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Self-efficacy of high school students after an AI-focused pre-college program: A two year impact study (Fundamental)

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Abstract

In this paper, we study the impact of a pre-college summer education program on students' self-efficacy as they progressed from high school to college. Specifically, we study how learning about neural networks and artificial intelligence in the pre-college program affects the professional formation of students in engineering and computer science undergraduate programs. We measure changes in students' self-efficacy, emotional learning, and readiness to join and contribute to the Artificial Intelligence (AI) workforce in this two-year impact study from Fall 2022 to Fall 2024. Thus, our findings are relevant for optimizing pre-college to college education pipelines to meet workforce needs in engineering, AI, and the Computer Science (CS) industry.

To study the impact of the pre-college AI education program on student progression, we conducted focus group interviews in Fall 2024, two years after the pre-college program. With thematic analysis, we quantify student and program outcomes by synthesizing four themes: social and emotional learning, self-efficacy, career readiness, and program impact. To formally validate human thematic analysis, we ask: (RQ1) What methods can validate heuristic thematic analysis for reliable study of qualitative data? To quantify the two-year impact of the program, we study (RQ2) whether the pre-college program enhanced students' confidence and readiness for a college major in computer science or related engineering disciplines. For a deeper understanding of students' perceptions and change in psychosocial behavior, we also study: (RQ3) Which specific aspects of self-efficacy and social and emotional learning are most affected among students who participated in the summer program? Our measurement instruments are pre-/post-course Likert surveys, thematic analysis of student focus groups, and a codebook-based quantitative analysis of student reflections. We report the correlations of our thematic analysis results with the pre- and post-course Likert surveys conducted when students were enrolled in the pre-college program. Our findings provide important insights on designing teaching approaches and future pre-college programs that enhance students' preparation for first-year engineering programs and careers in CS and AI.

1 Introduction

The need for a talented engineering workforce continues to grow at a rapid pace [1], while 4-year graduation rates are declining [2] and high attrition rates are observed in many engineering programs [3]. In 2024, the US Bureau of Labor Statistics [1] reported that the need for employment in STEM areas is expected to be 5% higher than in non-STEM careers. Educators and policy makers tackle this need in multiple ways: bridge programs for first-year college students [4], remedial coursework at universities [5], out-of-school experiences during high school [6], and many other engineering and STEM related outreach at all levels of the K-12 pipeline [7]. Thus, there is significant interest in understanding the impact of these programs [5, 8, 9, 10] on the preparation of students for engineering and STEM majors in college and their impact on the workforce. Toward that end, in this paper, we analyze the impact of a pre-college program on participants two years after the program was offered.

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Paper code: `https://github.com/pyEdTools/thematic`

Pre-college programs have been associated with diverse outcomes among participants, with many factors influencing these outcomes. Research has shown that short programs are great for outreach [11], while technical programs have been associated with increased student confidence [5]. Extended programs with a more rigorous curriculum focus (for example, programs that are longer than two weeks) can help with college readiness to some extent [12] but may suffer from limited availability [13] and can reflect broader social biases [14] that shape how students perceive and access these opportunities. In summary, it is well established that information barriers and systemic inequities of various types can hinder efficiency, participation, and success in STEM college education [15] and that pre-college programs can help address some of these gaps [5]. Such programs can create pathways to broaden participation in engineering and STEM [16], and can improve college readiness [17] among high school students. Consequently, the engineering education research community is often interested in evaluating the utility, effectiveness, and need for pre-college programs. Our research is in this direction as we seek strategies to expand participation in engineering and STEM fields, build foundational knowledge, and better prepare students for college and the workforce. Next, we review this research area to position our study in the appropriate context.

1.1 Background

For high school students who are preparing for college, self-efficacy [18] in learning is important and is a common metric used to study the impact of pre-college programs on students [10]. Although pre-college programs can introduce new technical topics, the key benefits for students who participate in such programs include building confidence [19], acquiring general know-how, gaining clearer perceptions of college [11], and understanding the educational landscape [8]. A related area of research is college readiness [17]. In recent years, there has been an increase in high school students advancing their technical knowledge in computer programming, calculus, and other subjects to prepare for engineering majors [20]. However, these opportunities are not easily accessible to all [13, 14] and the percentage of students who enroll in remedial coursework in college remains high [5]. Therefore, we aim to identify the key benefits students are gaining from these pre-college experiences. Studying this will help us develop clearer strategies for future pre-college programs to enhance equity, broaden participation, and guide the design of curricula.

A variety of pre-college programs exist to prepare students for majors in numerous fields. Our focus is on pre-college programs that cater to computer science (CS) and related engineering disciplines. Specifically, this paper examines the impact of a pre-college program on artificial intelligence (AI), which was attended by high school students from grades 9 to 12 during the summer of 2023. We previously explored how much these students learned about neural networks and its possible influence on their self-efficacy as engineers [21]. A key observation was that the survey data did not conclusively determine the impact on self-efficacy. Therefore, to supplement that study, we conducted focus group interviews with a subset of student volunteers who participated in this program two years earlier. So, in this paper, we study how we can use qualitative data from a focus group and its thematic analysis to draw definitive conclusions on students' college readiness and self-efficacy.

Similar studies have been conducted elsewhere; for instance, researchers at Rowan University examined the impact of a pre-college institute on student performance two years later and noted an increase in self-efficacy compared to the standard College Academic Self-Efficacy Scale (CASES) [22]. Additionally, increases in academic self-efficacy were observed pre- and post-program [23, 24, 25].

Along similar lines, we conduct qualitative data analysis to quantify the impact of the pre-college program. We propose an AI-based method to validate the heuristic approach taken by a human for thematic analysis. Using the results of the validated thematic analysis, we discuss emerging patterns that suggest increased self-efficacy among students. Thematic analysis also enables us to discuss self-efficacy and correlate it with surveys conducted 18 months ago about students' post-course reflections. This research aims to fundamentally explore which areas of self-efficacy are improved, what might not be helpful, and what students find beneficial. It also generates recommendations on college readiness directly from students involved in the focus group. These strategies and recommendations are intended for high school students, offering guidance on improving their college readiness, career preparation, and making college more enjoyable.

1.2 Context

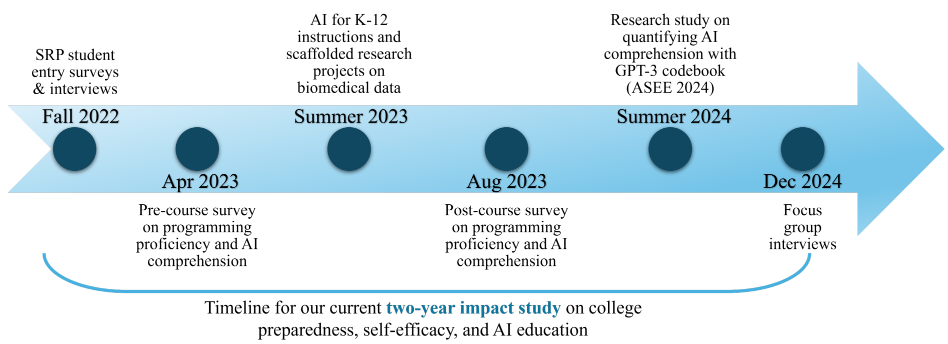

Figure 1: Timeline of the research study and the context

The pre-college program (PCP) examined in this paper, Summer Research Academy Program (SRP), was a four-week long summer initiative at the University of California Santa Barbara. Within the program, multiple educational tracks were offered. The first author (Dr. Shailja) offered a track in this program on "Diagnostic AI", covering topics in machine learning, artificial intelligence pipelines, and their applications in biomedicine and healthcare. The weekly schedule consisted of four 75-minute lectures, two 3-hour lab sessions, and a 3-hour research mentoring session. The course was delivered by three graduate students, with additional staff who managed the program logistics. A total of 30 students participated in this track. The primary expectation for the students was to present a Capstone project at the end of the course, demonstrating the application of AI techniques that they learned to a biomedical or healthcare dataset. The reader is referred to our previous publication [21] for a more detailed analysis of the components of the program, its outcomes, and the analysis of students' comprehension of the topics that were taught in the course.

Two surveys were conducted as part of the regular course instruction for continuous improvement. These surveys used a 5-point Likert scale to assess students' outlook, career readiness, role models, comprehension of AI, programming usage, and the importance of math and calculus. The questions also covered the participants' current school level, prior experience with computer programming, their planned major in college, and career interests and preferences. From the onset of the program to the focus group (refer to the timeline of activities in Figure 1), two years have elapsed, making this a two-year impact study. To study the impact of the program on student self-efficacy and college readiness, we conducted focus group interviews (in December 2024) with $N_{\text{foc}} = 7$ students and individual interviews with $N_{\text{ind}} = 5$ students who participated in the Diagnostic AI track of the PCP. Thus, in total, we recorded $N_{\text{total}} = 12$ audio recordings for the thematic analysis. All focus group interview questions and prompt items are listed in Appendix A, and individual interview questions are listed in Appendix B. The focus group participants reflect the demographics in terms of the school levels represented in the program. 60% of the PCP students (18 out of 30) were in their 11th grade during the program, and 3 out of 7 focus group participants belong to this category. These students reported being in their first year of college two years after the program. Additionally, the focus group included 2 participants who were in 10th grade during the PCP. These students reported being high school seniors (12th grade) two years after the program during the focus group study. Notably, 9th graders showed disproportionately high participation in the focus group; although only 3 were part of the program originally, 2 of these 3 accepted our invitation to join the focus group. This indicates a higher interest among younger students in being involved and learning how to prepare for college, which they may have perceived as a benefit of the focus group study. See Figure 2 for a visual illustration of the participants in the focus group and the PCP. The focus group was gender-balanced, with 3 women and 4 men.

The information obtained was recorded in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects. The research study was reviewed by the Research Compliance Office at the University of California Merced and

ID	School level (in 2025)	Grade level (during PCP)	Planned / current major
1	11th	9th	Bioinformatics
2	12th	10th	Data science
3	UG 1st year	11th	Artificial intelligence
4	UG 1st year	11th	Computer science
5	11th	9th	Computer science
6	12th	10th	Bioinformatics
7	UG 1st year	11th	Computer science

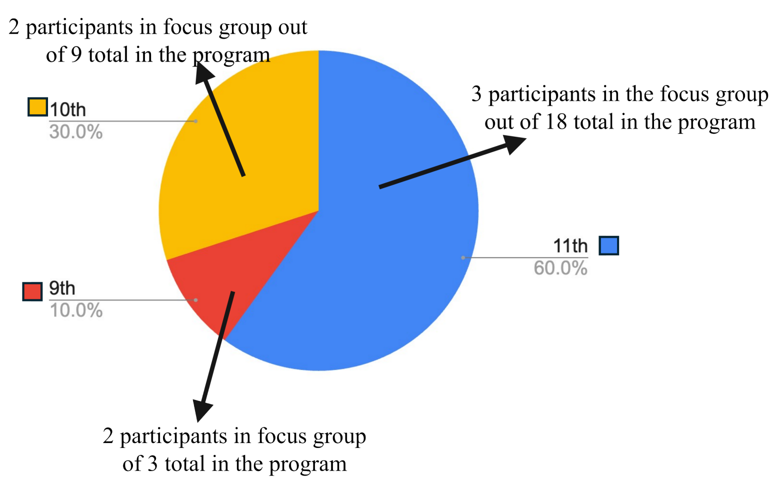

Figure 2: (left) Table shows student demographics based on school level: during the focus group in 2025, during the pre-college program (PCP) in 2023, and planned/current major in college. (right) Chart shows the distribution of all the 30 students who participated in the PCP. Arrows show the students who participated in the focus groups out of total students in each school level. For example, out of 9 total students in the program who were in 10th grade during PCP, two students participated in the focus group.

was deemed self-exempt under local IRB regulations.

1.3 Research questions

To study the impact of the pre-college AI education program on student progression two years later, we formulate three research questions.

1. (RQ1) What methods can validate heuristic thematic analysis with automated approaches for a reliable study of student reflections from qualitative data?
2. (RQ2) Does a pre-college program featuring directed research and communication mentoring enhance students' confidence and readiness for a college major in computer science or related engineering disciplines?
3. (RQ3) Which specific aspects of self-efficacy and social and emotional learning are most affected among students who participated in a rigorous summer program focused on AI?

RQ1 is a method-specific research question. By studying this question, we evaluate the process of thematic analysis from the transcripts of the focus group. With RQ2 and RQ3, we hope to gain a deeper understanding of students' perceptions and behaviors, particularly for students who are transitioning into undergraduate programs after participating in rigorous pre-college programs. This will help us recommend strategies to design future pre-college programs in this area.

1.4 Summary of contributions

Methodical contributions

1. Accelerated thematic analysis with the use of AI models to transcribe audio data.
2. Application of clustering-based methods, commonly used in engineering research but less so in education research, to validate the accuracy of human thematic analysis.

Insights into student behavior

1. Student confidence in achieving success in college increases due to participation in a rigorous program.
2. Thematic analysis reveals that students preparing to enter college show higher readiness, and those already in the first year of college recognize the importance of what they had learned from mentors and peers in the pre-college program.

Significance of research: The results provide new insights and tools to researchers who regularly perform thematic analysis to study the behavior of their participants. Our findings are also important for all educators who are designing new pre-college programs as we present an analysis of what aspects of self-efficacy can enhance among high school students who participate in such programs. Finally, for first-year college counselors and planners, our research offers insights into the skills that pre-college students benefit the most from before entering college.

2 Methods

2.1 Transcription using AI

To transcribe all the audio data collected from focus groups and individual interviews (see Appendix A and B for the questions), we developed and used an AI-based pipeline based on the Whisper AI model [26]. This approach for automated transcription has become increasingly common as it enables large-scale transcription of data in focus group or other qualitative studies. For example, mental health researchers recently showed how Whisper AI can enable efficient and accurate transcription [27]. For our study, we used Zoom video call recordings to collect the data. The audio files in the m4a format were converted to wav format using the Windows FFMPEG tool chain since Whisper AI requires wav audio files. Then, we used Whisper API to transcribe the audio to text files. Human oversight was required to verify the AI-generated transcripts. Specifically, we observed that the Whisper model often ran into hallucinations where, on not being able to transcribe a phrase, the AI model would generate an unrelated and arbitrary text in its place. All such instances of hallucinations were cleaned up. The text files were then shared with an unbiased human evaluator for thematic analysis, that is, this researcher was not involved in the design of the research questions or the design and delivery of the PCP.

2.2 Thematic analysis

For thematic analysis of the focus group and individual interview data, first, we manually read the data to familiarize ourselves with it and anonymized all human identifiers. In this process, we began to conceptualize how the thematic analysis process was going to manifest itself in our research. We started with our goal of measuring self-efficacy and college readiness from the data. Given the nature of the questions, our approach to thematic analysis was semantic and data-driven.

We generated the first iteration of codewords within the data by closely following the definition of a codeword in thematic analysis from Lester et al. 2020 [28, pg.100]: "A code is simply a short, descriptive word or phrase that assigns meaning to the data related to the researcher's analytic interests.". We note that to code a segment of the data, we need it to be relevant to the research questions. Since the interviewer's questions guide the subject matter of the data collection process, we only consider data that answer an interview question. We reviewed and revised the coding process in an iterative manner. Specifically, a undergraduate student researcher who was not involved in the delivery of this summer program performed the data coding. Then, this researcher discussed their work with the study PI to iteratively revise the results. The themes are summarized in Table 1, and a full list of codewords under each theme with their frequencies is given in Appendix C.

Table 1: Summary of themes, categories, descriptions, and code words

Theme	Category	Description	Codes with high frequency	Frequency
(T1) Social and Emotional Learning (The overall experience of the participants to include but not limited to thoughts, feelings, interests and perspectives.)	Emotional Experience	Participant experiences that brought about emotions.	Exciting	8
			Accomplished	2
			Proud	2
	Collaborative Experience	Experiences collaborating with others.	Experience with Team During PCP	4
			Getting Help from Others	3
			Bonding with Colleagues	3
	Perspectives	Participant thoughts and outlook on social and emotional subjects	Comparing High School to College	9
			Participants Describing the Experience	8
			Perspective on Deadlines	3
(T2) Self Efficacy (Participants belief in themselves to succeed and their readiness to succeed in an engineering program.)	Affected Confidence	Participants experiences that affected their confidence	Increased Confidence	13
			Learning From Others	9
			Achieving Accuracy	2
	Socio-emotional skills	The growth and development of participants throughout the study.	Self Reliance	2
			Development of Growth Mindset	1
			Developed Work Ethic	1
(T3) Career Readiness (Participants belief in themselves to succeed and their readiness to succeed in an engineering program)	College Preparedness	Methods to help overcome challenges and accomplish tasks.	Asking for Help	4
			Collaborating	4
			Discover Passions	3
	Challenges faced	Common challenges faced by the study participants as they developed skills to succeed in their chosen career paths	Building Programming Skills	3
			Finding Good Data	3
			Rigorousness of Program	2
	Professional formation	Development of soft skills	Time Management	5
			Learning to find resources	3
			Adjusting to New Environment	2
	Engineering skill development	The process of progressively developing and improving one's skills in a particular area until they reach a level of mastery	Problem Solving Skills	4
			Critical Thinking Skills	1
			Organizing Collaborative Projects	1
	AI Comprehension	Participants learning about various topics	Learned About Research Process	6
			Learning How Code	4
			Learning About Machine Learning	1
(T4) Program Impact (The overall impact of the program on participants.)	Affected Student Outcomes/Decisions	Shows a change in decision or outcome as a result of the research study.	Discovering Passions	12
			Achievement	6
			Planned Major and Choice of Career	4

After coding the data, we started searching for themes (patterns) within the data. Following the guide by Lester et al. 2020 [28], we engaged with the data in an inductive manner, where the undergraduate student researcher who was coding the data moved from isolated cases to broader interpretations of the data. In this process, we gradually developed categories by grouping similar codes together in an iterative and heuristic clustering process. Then, continuing with an inductive process, we developed emergent themes from the categories and classified each category into a broad theme. For a seamless analysis of this thematic coding process, we used an online tool called Delve (delvetool.com). We uploaded the anonymized data and then manually coded, classified, and organized it into themes in Delve's platform.

Finally, we exported the data from Delve to a CSV file for further refinement and effective organization of the thematic analysis. At this point, we collaboratively renamed and reorganized some of the categories and themes to better align with the existing engineering education literature. In conclusion, the thematic analysis output consists of themes/categories/codes in that order along with the frequency of each codeword. In summary, we thematically analyzed the participant responses using an online software called Delve. The process consisted of summarizing the relevant information from each response into codes, grouping those codes into categories, and finally grouping those categories into themes. Throughout the many iterations of the analysis, new codes were found, categories were altered, or in some cases removed, and codes were reclassified from one

Table 2: Seed words for themes

Themes	Theme names	Seed words
T1	Social and Emotional Learning	Exciting, Inspirational, Scary
T2	Self Efficacy	Solving New Problems, Finishing a Polished Project, Self Reliance
T3	Career Readiness	Academic Rigor, Discover Passions, Computer Programming
T4	Program Impact	Participant Joining Clubs, Achievement, Participating in Other Research Projects, Participant Teaching Others

category to another. After exporting the final results to a CSV file, we conducted further analysis and graphed the data to show the trends and/or patterns revealed by thematic analysis.

2.3 Validation of thematic analysis

For the validation of the thematic analysis, we performed an AI-based semantic clustering of the curated list of codes to validate whether the AI-driven clusters are similar to the human coding process. To capture the semantic relationships between the words, we employed the Sentence-BERT (Sentence Transformer) model, specifically the "all-MiniLM-L6-v2" variant [29]. This model was selected for its balance between computational efficiency and embedding quality, making it suitable for handling the dataset's size. A total of 95 codes were shuffled together regardless of the categories to reduce potential biases in the clustering algorithm. Few seed words were provided to give some context to the different themes, as shown in Table 2. Using the BERT transformer model, each code was transformed into a high-dimensional vector. Semi-supervised k-means clustering was used to create four clusters of the codewords (since the manual process consists of four themes). The initial cluster centers were derived from the seeds. Figure 3 shows a 2D visual representation of the clustering results using the Principal Component Analysis (PCA) technique.

Note: Dimension reduction was done only for visualization. The 384-dimensional embeddings were used for k-means clustering for quantify the validity of the themes. After clustering, we analyzed the coherence of each AI-predicted cluster (denoted as $\tilde{T}_1$ to $\tilde{T}_4$) with manually defined themes (T_1 to T_4). Note that the manual process results in clusters that are named as "themes", while the AI-driven process results in "clusters" that correspond to the themes. To evaluate this alignment of cluster assignments with predefined themes, we used an accuracy metric (A), which is defined as the ratio of the number of correctly clustered words to the total number of words in the cluster. Mathematically, this can be expressed as:

$$\text{Accuracy} = \frac{|\text{AI cluster} \cap \text{Manual theme}|}{|\text{AI cluster}|} \tag{1}$$

From Table 3, we observe that for the themes T_1 (social and emotional learning) and T_3 (career readiness), the automated clusters effectively captured the intended semantic groupings. Although

T_2 (self-efficacy) and T_4 (program impact) have a significant overlap with other themes. This shows that the themes T_2 and T_4 are broadly defined by the human analyst as "efficacy" and "program impact" and hence, they overlap with other two specific themes of social and emotional learning

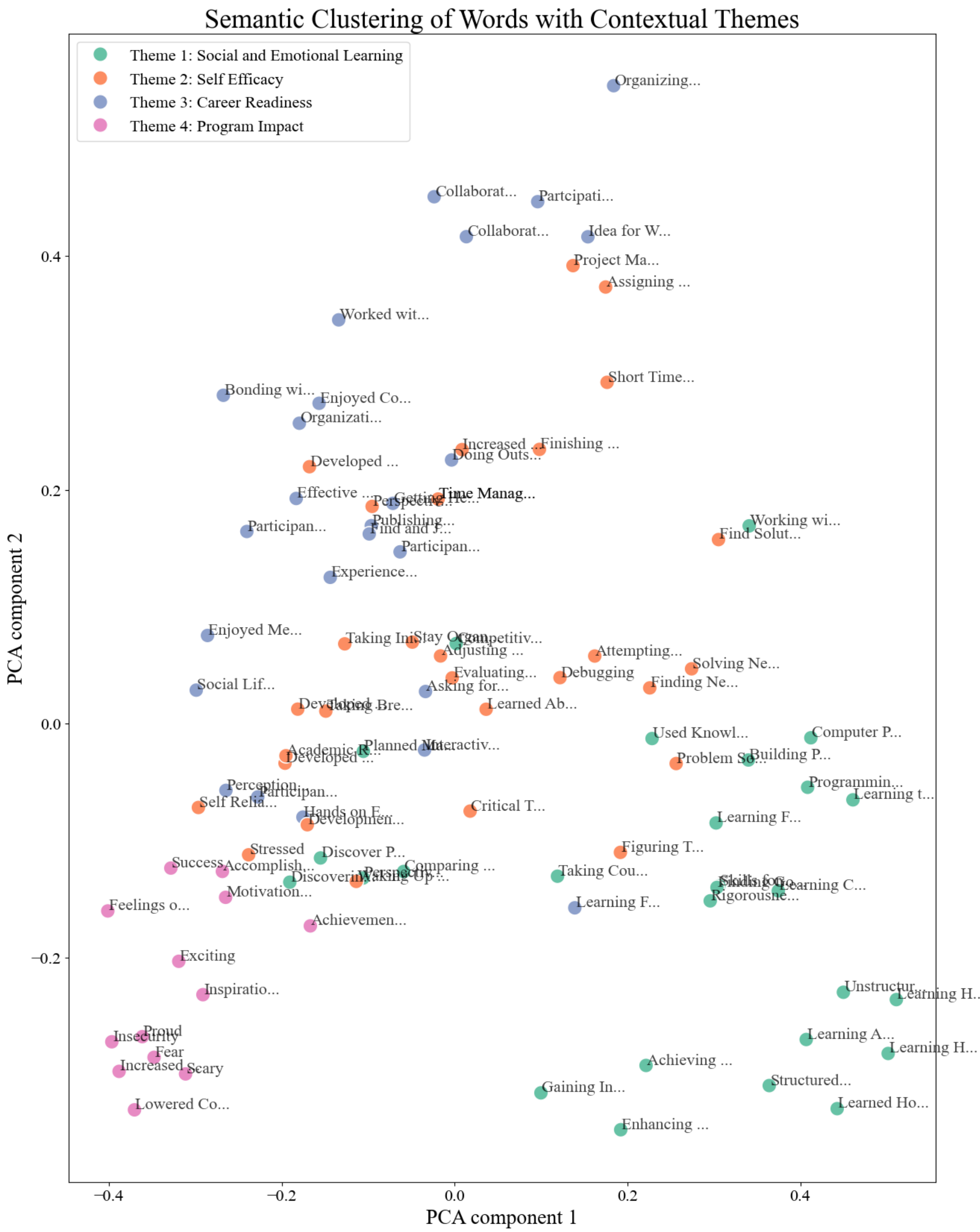

Figure 3: Scatter plot of word embeddings reduced to two dimensions using PCA. Words are grouped into four thematic clusters. Each point represents a word, color-coded according to its assigned theme, with labels indicating the specific codes.

Table 3: AI-based clustering ($\tilde{T}_1$ to $\tilde{T}_4$) accuracy compared to manual themes (T_1 to T_4)

AI-based clusters	Cluster Size	$A(\tilde{T}_i, T_1)$	$A(\tilde{T}_i, T_2)$	$A(\tilde{T}_i, T_3)$	$A(\tilde{T}_i, T_4)$
$\tilde{T}_1$	13	**0.77**	0.15	0.00	0.08
$\tilde{T}_2$	30	0.07	0.27	**0.67**	0.00
$\tilde{T}_3$	27	0.11	0.04	**0.74**	0.11
$\tilde{T}_4$	25	**0.44**	0.04	0.40	0.12

and career aspects of students. Another possible reason could be the imbalanced nature of the manual cluster sizes, in particular for each theme, the human coding process resulted in 26, 12, 50, and 7 codes respectively for the four themes. Future research could involve further tuning of the definitions of themes and a human-in-the-loop approach to develop a robust AI-based thematic analysis pipeline.

Overall, for the validation method, we conclude that the above approach provides an automated semi-supervised way to cluster codes into themes that are both meaningful and interpretable by aligning the human-proposed themes. The Python notebook is available on GitHub [30].

2.4 Correlations with quantitative data

In the pre-college program, we conducted two surveys: a pre- and a post-course survey. We included questions related to confidence, career preparation, college readiness, AI comprehension, and other social-emotional factors. For each question, the students rated their responses using a 5-point Likert scale. We selected a few questions related to the observed themes in the focus group to explore the changes in these variables over the last two years.

Previously [21], we reported indirect measurements of student self-efficacy using three related variables: (1) student confidence in speaking up about a technical area like AI, (2) student self-assurance and positive outlook for success in an AI career, and (3) outlook towards the field of AI. To correlate the Likert scale data with the thematic analysis, we considered all codes related to self-efficacy and career readiness since these were the two themes that were most relevant to the pre- and post- course survey questions. Regardless of the categories within the theme, we selected the 12 high-frequency codes and computed their correlations with the codes generated from thematic analysis.

3 Results

3.1 Impact on self-efficacy and SEL

The results of the thematic analysis for the theme on social and emotional learning are shown in Figure 4 and for self-efficacy in Figure 5.

For *social and emotional learning* (SEL), we observed that *collaborative learning*, *exciting*, and

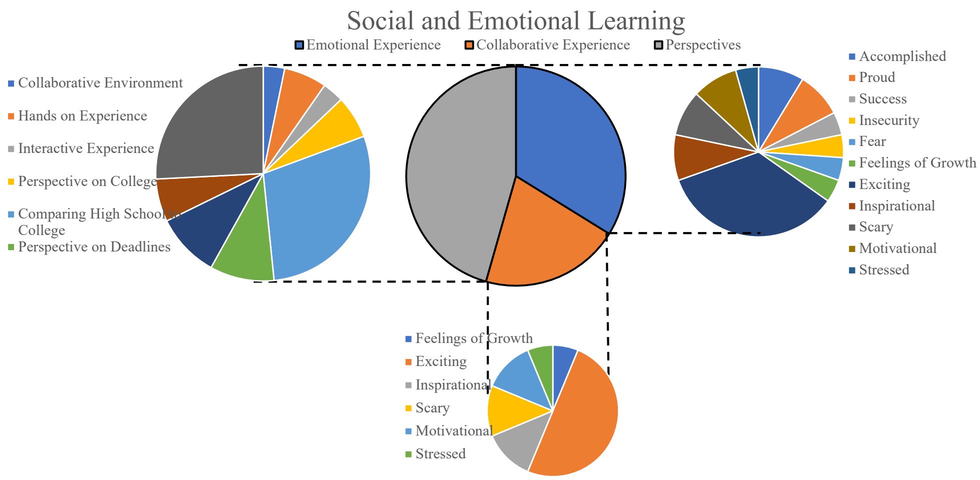

Figure 4: The cumulative frequency of codewords for the three different categories under the theme of "Social and Emotional Learning" are shown in the main pie chart. The three categories are shown by their respective pie-charts. The category pie charts consist of the coded words that describe the category. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

accomplished were the highest frequency codes in the categories of *perspectives*, *collaborative experience*, and *emotional experience* categories respectively.

For self-efficacy, we observe that *increased confidence* and *self-reliance* were the highest frequency codes in the categories of *affected confidence* and *socio-emotional skills* respectively. Among these, *affected confidence* was the most frequent category.

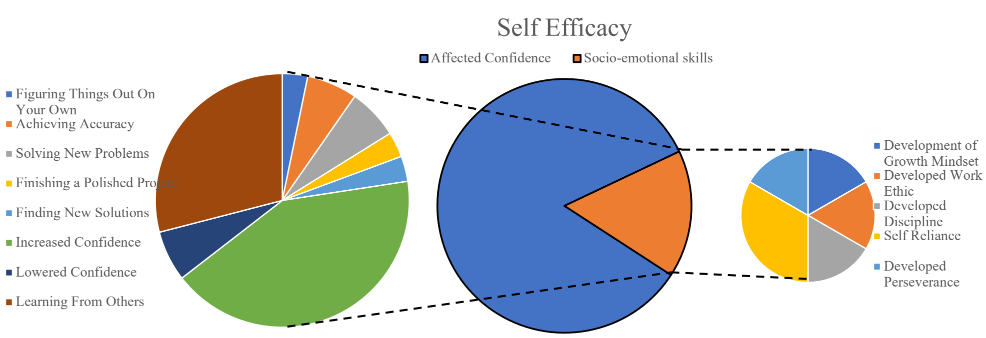

Figure 5: The cumulative frequency of codewords for the two different categories under the theme of "Self-Efficacy" are shown in the main pie chart. The two categories are shown by their respective pie-charts. The category pie charts consist of the coded words that describe the category. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

3.2 Correlation with quantitative surveys collected two years prior

We correlated the thematic analysis of self-efficacy with quantitative data from pre- and post-course surveys to address RQ3. In Figure 6A, we observe an increase in the students' ability to understand and communicate AI research as derived from the post-survey results. A central element of the course structure was research mentoring and team building guided by a communication TA. The research mentoring process creates a supportive environment with new advisers and role models. We reported a statistically significant change in students' self-assurance in identifying advisers and role models in AI and CS (see Figure 6B). Finally, being able to follow the latest advances in the field is an essential skill for any practitioner in a fast-paced field. Associated with this, we observed a significant increase in students' self-belief in AI being able to solve complex problems in the future (see Figure 6C).

We can observe the correlation of Likert survey results with the thematic analysis results in Fig-

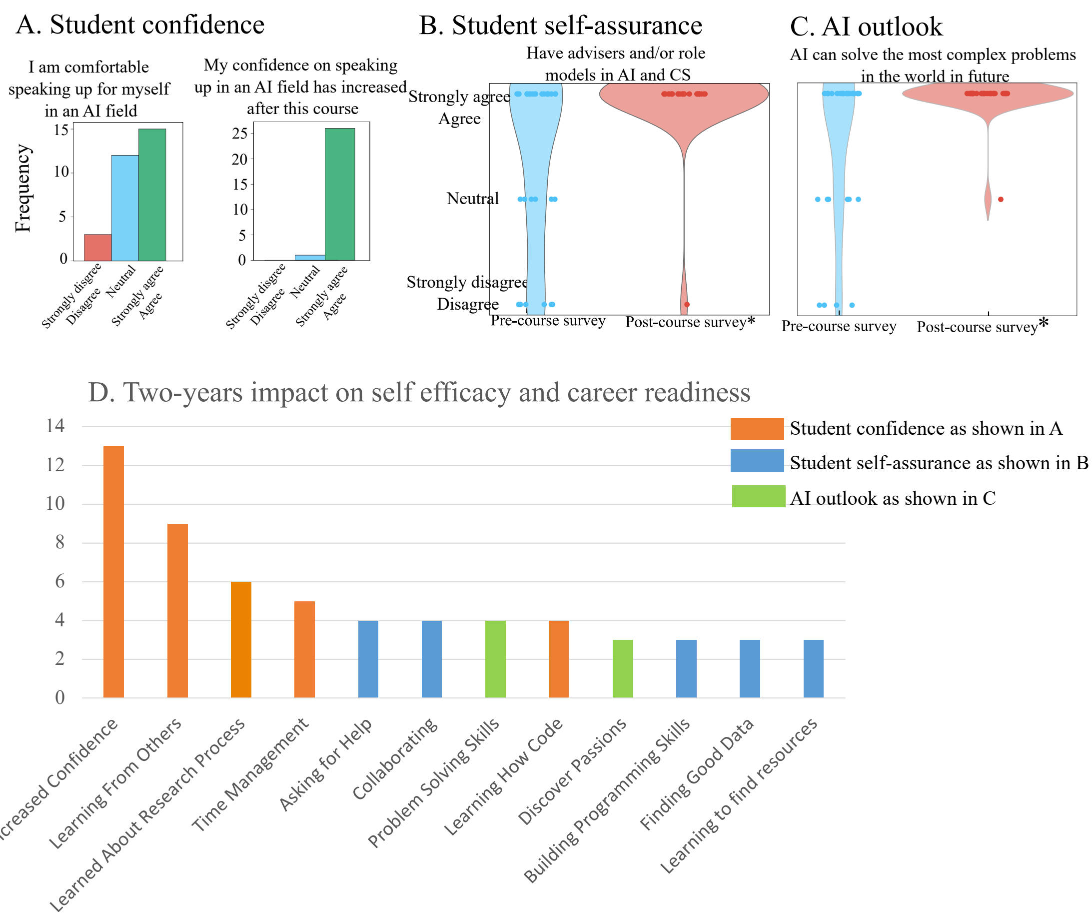

Figure 6: (A) Pre- and post-course survey responses on questions related to speaking up about AI. (B) Student self-assurance increased significantly in post-course survey as they reported having advisers or role models in CS. (C) Students' outlook towards the field of AI being transformative in the future increased significantly. (D) The codes with highest frequencies under the theme of self efficacy and career readiness and its coherence with the earlier pre- and post- course surveys.

ure 6D. Here, the orange colored codes reflect the confidence of students as shown in A, the green codes reflect student self-assurance as shown in B, and the blue codes reflect the AI outlook of the students. Therefore, this qualitative validation of self-efficacy confirms most of the earlier quantitative findings in the post-course survey, especially in the category of “increased student confidence”. On the other hand, we note that even though we observed a statistically significant difference in Figure 6C on “AI outlook”, we did not observe much qualitative evidence to support this conclusion. This discrepancy may reflect an acquiescence bias, in which students have a tendency to select a positive response option believing in AI-hype.

This supports the general understanding of pre-college courses (that we discussed in the Introduction): while students may not necessarily master technical topics or develop an advanced outlook in the topics that were taught, they often become more confident and self-assured after participating in these programs and as they transition into college. It is crucial to recognize that technically advanced pre-college programs, like the one examined in this paper, are not equitably accessible and are disproportionately available to privileged students. This research aims to identify and highlight the most effective aspects of such programs to inform the design of future initiatives that can be offered more broadly, thereby expanding participation in pre-college programs.

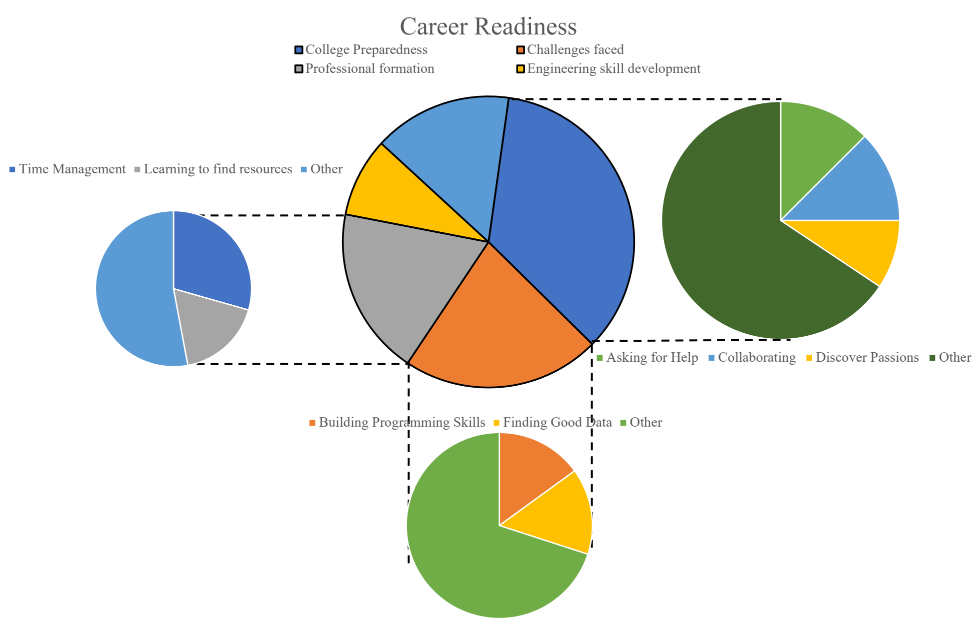

Figure 7: The cumulative frequency of codewords for the five different categories under the theme of “Career Readiness” are shown in the main pie chart. We select three out of the five categories for the sub pie charts that show some of the highest frequency code words. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

3.3 Impact on career readiness and program impact

Under *career readiness* theme, *college preparedness* was the most frequently occurring category with *time management* as most frequently occurring code word (see Figure 7). For the *program*

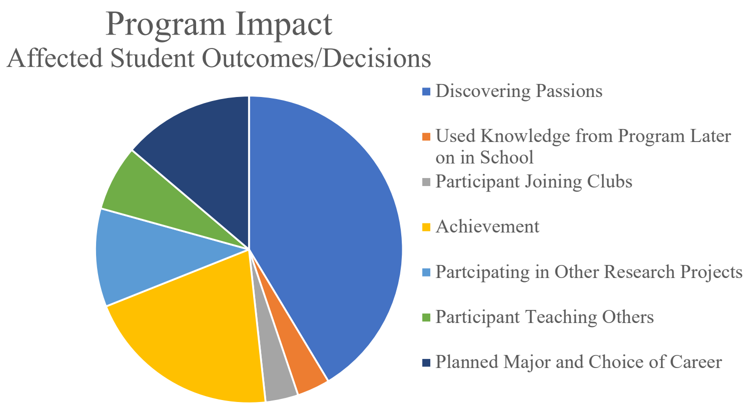

Figure 8: The cumulative frequency of codewords for the theme of "Program Impact". This theme has only one category, so there is one pie chart showing the distribution of the frequency of the code words. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

impact theme, we defined only one category namely *affected student outcomes/decisions* as this directly measures the output of the program. Within this category, *planned major* and *choice of career* were the most frequently occurring code words (see Figure 8). This demonstrates how the program helped the students to solidify their career choices. It is important to note that these students were highly motivated students as indicated by the pre-course survey where most of them listed computer science and data science as their intended majors.

3.4 Insights from thematic analysis

Overall, the mentoring aspects of the program supported positive emotional growth, a strong collaborative environment, improved self-efficacy, career readiness, and meaningful program impact addressing RQ2. Effective teamwork and bonding with peers were the main discussion items in the focus group, which improved both social and professional skills. Significant improvements in confidence and socio-emotional skills indicate that participants feel more capable and prepared for future challenges. Given the concise and compact nature of the program, students developed essential academic, technical, and professional skills, with proactive strategies to overcome challenges. Finally, the program effectively influenced participants' academic decisions, career planning, and continued engagement in research. There were also occurrences of negative emotions represented by code words such as *insecurity, fear, scary, stressed, competitive environment for college applications, lowered confidence when seeing others succeed in tasks, unstructured learning, and short time frame for project completion*. These provide important insights into the design of future pre-college programs. For example, providing additional support for participants and focusing more on developing a sense of belonging could help alleviate negative emotions associated with stress among pre-college students. Indeed, one of the focus group participants noted that, at the outset of the PCP, they felt stressed when they perceived all other participants as "a competing applicant" in the "college applications race". But since they spent another year in high school and had the opportunity to reflect on the experiences of the pre-college program, they felt a higher sense of belonging from the fact that "we are all in the same boat".

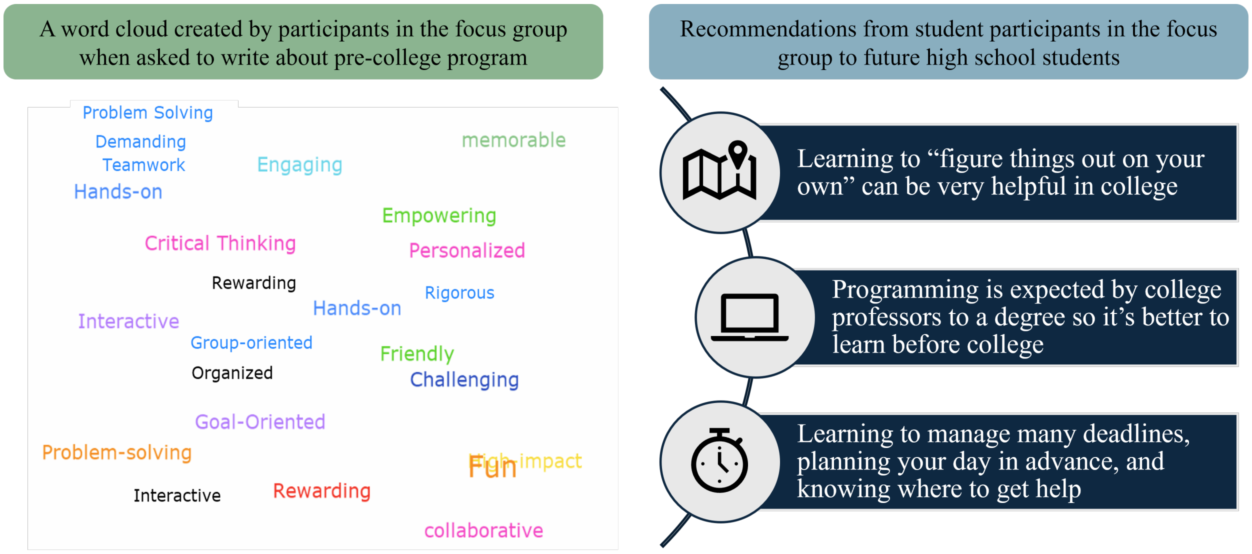

Figure 9: (left) Student analysis: A word cloud created by the focus group participants during the live session when asked to reflect on the pre-college program in one word/phrase. (right) Emergent recommendations from the two year impact study for college preparation

4 Conclusions

In this paper, we study the impact of a pre-college AI education program (with directed research and communication mentoring) on student progression as they prepare to enter college. We conducted a focus group study and individual interviews to generate a total of 12 audio transcripts from volunteers who participated in this pre-college program two years ago (total enrollment in the program was 30). With this qualitative data, we conducted thematic analysis to identify four main themes: social and emotional learning, self-efficacy, career readiness, and the impact of the program. To validate this thematic analysis, we presented a method to compute the accuracy of human thematic analysis with a machine learning approach. We found that two of the human-coded themes were highly aligned with our automated clustering approach, while the other two were not as highly aligned. However, the unaligned categories did not show confounding behavior with the other themes, so we finalized the four themes from the focus group. We correlated the thematic analysis results with the quantitative results obtained 18 months ago in the post-course survey after the pre-college program to qualitatively confirm that students exhibited an increased confidence. However, we note that the quantitative pre- and post-course surveys suggested an enhanced student outlook on the field of AI, a finding not ascertained in the focus groups or thematic analysis. This discrepancy may reflect an acquiescence bias evident in the students' responses to the Likert surveys after the program. Finally, we conclude this paper with recommendations (see Figure 9) that the student participants generated in their discussion during the focus group geared toward future high school students as they prepare for college.

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A Appendix

All focus group interview questions and prompt items are given below, starting with the introduction section that describes the logistics of the focus group.

A.1 Introduction and expectations

Research goal: What is the impact of the pre-college program on students' readiness for senior-year of high school/first-year of college?

Why focus group? To find common issues of shared importance and generate new ideas for recommendation.

How can this be a helpful learning experience for you? The group consists of pre-college or first-year college participants. You can learn from others' reflections and perceptions and gain useful strategies to succeed in college.

Confidentiality: All responses shared in this focus group will be kept confidential, that is, will never be shared in any form to the public. Similarly, you are requested to not share any identifiable information out of this group.

Anonymity: All data collected in the video recording will be anonymized by me. University researchers will analyze anonymized data.

Transparency: All analysis and our research will be made available to you before it is published.

Courteous: Be courteous and respectful of others' opinions and ideas.

Forthcoming: All ideas are welcome and appreciated. The research does not have any bearing on personnel/career decisions.

Consent process here.

A.2 A word cloud of reflections about Diagnostic AI course

Students were shown a list of adjectives that they could use (they were told that they could use their own). Here is the list of adjectives shown to the students:

Engaging,	Playful,
Interactive,	Competitive,
Demanding,	High-impact,
Overwhelming,	Pressuring,
Unique,	Inclusive,
Tailored,	Empowering,
Self-directed,	Flexible,
Organized,	Draining,
Critical-thinking,	Alienating,
Goal-oriented,	Teamwork,
Problem-solving,	Difficult,
Rigid,	Confusing,
Isolating,	Friendly,
Exciting,	Impersonal,
Fun,	Memorable,
Uplifting,	Hands-on,
Rewarding,	Adventure

A.3 Mastery learning

Prompt 1 (structured): In a few words, what was the most challenging aspect of the Diagnostic AI course in Summer 2022?

Prompt 2 (structured): How did you overcome these challenges? Restrict your answer to a few words.

Open-ended prompt (slide 8): Compare your experiences and reflect on each other's thoughts.

A.4 How can college be fun?

From your experience, what are the best strategies for someone to be prepared for college?

What kind of prior preparation (high school activities) are most impactful?

A.5 Perceptions on social modeling

How did you see other students who participated in this pre-college program?

What were your initial reactions and how did your perception evolve?

A.6 Positive emotion and its impact on college readiness

Students were asked to annotate to fill out the following table:

Participant ID	Positive emotions associated	Major in college / planned major / choice of career
SAMPLE	I feel proud when I can design a system to behave in a desired manner so it can be most helpful. So, I want to study CS and design intelligent systems.	Computer Science. Build intelligent systems as an engineer.
Participant 1		
Participant 2		
Participant 3		
Participant 4		

A.7 Conclusions

Students were asked to answer the following question on Zoom chat:

What is your one sentence summary of today's discussion?

B Appendix B

B.1 Individual interview questions

Students were asked the following questions during the individual interviews. The questions were formulated using Bandura's self-efficacy framework [18]. The subtitles in parenthesis are noted only for research purposes here and were not used in the actual questions asked.

1. (mastery learning) Can you share an experience from the SRP (generally) where you tackled a difficult concept or project task? As you share that experience, can you share the influence of that achievement on your confidence as you are entering the first year in college?

2. (social modeling) Describe a time in the diagnostic AI course where you observed someone else succeeding at a task (as part of a group activity, or when working on projects with peers) and that influenced your own confidence in tackling CSE/engineering/AI tasks? You may think about the formation of role models, impact of mentoring, or how you learn from others' successes?

3. (social persuasion) How did the encouragement (or critical feedback) from instructors or peers influence your confidence in your ability to learn AI or pursue engineering? Are there any specific instances of creativity or changed confidence levels where you may have recalled the course or the SRP in your career journey?

4. (positive emotion) Can you recall a time from the program where you felt the most excited about something or enjoyed the most?

    - Reflect on how your satisfaction or dissatisfaction from the SRP influenced your confidence and motivation as you began your first year in college?
    - What influenced your decisions after the program?

Appendix C

The categories, code words and their frequencies are listed in the four tables below corresponding to each theme.

Table 4: Self Efficacy Codewords

Category	**Code**	**Frequency**
Affected Confidence	Figuring Things Out On Your Own	1
	Achieving Accuracy	2
	Solving New Problems	2
	Finishing a Polished Project	1
	Finding New Solutions	1
	Increased Confidence	13
	Lowered Confidence	2
	Learning From Others	9
Socio-emotional skills	Development of Growth Mindset	1
	Developed Work Ethic	1
	Developed Discipline	1
	Self Reliance	2
	Developed Perseverance	1

Table 5: Social and Emotional Learning Codewords

Category	Code	Frequency
Emotional Experience	Accomplished	2
	Proud	2
	Success	1
	Insecurity	1
	Fear	1
	Feelings of Growth	1
	Exciting	8
	Inspirational	2
	Scary	2
	Motivational	2
	Stressed	1
Collaborative Experience	Worked with Others Outside Group	2
	Getting Help from Others	3
	Experience with Team During SRA	4
	Enjoyed Collaborating	1
	Enjoyed Meeting People with Similar Interests	1
	Bonding with Colleagues	3
Perspectives	Collaborative Environment	1
	Hands on Experience	2
	Interactive Experience	1
	Perspective on College	2
	Comparing High School to College	9
	Perspective on Deadlines	3
	Perception of Peers	3
	Competitive Environment for College Apps	2
	Participants Describing the Experience	8

Table 6: Career Readiness Codewords

Category	Code	Frequency
College Preparedness	Time Management	1
	Organization	1
	Academic Rigor	2
	Discover Passions	3
	Computer Programming	1
	Social Life	1
	Taking Initiative	1
	Find and Join Academic Clubs	2
	Assigning Work/Tasks	1
	Unstructured Learning	1
	Structured Learning	2
	Find Solutions Using the Internet	1
	Learning From Diverse Resources	2
	Taking Breaks	2
	Asking for Help	4
	Collaborating	4
	Taking Courses	1
Challenges faced	Publishing Research Paper	1
	Programming complex algorithms	1
	Working with New Programs	1
	Debugging	2
	Building Programming Skills	3
	Learning Course Material	1
	Rigorousness of Program	2
	Enhancing Accuracy of Model	1
	Finding Good Data	3
	Evaluating Research Correctness	1
	Idea for What Project to Do	2
Professional formation	Waking Up Early	2
	Gaining Intuition About a Concept	2
	Doing Outside Research	2
	Adjusting to New Environment	2
	Time Management	5
	Learning to find resources	3
	Effective organization	1
Engineering skill development	Project Management	1
	Problem Solving Skills	4
	Critical Thinking Skills	1
	Organizing Collaborative Projects	1
AI Comprehension	Learning How to Build a Mathematical model	1
	Skills for Computer Vision Development	1
	Learning How Code	4
	Learning About Machine Learning	1

Table 7: Program Impact Codewords

Category	**Code**	**Frequency**
Affected Student Outcomes/Decisions	Discovering Passions	12
	Used Knowledge from Program Later	1
	Participant Joining Clubs	1
	Achievement	6
	Participating in Other Projects	3
	Participant Teaching Others	2
	Planned Major and Choice of Career	4