores of these 28 students for data analysis. In the following section, we present the result of the data analysis.

IV. Data Analysis

In this study, students' performance was evaluated in a formative style based on three major assignments, three lecture tests, and three lab tests, and multiple quizzes and class activities during the semester. Each assessment had a certain contribution to the final grade: Assignment 30%, Lecture test 30%, and Lab test 30%, and class activities 10%. Participants' grade distribution in the course is presented in Fig. 3.

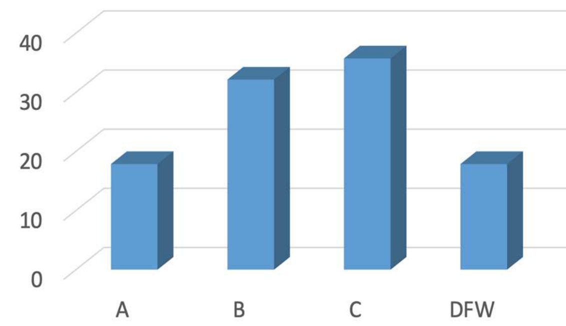

Fig. 3. Participants' grade distribution in the course

As mentioned earlier we employed a standard tool called the "Student Attitudes Toward STEM (S-STEM) Survey" which is a standard self-report tool to measure students' self-efficacy. This is a five-point Likert Scale tool including 20 questions (selected for this study) with the answers ranging from strongly disagree = 1 to strongly agree = 5. The theme of the questions is grouped into two categories of Computer science (CS), learning/social skills (L&S). The list of questions is provided in Table 1.

The students were asked to self-report and provide answers to these questions. Fig. 4 present distribution of students' answers to the 9 questions in the Science category and Fig. 5 show students' answers to the 11 questions in the learning/social skills category.

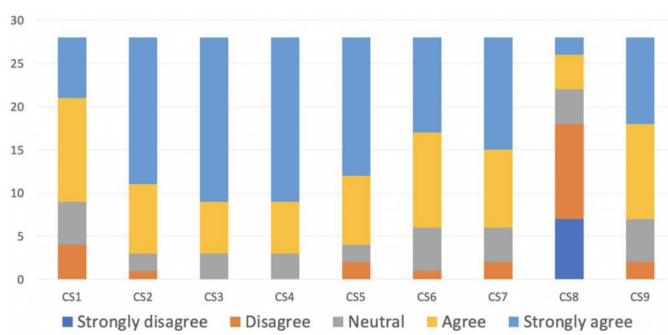

Fig. 4. Distribution of students' answers to the Science category in the S-STEM tool

In order to test the null hypotheses, we apply the chi-square test, and to measure the strength of association between parameters (i.e. self-efficacy, emotion, and performance) we adopt Spearman's rank correlation coefficient method. The first Null hypothesis states: there is a correlation between students' initial self-efficacy and individual performance.

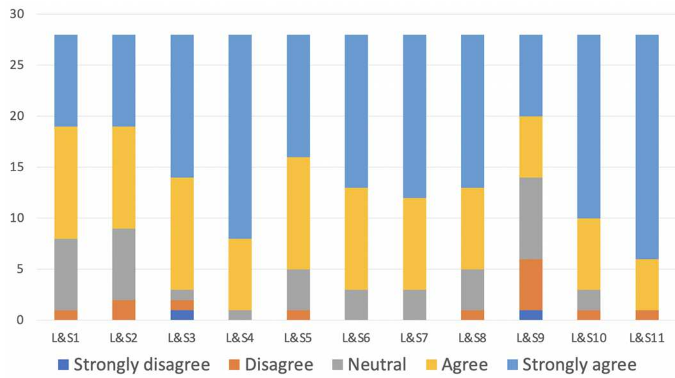

Fig. 5. Distribution of students' answers to the learning/social skills category in the S-STEM tool

We use the chi-square test and measure the two-tailed p-value with the confidence level of 0.05. The calculated p-value is 0.61 which is higher than the confidence level of 0.05. Therefore, the Null hypothesis cannot be rejected. We conclude that there is a statistically significant correlation between students' self-efficacy and their performance.

After identifying the correlation, we measure the strengths of the association between self-efficacy and performance. Researchers such as Norman G. (2010) suggest that both parametric and non-parametric methods can be applied to the ordinal data and Likert-scaled data [30]. We applied Spearman's rank correlation coefficient, which is a nonparametric (distribution-free) rank statistic method [31]. This method describes the relationship between two variables based on a monotonic function, without making any assumptions about the frequency distribution of the variables [31]. The range of coefficient value (r_s) is between -1 and 1. The closer r_s is to +1 or -1, means the two variables have a stronger monotonic relationship. In Spearman's rank correlation coefficient, the value of r_s determines the strength of the correlation and is calculated based on Equation (3)[32].

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{3}$$

where:

d = difference in ranks for variables

n = number of cases

Table 2. shows the interpretation of the r_s value in Spearman's rank correlation coefficient [32]. The calculated value of r_s is 0.11 which denotes a positive yet very weak association between the two variables of self-efficacy and performance.

Next, we test the second Null hypothesis which states there is a correlation between students' self-efficacy and positive sentiments in low-stake teams. In this step again like the previous one, we test the hypothesis using the chi-square test and measure the intensity of the relationship by applying Spearman's rank correlation coefficient.

The calculated p-value for the frequency of positive emotions (vectors with comp>0) is 0.77 and the p-value for the intensity of the positive sentiments is 0.75. For both variables, the calculated p-value is higher than the confidence level of 0.05, so the Null hypothesis is not rejected which indicates there is a statistically significant correlation between students' self-efficacy and their positive sentiments.

TABLE 2. INTERPRETATION OF THE RS VALUE

rs value	Interpretation
00-.19	very weak
.20-.39	weak
.40-.59	moderate
.60-.79	strong
.80-1.0	very strong

The Spearman's Correlation Coefficient test shows the result of rs = 0.06 for both the frequency and the intensity of positive emotions which means the association between self-efficacy and positive emotion (frequency and intensity) is very weak. The results of the chi-square test and Spearman's rank correlation coefficient are presented in Table 3.

TABLE 3. THE RESULTS OF CHI-SQUARE TEST AND THE SPEARMAN'S RANK CORRELATION COEFFICIENT

	Self-efficacy	
	Spearman's Rank Correlation Coefficient (rs Value)	Chi-Square (P-Value)
Performance	0.11	0.61
Frequency of pos sentiments	0.06	0.77
Intensity of pos sentiments	0.06	0.75

As mentioned earlier the self-efficacy questions are categorized into two themes of computer science and cognition/social skills. In our data analysis, we investigate which questions in each category are more related to the performance. In other words which self-efficacy dimensions have more potential to impact students' performance. For this purpose, we applied Principal Component Analysis (PCA) method to identify the main dimensions that better represent the self-efficacy with students' performance as the target value. PCA is an unsupervised statistical method for reducing the feature space dimension to the most critical ones while preserving as much 'variability' (i.e., statistical information) as possible [34].

By creating a new feature (component) based on the linear combination of initial features PCA reduces the number of features in the dataset. The dimensionality reduction is one of the main features of this method that makes it effective in developing predictive models [36].

The steps to identify the best number of components for maintaining the originality of the dataset are 1) identifying the covariance matrix of the original 20 features in the self-efficacy tool, 2) calculating the eigenvalue and eigenvector for each feature, 3) sorting the eigenvalues in descending order and 4) retaining the components that have eigenvalues higher than 1.

The scatter plot of eigenvalues is presented in Fig. 6, where the horizontal axis shows the features of the self-efficacy tool, and the vertical axis shows the corresponding eigenvalues. The result confirms we need only seven components (highlighted in red color) to represent the self-efficacy dataset.

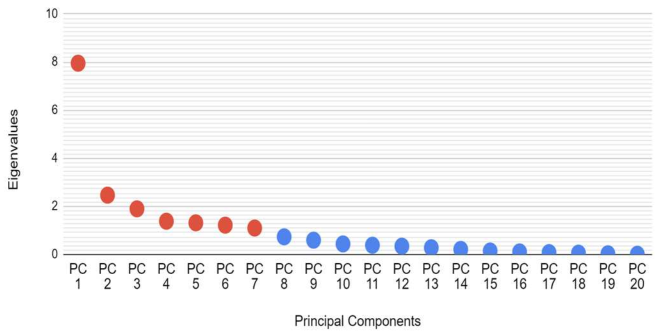

Fig. 6. Scatter Plot of the Eigenvalues of the Principal Comp

To interpret each principal component in terms of the original variables, we measure the magnitude of the coefficients of the original 20 features. Larger absolute values of coefficients indicate that the corresponding component (i.e., the question in the self-efficacy tool) has more importance in terms of the target value which is performance. The self-efficacy questions related to the top seven principal components are listed in Table 4. Since the maximum coefficient values of the two components were related to one question the total number of 6 questions are identified based on the seven principal components.

TABLE 4. S-STEM QUESTIONS [27]

ID	PRINCIPAL COMPONENT	SELF-EFFICACY QUESTION
CS7	PC-4 PC-5	Computer science will be important to me in my life's work.
L&S2	PC-1	I am confident I can respect the differences of my peers.
L&S4	PC-6	I am confident I can respect the differences of my peers.
L&S9	PC-3	I am confident I can manage my time wisely when working on my own.
L&S10	PC-2	When I have many assignments, I can choose which ones need to be done first.
L&S11	PC-7	I am confident I can work well with students from different backgrounds.

The result of our analysis shows that out of six questions (each represented by a principal component), five of them belong to the category of learning and social skills and only one belongs to the computer science category. This confirms that students' self-efficacy about their learning and social skills plays a key role in their overall performance in the course. This is an important finding since it cues instructors and educators to pay particular attention to the students with lower scores in these questions and provide effective pedagogical interventions to improve their learning experience.

The responses to the identified six self-efficacy questions are plotted in the divergent stacked bar chart in Fig.7.

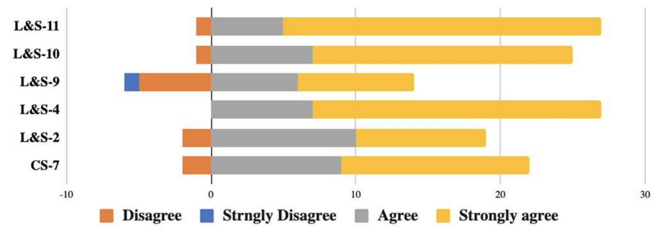

Fig. 7. Divergent Stacked Bar of the Self-Efficacy Questions

Fig.7 shows question L&S-9 has the most negative score (i.e., disagree and strongly disagree) which asks if students can manage their time when they work on their own, and question L&S-11 has the highest positive score (i.e., strongly agree) which shows students' confidence in working with other people with different backgrounds. This indicates that students' social skills and their interest in teamwork and confidence in managing diversity positively impact how they perform in the course.

V. CONCLUSION

In this study, we explore the impact of self-efficacy on students' performance in CS1 collaborative active learning class. We also analyze the correlation between students' positive emotions in low-stake team discussions and their self-efficacy. To measure the level of students' self-efficacy we apply a standard self-report tool (S-STEM). This tool measures students' self-efficacy about computer science, learning, and social skills. The sentiments are extracted from students' conversations as they work in low-stake teams in a CS1 class and discuss the course content with their assigned peers. By applying Natural Language Processing (NLP) algorithm we conduct sentiment analysis and detect valence and polarity of sentiments from the conversations. The output of this algorithm the frequency and intensity of positive sentiment scores in students' speech during the semester.

By applying the chi-square test and Spearman's rank correlation coefficient method we test the hypothesis and measure the intensity of association between parameters of self-efficacy, performance, and emotion. The result of our data analysis shows a statistically significant positive correlation between self-efficacy and performance, which aligns with the findings of the previous research. Data shows the correlation of self-efficacy and students' positive sentiments while engaged in low-stake team discussions is statistically significant but not as strong as the association between self-efficacy and performance.

One of the main contributions of this study is to investigate which sub-dimensions of self-efficacy most correlate with performance. By applying the PCA method we reduce the dimension of self-efficacy features to the most critical ones in terms of performance as the target value. The dimensionality reduction methods resulted in 7 principal components. Accordingly, we identified the questions of self-efficacy that most impact the performance score. Data shows that students' self-efficacy in interpersonal skills and learning ability most impact their performance. This finding is an important support for collaborative active learning in which peer learning is achieved through students' communication.

The early result of our data analysis is promising to conduct this method on a larger population of students and derive more generic conclusions. We believe the finding of this research can help educators to identify the students who experience emotional obstacles or have low levels of self-efficacy earlier in the semester and provide the required assistance to them.

A. Futue work

In future work, we will apply this method to different classes in computing and software engineering to analyze a larger population of students. In the study design, we will have more focus on team dynamics and attributes to pursue a hypothesis that collaborative active learning can improve both interpersonal skills and individual performance. We will inspect the correlation of self-efficacy with performance and emotion in teams consisting of only males or only females to compare the result in each population. We will also consider other sentiments and emotional states of students like joy, happiness, anger, etc. in our analysis.

In this study, we employed the questions of the S-STEM tool with a Likert Scale format. In the future study, we will also include open-ended questions of this instrument and by applying NLP methods extract information from students' narratives for more in-depth analysis.

REFERENCES

[1] Arguedas, M., Daradoumis, T., & Xhafa, F. (2014, July). Towards an emotion labeling model to detect emotions in educational discourse. In 2014 Eighth International Conference on Complex, Intelligent and Software Intensive Systems (pp. 72-78). IEEE.

[2] Laguador, J. M. (2013). Developing students' attitude leading towards a life-changing career. Educational Research International, 1(3), 28-33.

[3] Bacay, T. E., Dotong, C. I., & Laguador, J. M. (2015). Attitude of Marine Engineering Students on Some School-Related Factors and their Academic Performance in Electro Technology 1 and 2. Studies in Social Sciences and Humanities, 2(4), 239-249.

[4] Cohn, E., Cohn, S., Balch, D. C., & Bradley Jr, J. (2004). The relation between student attitudes toward graphs and performance in economics. The American Economist, 48(2), 41-52.

[5] Dehbozorgi, N., Maher, M. L., & Dorodchi, M. (2020, October). Sentiment Analysis on Conversations in Collaborative Active Learning as an Early Predictor of Performance. In *2020 IEEE Frontiers in Education Conference (FIE)* (pp. 1-9). IEEE.

[6] Munezero, M., Montero, C. S., Mozgovoy, M., & Sutinen, E. (2013, November). Exploiting sentiment analysis to track emotions in students' learning diaries. In Proceedings of the 13th Koli Calling International Conference on Computing Education Research (pp. 145-152). ACM.

[7] Wilson, K., & Narayan, A. (2016). Relationships among individual task self-efficacy, self-regulated learning strategy use and academic performance in a computer-supported collaborative learning environment. Educational Psychology, 36(2), 236-253.

[8] Lishinski, A., Yadav, A., Good, J., & Enbody, R. (2016, August). Learning to program: Gender differences and interactive effects of students' motivation, goals, and self-efficacy on performance. In Proceedings of the 2016 ACM Conference on International Computing Education Research(pp. 211-220). ACM.

[9] Hórreo, V. S., & Carro, R. M. (2007, September). Studying the impact of personality and group formation on learner performance. In International Conference on Collaboration and Technology (pp. 287-294). Springer, Berlin, Heidelberg.

[10] Ballen, C. J., Wieman, C., Salehi, S., Searle, J. B., & Zamudio, K. R. (2017). Enhancing diversity in undergraduate science: Self-efficacy drives performance gains with active learning. CBE—Life Sciences Education, 16(4), ar56.

[11] Maras, P., & Kutnick, P. (1999). Emotional and behavioural difficulties in schools: Consideration of relationships between theory and practice. Social Psychology of Education, 3(3), 135-153.

[12] Aivaloglou, E., & Hermans, F. (2019, February). Early programming education and career orientation: the effects of gender, self-efficacy, motivation and stereotypes. In Proceedings of the 50th ACM Technical Symposium on Computer Science Education (pp. 679-685).

[13] Vennila Ramalingam, Deborah LaBelle, and Susan Wiedenbeck. 2004. Self-efficacy and Mental Models in Learning to Program. In Proceedings of the 9th Annual SIGCSE Conference on Innovation and Technology in Computer Science Education. ACM, 171–175.

[14] Felienne Hermans and Efthimia Aivaloglou. 2017. Teaching Software Engineering Principles to K-12 Students: A MOOC on Scratch. In Proceedings of the 39th International Conference on Software Engineering: Software Engineering and Education Track. IEEE Press, Piscataway, NJ, USA, 13–22.

[15] Kathryn M. Rich, Carla Strickland, T. Andrew Binkowski, Cheryl Moran, and Diana Franklin. 2017. K-8 Learning Trajectories Derived from Research Literature: Sequence, Repetition, Conditionals. In Proceedings of the 2017 ACM Conference on International Computing Education Research (ICER '17). ACM, New York, NY, USA, 182–190.

[16] Linda Seiter and Brendan Foreman. 2013. Modeling the Learning Progressions of Computational Thinking of Primary Grade Students. In Proceedings of the Ninth Annual International ACM Conference on International Computing Education Research. ACM, 59–66.

[17] Christine Alvarado, Gustavo Umbelino, and Mia Minnes. 2018. The Persistent Effect of Pre-College Computing Experience on College CS Course Grades. In Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18). ACM, New York, NY, USA, 876–881.

[18] Chris Wilcox and Albert Lionelle. 2018. Quantifying the Benefits of Prior Programming Experience in an Introductory Computer Science Course. In Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18). ACM, New York, NY, USA, 80–85.

[19] Alex Lishinski, Aman Yadav, Jon Good, and Richard Enbody. 2016. Learning to Program: Gender Differences and Interactive Effects of Students' Motivation, Goals, and Self-Efficacy on Performance. In Proceedings of the 2016 ACM Conference on International Computing Education Research. ACM, 211–220.

[20] Mary Beth Rosson, John M. Carroll, and Hansa Sinha. 2011. Orientation of Undergraduates Toward Careers in the Computer and Information Sciences: Gender, Self-Efficacy and Social Support. Trans. Comput. Educ. 11, 3, Article 14 (Oct. 2011), 23 pages.

[21] Shari L. Britner and Frank Pajares. 2006. Sources of science self-efficacy beliefs of middle school students. Journal of Research in Science Teaching 43, 5 (2006), 485–499.

[22] Robert W Lent and Gail Hackett. 1987. Career self-efficacy: Empirical status and future directions. Journal of Vocational Behavior 30, 3 (1987), 347 – 382.

[23] Jung, D. I., & Sosik, J. J. (1998). Group potency and collective efficacy: Predictive validity, level of analysis, and effects of performance feedback on future group performance. Paper In M. T. Brannick, E. Salas, & C. W. Prince (Eds.), Team performance assessment and measurement: Theory, methods, and applications (pp. 19–43). Mahwah, NJ, USA: Lawrence

[24] Malinauskas, R. K. (2017). Enhancing of Self-Efficacy in Teacher Education Students. European Journal of Contemporary Education, 6(4), 732-738.

[25] Christopher Watson, Frederick W.B. Li, and Jamie L. Godwin. 2014. No Tests Required: Comparing Traditional and Dynamic Predictors of

Programming Success. In Proceedings of the 45th ACM Technical Symposium on Computer Science Education. ACM, 469–474.

[26] Marcus Credé and L. Alison Phillips. 2011. A meta-analytic review of the Motivated Strategies for Learning Questionnaire. Learning and Individual Differences 21, 4 (2011), 337 – 346.

[27] Unfried, A., Faber, M., Stanhope, D. S., & Wiebe, E. (2015). The development and validation of a measure of student attitudes toward science, technology, engineering, and math (S-STEM). Journal of Psychoeducational Assessment, 33(7), 622-639.

[28] Schwarzer, R., Bäßler, J., Kwiatek, P., Schröder, K., & Zhang, J. X. (1997). The assessment of optimistic self-beliefs: comparison of the German, Spanish, and Chinese versions of the general self-efficacy scale. Applied Psychology, 46(1), 69-88.

[29] Chen, I. S. (2017). Computer self-efficacy, learning performance, and the mediating role of learning engagement. Computers in Human Behavior, 72, 362-370.

[30] Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. Advances in health sciences education, 15(5), 625-632.

[31] Hauke, J., & Kossowski, T. (2011). Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data. Quaestiones geographicae, 30(2), 87-93.

[32] Mukaka, M. M. (2012). A guide to appropriate use of correlation coefficient in medical research. Malawi medical journal, 24(3), 69-71.

[33] Bartimote-Aufflick, K., Bridgeman, A., Walker, R., Sharma, M., & Smith, L. (2016). The study, evaluation, and improvement of university student self-efficacy. Studies in Higher Education, 41(11), 1918-1942.

[34] Hess, A. S., & Hess, J. R. (2018). Principal component analysis. Transfusion, 58(7), 1580.

[35] https://www.fi.ncsu.edu/pages/about-the-student-attitudes-toward-stem-survey-s-stem/. Last accessed April 2021.

[36] Dehbozorgi, N. (2020). Sentiment Analysis on Verbal Data from Team Discussions as an Indicator of Individual Performance (Doctoral dissertation, The University of North Carolina at Charlotte).