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 the 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. These measurements are important in light of the need to develop an AI-trained workforce. 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 conduct focus group interviews with the participants of this program. To validate the human thematic analysis, we ask: (RQ1) What methods can validate heuristic thematic analysis with automated approaches for a reliable study of student reflections from qualitative data? With a validated thematic analysis approach, we measure the change in the preparedness and transition into undergraduate programs.

Since the topic of the pre-college program was at the intersection of health and CS, we observed that 77% of the students indicated an interest in computer science or data science as their preferred major in college while the rest were interested in biology, with 3% undecided. Two years after this 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, 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? To study these questions, our measurement

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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 participating 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

Pre-college programs for high school students can be transformative in students' preparation for college. Short programs are great for outreach, while technical programs can enhance confidence among high school students. Extended programs (longer than one or two weeks) may help with college readiness to an extent but often suffer from limited availability and low participation due to costs, time constraints, and other factors. Another category of pre-college programs is the organization of competitions. These initiatives have the potential to increase university enrollment from local communities by providing outreach that includes technical elements along with it being a fun experience for participants. In summary, it is well established that information barriers of various kinds hinder the efficiency, participation, and success in STEM college education [1] and that pre-college programs help address these gaps. Such programs can create pathways to broaden participation in engineering and STEM [2], and can enhance college readiness among high school students. Consequently, the engineering education research community is often interested in evaluating the utility, effectiveness, and the need for such 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. We review this research area next to position our study within the appropriate context.

1.1 Background

At the pre-college level for high school students preparing for college, self-efficacy in learning is an important measure. While pre-college programs may introduce new technical topics, the key benefits for students who participate in such programs include building confidence, acquiring general know-how, gaining clearer perceptions of college, and understanding the educational landscape. Self-efficacy, first introduced by Bandura [3], is a crucial psychosocial measure and continues to be an active area of research in educational literature [4]. Research shows that pre-college programs positively influence the self-efficacy of students who later attend college, making it a common metric in these programs and a major subject of study regarding its impact on students. A related area of research is college readiness. Over the last few years, there has been an increase in high school students enhancing their technical knowledge in computer programming, calculus, and other subjects to prepare for engineering majors in advance. However, these opportunities are not readily accessible to all. Therefore, we aim to identify the key benefits students are gaining from these experiences. This understanding will help us develop clearer strategies for future pre-college programs to enhance equity and broaden participation.

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 and related engineering disciplines. Specifically, this paper examines the impact of a pre-college program on artificial intelligence, 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 [5]. A key observation was that the quantitative 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 prior. So, in this paper, we study how we can use qualitative data from 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 with the standard College Academic Self-Efficacy Scale (CASES) [6]. Additionally, increases in academic self-efficacy were observed pre- and post-program [7, 8, 9]. Beyond self-efficacy, research has also explored how pre-college programs enhance college readiness [10], stimulate interest in STEM [11], and prepare students for careers in STEM [12, 13].

Along similar lines, we conduct qualitative data analysis, validate the heuristic approach taken by a human for thematic analysis, and then analyze the resulting themes to identify 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 enhanced, what might not be helpful, and what students find beneficial. It also generates recommendations directly from the students involved in the focus groups on college readiness. These strategies and recommendations are intended for high school students, offering guidance on enhancing their college readiness, career preparation, and making college more enjoyable.

1.2 Context

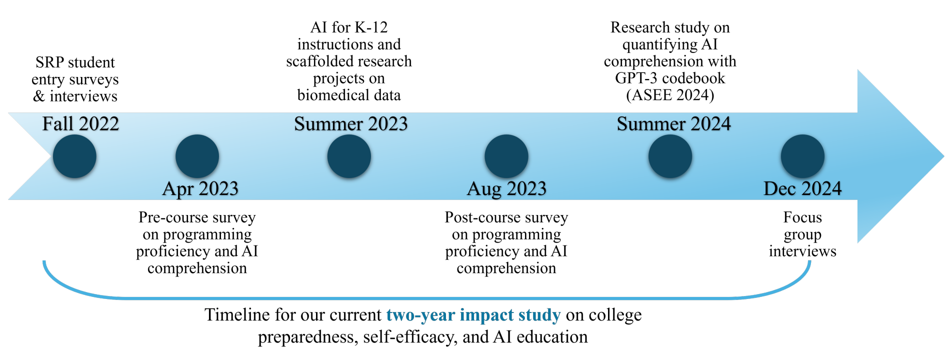

Figure 1: Timeline of the research study and the context

The pre-college program (PCP) examined in this paper, referred to as the Summer Research Program (SRP) (anonymized), was a four-week long summer initiative at a large western United States university. Within the program, multiple educational tracks were offered. One of the authors in this submissions offered a track under this program on “Diagnostic AI”, which covered 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 managing program logistics. A total of 30 students participated in this track. The primary expectation for the students was to deliver a Capstone project presentation at the end of the course, demonstrating the application of AI techniques learned to a biomedical or healthcare dataset. The reader is referred to our previous publication [5] for a more detailed analysis of the program’s components, its outcomes, and analysis of students’ comprehension of the topics that were taught in the course.

Two surveys were conducted as part of the regular instruction of the course for continuous improvement. These surveys employed 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. 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. For this research on studying the impact of the program on students’ self-efficacy and college readiness, we conducted focus group interviews (in December 2025) with $N_{\text{foc}} = 7$ students and individual interviews with $N_{\text{ind}} = 5$ students who participated in the Diagnostic AI course under the PCP. Thus, in total, we recorded $N_{\text{total}} = 12$ audio recordings in total for the thematic analysis. All the focus group interview questions and prompt items are listed in Appendix A and individual interview questions are listed in Appendix B. z The focus group participants reflect the demographics in terms of school levels represented in the program. 60% of the students in the PCP were in their 11th grade during the program, and approximately 43% of the focus group participants belong to this category (3 out of 7). These stu-

ID	School level (in 2025)	Grade level (during PCP)	Planned / current major
1	High school junior	9th	Bioinformatics
2	High school senior	10th	Data science
3	College first-year	11th	Artificial intelligence
4	College first-year	11th	Computer science
5	High school junior	9th	Computer science
6	High school senior	10th	Bioinformatics
7	College first-year	11th	Computer science

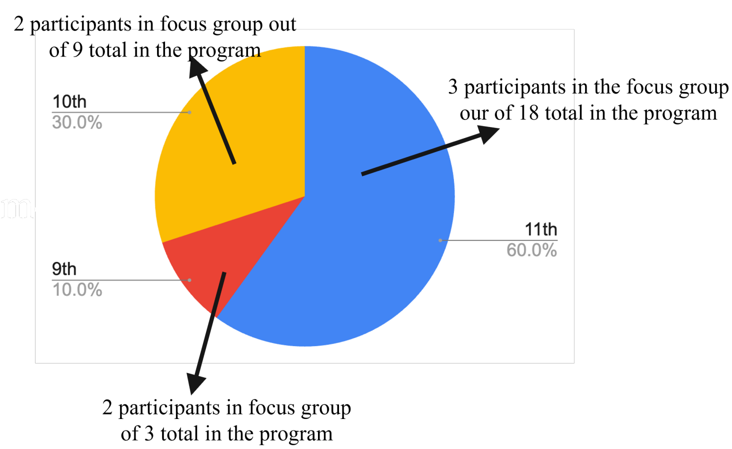

Figure 2: (left) Table shows student demographics based on school level: during the pre-college program (PCP), during the focus group, and planned/current major in college. (right) Chart shows the distribution of students who participated in the focus groups out of total students in that grade level in the program.

dents reported being in their first year of college two years after the program. Additionally, 30% of students in the PCP were in their 10th grade, with 28% of focus group participants from this category (2 out of 7). 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. Overall, the demographics of the focus group participants mirrored the original program participation (see Figure 2 for details). The focus group was also gender-balanced, with 3 females and 4 males.

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 conducted was reviewed by Research Compliance Office at Anonymous University and was deemed as Self-Exempt under the IRB regulations.

1.3 Research questions

To study the impact of the pre-college AI education program on student progression two years down the line, 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, AI-focused technical summer program?

RQ1 is a methods research question. We evaluate the process of thematic analysis of focus group interview transcripts by focusing on validation of human clustering. 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 large language 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. Increased in self efficacy especially confidence in achieving success in college due to participation in a rigorous program.
2. Readiness for college is increased and those already in first-year of college show importance of what they had learned from mentors and peers.
3. Thematic analysis highlights the most appreciated aspects of the program, which will inform the future design of the program.

Significance of research: The results of this paper provide new methodical insights and pipelines to education researchers who regularly conduct thematic analysis to study 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 this program. 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 [14]. 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 [15]. For our study, we used Zoom video call recordings to collect the data. The Zoom audio recorded files in the .m4a format were converted to .wav format using the Windows FFMPEG toolchain since Whisper AI requires .wav audio files. Then, we used Whisper to transcribe the audio to text files, which were then used for thematic analysis.

2.2 Thematic Analysis

For thematic analysis of the focus group and the individual interview data, first, we manually read the data to familiarize ourselves with it and anonymize 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.

2.2 Thematic Analysis

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
	Emotional Experience	Participant experiences that brought about emotions.	Experience with Team During PCP	4
			Getting Help from Others	3
			Bonding with Colleagues	3
	Perspectives	Paricipant 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

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

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 [16, 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 answers an interview question. We reviewed and revised the coding process in an iterative manner. Specifically, an undergraduate student researcher who was not involved in any manner with the delivery of this summer program performed the coding of the data. Then, the undergraduate researcher discussed their work with the study PI to iteratively revise the results.

After coding the data, we started searching for themes (patterns) within the data. Following the guide by Lester et al. 2020 [16], 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 process of clustering. Then, continuing with an inductive process, we developed emergent themes from the categories and classified each category to a broad theme. For seamless analysis of this thematic coding process, we used an online tool called Delve (delvetool.com). We uploaded all data to be analyzed and then manually coded, classified,

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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

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 research literature. In conclusion, the thematic analysis output consists of themes/categories/codes in that order along with frequency of each codeword. To summarize, we thematically analyzed the participants 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 analysis, new codes were found, categories were altered or in some cases removed, and codes were reclassified from one category to another. This data was exported to a CSV file and organized, summarized, and graphed to show the trends and/or patterns that the thematic analysis discovered.

2.3 Validation of thematic analysis

For validation of thematic analysis, we performed an AI-based semantic clustering of the curated list of codes to validate whether the AI-driven clusters are simmilar as the manual coding process by the human (an undergraduate student researcher). To capture the semantic relationships between the words, we employed the Sentence-BERT (Sentence Transformer) model, specifically the "all-MiniLM-L6-v2" variant [17]. This model was selected for its balance between computational efficiency and embedding quality, making it suitable for handling the dataset's size. A

Table 3: Clustering accuracy wrt to manual themes

AI-based clusters	Cluster Size	$A(Ti, T1)$	$A(Ti, T2)$	$A(Ti, T3)$	$A(Ti, T4)$
T1	13	**0.77**	0.15	0.00	0.08
T2	30	0.07	0.27	**0.67**	0.00
T3	27	0.11	0.04	**0.74**	0.11
T4	25	**0.44**	0.04	0.40	0.12

total of 95 codes were shuffled together irrespective of the categories to reduce potential biases in the clustering algorithm. A few seed words were provided to give some context to the different themes as shown in Table 2. Using the transformer model, each code was transformed into a

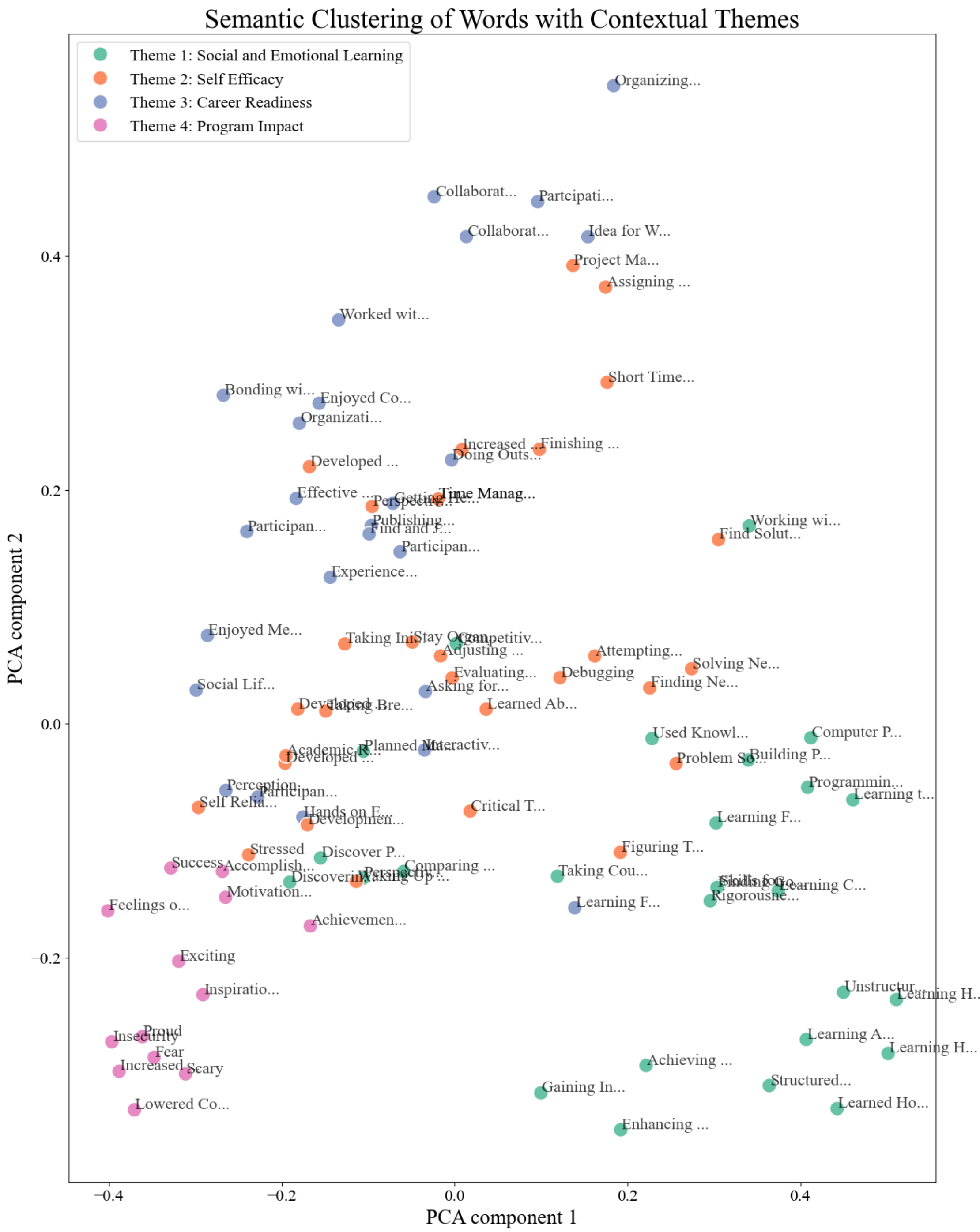

Figure 3: Scatter plot of word embeddings reduced to two dimensions using PCA. Words are grouped into four thematic clusters. Each point represents a word, color-coded according to its assigned theme, with labels indicating the specific codes.

high-dimensional vector. Semi-supervised K-means clustering was used to cluster the codes into four clusters (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 quantifying the validity of the themes. After clustering, we analyzed the coherence of each AI-predicted cluster with the manually defined themes. 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 the 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 and Figure 4, we observe that for the themes T1 (social and emotional learning) and T3 (career readiness), the automated clusters effectively captured the intended semantic groupings. While T2 (self-efficacy) and T4 (program impact) have significant overlap with other themes. This shows that T2 and T4 themes are broadly defined by the human analyst as efficacy and program impact and hence have overlap with other two specific themes of social and emotional learning, and career aspects of the 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 tuning the definitions of

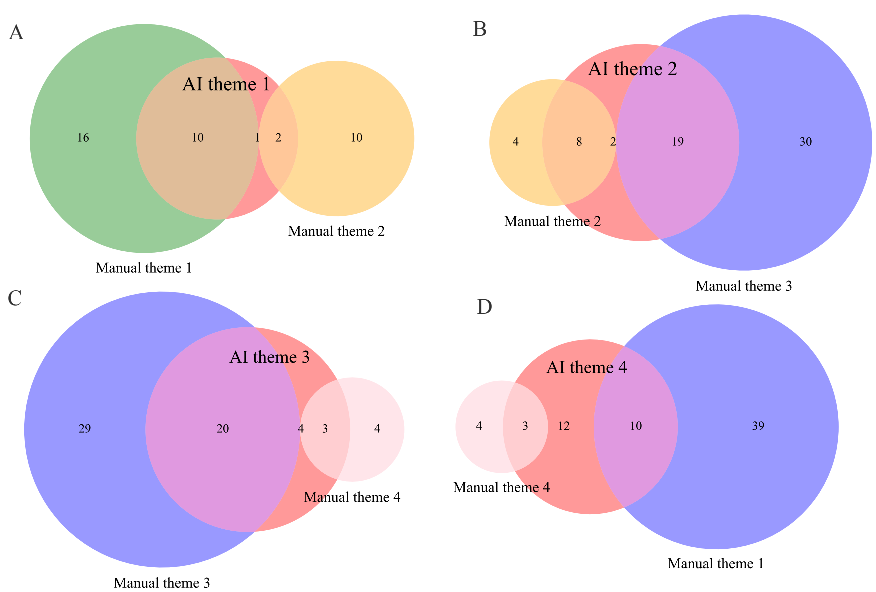

Figure 4: (A-D) Venn diagrams illustrating the overlap between AI themes 1-4 with respect to their respective manual clusters and one another cluster which overlaps with them. This visualization emphasizes the common and unique words associated with the AI-driven clusters of themes compared to the manually categorized themes.

themes further 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 of the analysis is available on GitHub to promote wider use by other researchers [18].

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, comprehension of AI, and other social-emotional factors. For each of the questions, we asked students to rate their responses using a 5-point Likert scale. We select 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 [5], we reported indirect measurements of student self-efficacy using three related variables: (1) student confidence on 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. Irrespective 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

Results from the thematic analysis are shown in Figure 6, 7, 8, and 9 corresponding to the themes T1 (social and emotional learning), T2 (self-efficacy), T3 (career readiness), and T4 (program impact) respectively.

3.1 Impact on self-efficacy and SEL

For *social and emotional learning* (SEL), we observe that *collaborative learning*, *exciting*, and *accomplished* were the highest frequency codes in the categories of *perspectives*, *collaborative experience*, and *emotional experience* categories respectively.

For self efficacy, we observe *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 frequently occurring categories.

We correlated the thematic analysis of self-efficacy with quantitative data from pre- and post-course surveys to address RQ3. In Figure 5A, 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

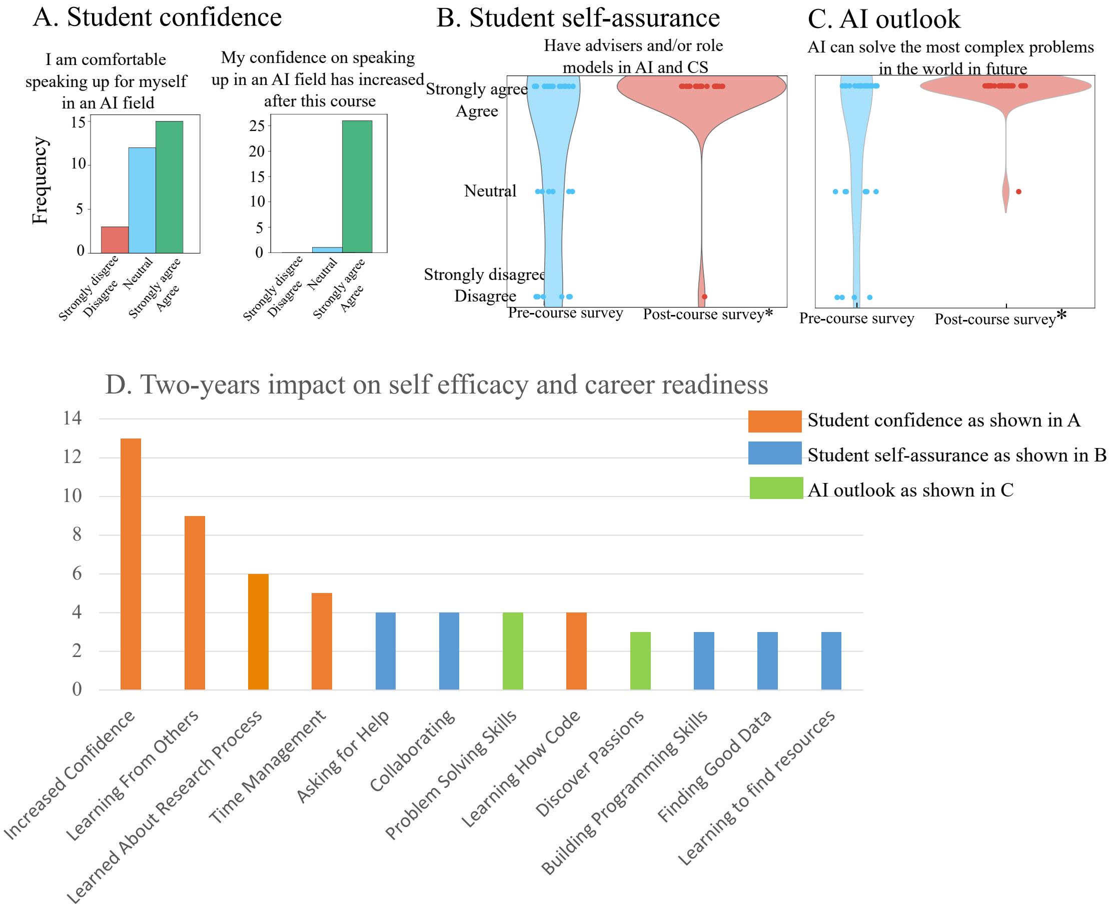

Figure 5: (A) Pre- and post-course survey responses on questions related to speaking up about AI. (B) Student self-assurance increased significantly in post-course survey as they reported having advisers or role models in CS. (C) Students' outlook towards the field of AI being transformative in the future 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.

course structure was the research mentoring and team building guided by a communication TA. The process of research mentoring 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 5B). Finally, being able to follow the latest advances in the field is an essential skill to any practitioner in a fast-paced field. Corresponding to this, we noted a significant increase in students' self-belief on AI being able to solve complex problems in the future (see Figure 5C).

We can observe the correlation of these Likert survey results with the results from the thematic analysis in Figure 5D. Here, the orange colored codes reflect student confidence as shown in A, 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 confirm 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

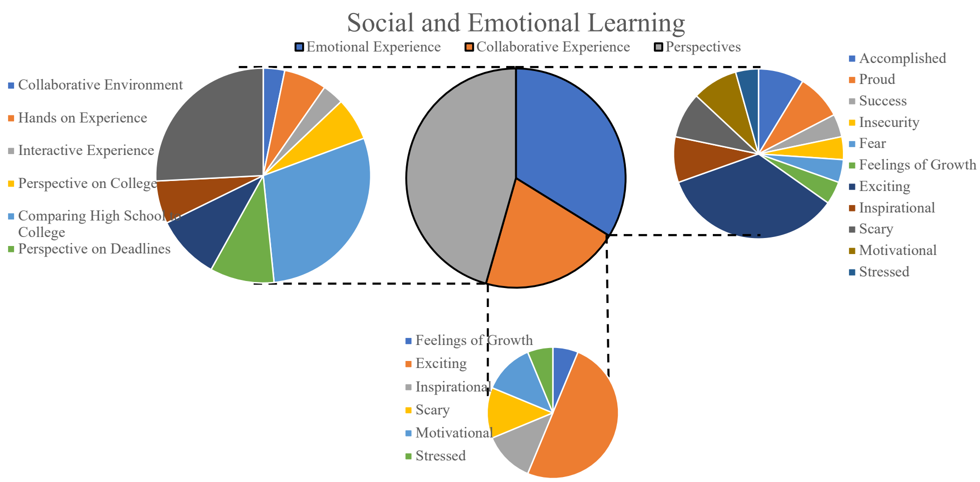

Figure 6: The cumulative frequency of codewords for the three different categories under the theme of "Social and Emotional Learning" are shown in the main pie chart. The three categories are shown by their respective pie-charts. The category pie charts consist of the coded words that describe the category. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

difference in Figure 7C on "AI outlook", we did not observe much qualitative evidence to back up 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 high-

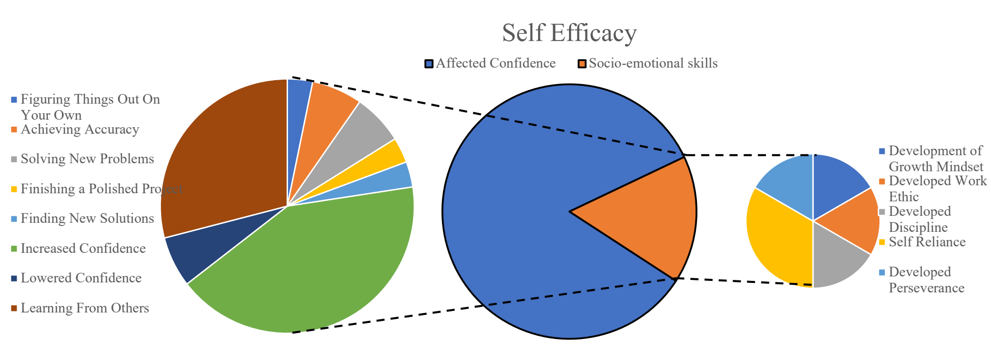

Figure 7: The cumulative frequency of codewords for the two different categories under the theme of "Self-Efficacy" are shown in the main pie chart. The two categories are shown by their respective pie-charts. The category pie charts consist of the coded words that describe the category. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

light 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.

3.2 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. For the *program 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. This demonstrates how the program helped the students to solidify their career choices. It is important to note that these student were highly motivated students as indicated by the pre-course survey where most of them listed as computer science and data science as their intended majors.

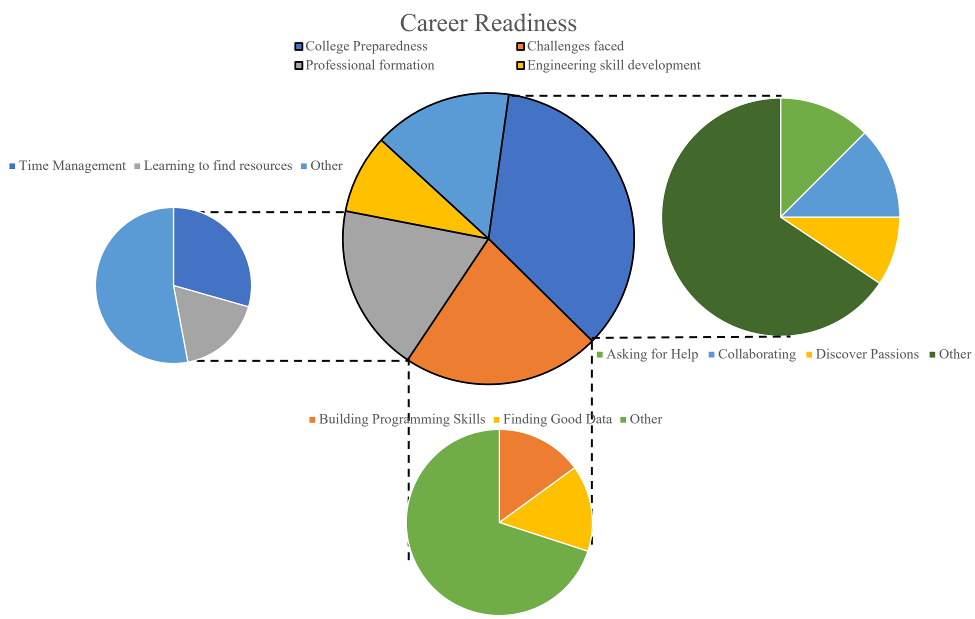

Figure 8: The cumulative frequency of codewords for the five different categories under the theme of “Career Readiness” are shown in the main pie chart. We select three out of the five categories for the sub pie charts that show some of the highest frequency code words. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

3.3 Insights from thematic analysis

Overall, the mentoring aspects of the program helped in the positive emotional growth, strong collaborative environment, enhanced self efficacy, career readiness, and meaningful program impact addressing RQ2. Effective teamwork and bonding with peers were prevalent discussion items in the focus group, enhancing both social and professional skills. Significant improvements in confidence and socio-emotional skills indicate that participants feel more capable and prepared for

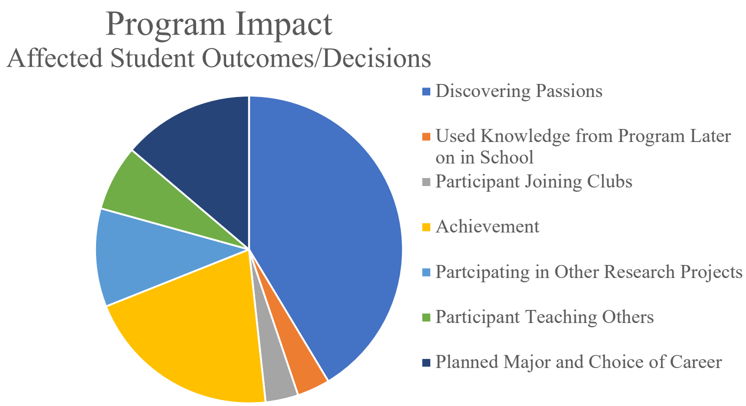

Figure 9: The cumulative frequency of codewords for the theme of "Program Impact". This theme has only one category, so there is one pie chart showing the distribution of the frequency of the code words. Each pie chart features its own legend and matching colors across different charts do not signify any meaningful connections.

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 the code words such as insecurity, fear, scary, stressed, competitive environment for college applications, lowered confidence when seeing others succeed at 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 participant noted that, at the outset, they felt stressed out when they perceived all other participants as "a competing applicant" in the "college applications race". But as they spent another year in high school and had chances to reflect on the pre-college program experience, they felt a higher sense of belonging from the fact that "we are all in the same boat". We also note that being transparent about the design and expectation of the program can also enhance the program's effectiveness and promote an inclusive environment.

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 the human thematic analysis with a machine learning approach. We found that two of the human-

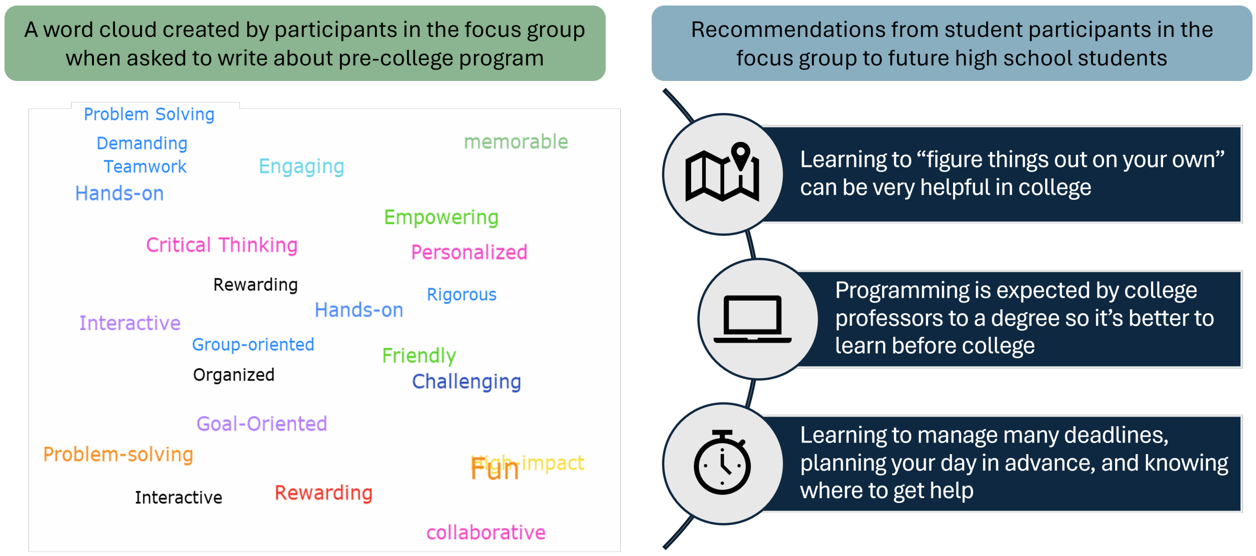

Figure 10: (left) Student analysis: A word cloud created by the focus group participants during the live session when asked to reflect on the pre-college program in one word/phrase. (right) Emergent recommendations from the two year impact study for college preparation

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 and thus, 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. We noted, however, 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 10) that the student participants generated in their discussion during the focus group geared towards future high school students as they prepare for college.

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A Appendix

All the focus group interview questions and prompt items:

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 [3]. 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?