A Quantitative Analysis of a Summer Bridge Program's Impact on Students' Non-Academic Indicators

Shreya Gupta
EECS
University of California, Berkeley
Berkeley, CA, USA
shreya.g@berkeley.edu

Chetan Goenka
EECS
University of California, Berkeley
Berkeley, CA, USA
cgoenka@berkeley.edu

Narges Norouzi
EECS
University of California, Berkeley
Berkeley, CA, USA
norouzi@berkeley.edu

***Abstract*—This full research paper investigates the significance of a summer bridge program on the non-academic metrics of incoming freshman computing students at an R1 institution in the United States. Summer bridge programs are designed to increase academic major preparedness, reduce attrition, and provide other opportunities such as faculty networking and community building. Our team designed and delivered a summer bridge program to serve students from historically marginalized groups in Computer Science and Engineering. We offered the program to cohorts of 35-55 students annually from 2020 through 2023. Due to COVID-19, the program was offered online in 2020 and 2021 and then moved to an in-person version in 2022 and 2023.**

To measure the impact of the summer program, we utilized a closed-ended Likert-scale survey both before and after the program. The survey aimed to evaluate 10 principal non-academic factors that have been proven to influence student retention in the major. These factors include students' mathematics and programming self-concept, science motivation, science identity, help-seeking and concealment attitude, growth mindset, peer community, sense of belonging, and awareness of and accessibility to resources. Survey results were consolidated and used for quantitative analyses to address three research questions:
RQ1: In what way, if at all, does participation in the program affect students' non-academic indicators?
RQ2: What is the difference in impact between online (2020, 2021) and in-person (2022, 2023) program modalities?
RQ3: How did participants' perceptions of the program differ across the two modalities?

***Index Terms*—equity, sense of belonging, science motivation, self-efficacy, bridge programs, modality**

I. Introduction

Summer bridge programs for students in Science, Technology, Engineering, and Mathematics (STEM) disciplines are becoming increasingly available at 4-year institutions [1]–[3]. Students participate in these multi-week intensive experiences in the summer before their first semester of college. These programs tend to provide short courses for academic readiness, networking opportunities with faculty and peers, and exposure to the resources available at the institution. Most of these programs are being developed with 1) academic success goals, 2) psycho-social goals, and 3) department-level goals, as explained in an analysis of 25 years of STEM summer bridge programs [4], [5].

We develop a summer bridge program for computing students entering a computing major at the University of California Santa Cruz. The goals of this program are to equip students with essential skills for 1) programming courses, 2) engineering mathematics courses, 3) fostering a growth mindset [6], 4) cultivating self-efficacy and confidence, 5) nurturing peer connections, and 6) enhancing their sense of belonging.

Non-academic indicators such as these are very crucial in improving college retention [7]–[10] and can enable underserved students to achieve upward social mobility after successfully graduating with a degree from college [11], [12]. Furthermore, the non-academic indicators that the program accounts for are linked to overall positive attitudes and a supportive academic environment.

The bridge program was online in the years 2020 and 2021 and in-person during 2022 and 2023. For the in-person program, all students from the cohort had their meals together, participated in team-building events in the dorms, and attended a one-day trip at the end of the program for additional community building. These activities did not take place during the online version of the program. The only community-building activity in the online program was afternoon "coffee and play" Zoom sessions that students could opt-in to join, and it was moderated by a trained undergraduate mentor staff.

Prior work has involved analyzing the impact of summer bridge programs on retention rates directly, without considering modality [1], [3]. Therefore, our work builds on an existing work [13], which introduces the idea of measuring the impact of summer bridge programs across modalities and the idea of statistically measuring the direct influence on key non-academic indicators.

The detailed analysis in this paper accentuates the importance of distinguishing between online and in-person modalities of summer bridge programs, especially given the greater funding requirements for in-person programs. An in-person program requires funding for housing, meals, transportation, and other logistical aspects, which not only increase the overall cost but also inherently limit the number of students that can be accommodated. This limitation is a significant concern for equity-focused programs aiming to support underserved students. Understanding the specific impacts of each modality is crucial for allocating resources effectively and ensuring that the investments made into these programs yield the maximum possible benefit in terms of enhancing non-academic indicators, such as a sense of belonging, self-efficacy, and resource awareness. Given the constraints of available funding, making informed decisions on whether to invest more heavily in in-person experiences, with their associated costs, or to leverage the broader reach but potentially different impacts of online programs, is a pivotal consideration in the strategic planning and implementation of these educational initiatives.

In this work, we use A/B testing to identify several statistically significant non-academic indicators that are positively affected after participation in the summer bridge program, and we use pre- versus post-ratio analysis to compare how the effects of the program vary between the online and in-person modalities. We also conduct sentiment analysis on students' written responses to gauge the attitude of students towards the different modalities of the program, providing valuable insights into their perceptions, preferences, and engagement with the program's components.

Using the techniques above, we aim to quantify the:
(1) Impact of the summer bridge program in changing the outlook of participants regarding the specific elements within each non-academic indicator/category,
(2) Differences in effectiveness of the bridge program across two program modalities (online and in-person), and
(3) Differences in students' perception of the program across the two program modalities.

We are able to achieve these goals by analyzing the results of A/B tests, evaluating pre- versus post-program score distributions, and conducting sentiment analysis of students' written responses.

II. Methodology

A. Creating the Cohorts

The program is designed for incoming underserved students who are eligible upon meeting two or more of the following:
1: They are the first in their family to attend a four-year college/university (commonly known as first-generation students),
2: They may have limited financial resources or experienced socio-economic challenges (low-income, financial need), and
3: They are from historically underrepresented or marginalized groups who typically do not pursue STEM studies.
We observed that most of the students in our cohorts lack prior mathematics and programming preparation. This preparation equity gap is what the program aims to bridge.

In the years 2020-2023, the students enrolled in each of the 4 summer program cohorts were surveyed pre- and post-attendance. There is a slight difference in the sample size between the online and in-person cohorts with the in-person cohort being larger. However, this difference does not add substantial bias to our study because of the methods we use to analyze the difference in pre- and post-program scores. Table I outlines the number of students who completed both pre- and post-surveys for each cohort.

TABLE I: Number of students who completed both pre- and post-surveys in each Year.

Year	Number of Students
2020	25
2021	21
2022	31
2023	22

The survey consisted of a validated questionnaire with 68 questions, encompassing participants' experiences in STEM education, attitudes toward seeking assistance, sense of belonging, and accessibility to resources vital for thriving in Computing [13], [14]. This quantitative data has helped us understand how students feel about programming, mathematics, science, their peer community, and the campus and its resources. Using data from both the pre- and post-surveys, we can identify changes in students' attitudes following the completion of the program. The survey questions were divided into 10 categories, each of which served as an assessment method for one of the six program goals mentioned above. The goals and corresponding question categories are listed in Table II.

TABLE II: Program goals and assessment methods.

Program Goal	Question Categories
Programming preparedness	1) Academic self-concept [15] 2) Science motivation [16]
Mathematics preparedness	Same as above but adapted for mathematics
Growth mindset	1) Help-Seeking assessment [17] 2) Concealment assessment [17] 3) Growth mindset assessment [18]–[20]
Self-efficacy	1) Academic self-concept [15] 2) Science identity [21], [22]
Peer community	Peer community assessment [23]
Campus belonging	Sense of belonging to campus scale [24]

B. Pre-Program and Post-Program Survey Format

We analyzed pre- and post-program surveys from the summer bridge programs held from 2020 to 2023. The survey is designed to collect non-academic indicators, with the questions covering 10 primary categories, each with 2 to 12 questions on the Likert scale. Every category's answers are on a scale of 1-6, except for Help-Seeking and Concealment, which are on a scale of 1-4. Taking into account these differences, the scores were scaled before being used in the A/B tests for consistency.

The pre- and post-surveys consisted of the same set of questions to evaluate the program's impact. The question categories are listed in Table III. It is important to note that some of these questions are worded negatively, which means that the lower the scores input by students, the more positive the results are. To ensure fairness and consistency in testing results, the scores were reversed during evaluation so that for all questions, a higher score always indicates a more positive result. The questions that were negatively worded are:

1. Mathematics self-concept: Q2, Q4, Q6, Q8, and Q10.
2. Programming self-concept: Q2, Q4, Q6, Q8, and Q10.
3. All questions in the Concealment category.
4. All questions in the Mindset category.

C. A/B Testing of Post versus Pre-Program

We conducted an A/B test for all questions in each category to examine whether students' responses in the post-program survey were different due to random chance or not. The results of each A/B test tell us whether or not the pre- and post-scores came from the same underlying distribution, which is important since the goal of this study is to see if there is a statistically significant difference in pre- versus post-scores.

A total of 136 A/B tests were conducted spanning the two modalities (68 tests each for online and in-person) and every question within each of the 10 different categories. We chose this test as it allows for controlled, randomized, and quantitative comparisons. Using this method, we are able to isolate the impact of the program across the two modalities. Therefore, it helps us ensure that the findings are robust and applicable to real-world educational settings.

For each A/B test, we set up the same null hypothesis:
"In the population, the distribution of scores is the same before students completed the [online/in-person] program as after. Any difference in the sample is due to chance."
If any of the results favor the null hypothesis, this would mean that there is no statistically significant difference between the average of pre-scores and post-scores and that it is hard to quantify the impact that the summer bridge program had on students for the specific question.

For the A/B test, we first calculated the test statistic for each of the questions separately:

$$\text{observed difference} = \text{mean post-scores - mean pre-scores}$$

We shuffled the pre- and post-labels and calculated the test statistic for 1000 simulated samples. This step mitigates the effects of differences in sample size, as we are able to replicate the distribution of pre- and post-program scores while ensuring that we have the same large sample size to test on. We plotted the distribution of simulated differences and compared it to the original observed difference to see if the results favored the null hypothesis or one of two alternative hypotheses. We used a p-value cut-off of **5%**.

1) Alternative Hypothesis: Depending on the observed difference for the question, the alternative hypothesis can have two different directions.
1. If the observed difference is POSITIVE: If the post-program average score is greater than the pre-program average score, the observed difference is positive. In this case, we calculate the proportion of points *above* the observed difference; this is our p-value. If this p-value is less than the p-value cut-off (5%), we have a statistically significant directional difference in post-program vs. pre-program scores, which favors the alternative hypothesis:
"In the population, the post-program scores are *higher*, on average, than pre-program scores."
2. If the observed difference is NEGATIVE: If the post-program average score is lesser than the pre-program average score, the observed difference is negative. In this case, we calculate the proportion of points *below* the observed difference; this is our p-value. If this p-value is less than the p-value cut-off (5%), we have a statistically significant directional difference in post-program vs. pre-program scores, which favors the alternative hypothesis:
"In the population, the post-program scores are *lower*, on average, than pre-program scores."

D. Post vs. Pre-Program Ratio

Given the goal of the program, the optimum outcome of the program would be for the ratio of post- vs. pre-scores to be greater than 1 for all students. A ratio greater than 1 indicates that students either feel more confident, well-equipped, or supported after the program- depending on the question for which we generate the ratio. Therefore, we compare the distribution of ratios for each of the two modalities using an overlaid histogram for all questions within each of the categories. If the distribution shows a higher concentration of points above the line of $ratio = 1$, it indicates that post-program scores were greater than pre-program scores for the particular question. This method also minimizes the effect of different sample sizes because we compare probability densities instead of raw counts.

E. Sentiment Analysis

There were 11 optional, free-response qualitative questions asked to students in the post-program survey:
1. How comfortable do you feel connecting with others (peers, staff, faculty) at BSOE (Baskin School of Engineering)? Do you have any concerns about forming connections?
2. How comfortable do you feel connecting with others (peers, staff, faculty) at UC Santa Cruz? Do you have any concerns about forming connections?
3. How do you feel about navigating social connections (with peers, staff, and faculty) at BSOE?
4. How do you feel about navigating social connections (with peers, staff, and faculty) at UC Santa Cruz more broadly?
5. In what ways, if at all, were your parents or other family members supportive of your attending the BEES summer academy?
6. Are there other forms of support that you wish your parents or other family members could provide?
7. What was the highlight of your experience in the BEES Summer academy?
8. What was the most challenging part of your experience in the BEES Summer academy? How did you deal with this?
9. In what ways did the BEES Summer academy help you?
10. In what ways was the academy not helpful to you? What would have been more helpful?
11. Is there anything else that you would like to share with us that we did not ask or missed?

TABLE III: List of categories and their respective questions in pre- and post-survey.

Categories	Questions
Mathematics self-concept	1: Mathematics is one of my best subjects, 2: I often need help in mathematics, 3: I look forward to mathematics classes, 4: I have trouble understanding anything with mathematics in it, 5: I enjoy studying for mathematics, 6: I do badly in tests of mathematics, 7: I get good grades in mathematics, 8: I never want to take another mathematics course, 9: I have always done well in mathematics, 10: I hate mathematics.
Programming self-concept	1: Programming is one of my best subjects, 2: I often need help in programming, 3: I look forward to programming classes, 4: I have trouble understanding anything with programming in it, 5: I enjoy studying for programming, 6: I do badly in tests of programming, 7: I get good grades in programming 8: I never want to take another programming course, 9: I have always done well in programming, 10: I hate programming.
Science motivation	1: The science I learn is relevant to my life, 2: The science I learn is more important to me than the grade I receive, 3: The science I learn relates to my personal goals, 4: I find learning the science interesting, 5: I enjoy learning the science, 6: Understanding the science gives me a sense of accomplishment, 7: I put enough effort into learning the science, 8: I prepare well for the science tests, 9: I use strategies that ensure I learn the science well, 10: If I am having trouble learning the science, I try to figure out why, 11: I think about how learning the science can help my career, 12: I think about how learning the science can help me get a good job.
Science identity	1: In general, being a STEM scientist is an important part of my self-image, 2: I have a strong sense of belonging to the community of STEM scientists, 3: Being a STEM scientist is an important reflection of who I am, 4: I have come to think of myself as a ‘STEM scientist.
Help-Seeking	1: I ask for help understanding the material, 2: I get some help to understand the material better, 3: I ask the teacher to go over it with me, 4: I ask the teacher to explain what I didn’t understand, 5: I get some help on the parts I didn’t understand.
Concealment	1: I stay away from people, 2: I don’t want to see anyone, 3: I don’t want to talk to anyone about it, 4: I don’t want to talk about it, 5: I try to keep people from finding out, 6: I make sure nobody finds out, 7:I try to hide it, 8: I don’t tell anyone about it.
Mindset	1: You can learn new things, but you can’t really change your basic intelligence, 2: Your intelligence is something about you that you can’t change very much, 3: You have a certain amount of intelligence, and you really can’t do much to change it.
Peer Community	1: I anticipate feeling connected to my peers in the Baskin School of Engineering (BSOE) community, 2: I anticipate feeling connected to my peers around me at UC Santa Cruz.
Campus Belonging	1: I see myself as part of the campus community, 2: I feel that I am a member of the campus community, 3: I feel a sense of belonging to my campus.
Resources	1: I am aware of the resources available for students at UC Santa Cruz, 2: I know where to find my college advisor, 3: I know how to access help from financial aid services, 4: I know where I can go to for advice for my classes and schedule, 5: I know where I can go to for advice for my career and job search, 6: I know how to locate resources on campus that assist with tutoring, 7: If I am experiencing a disability I know where to go for help, 8: If I am having a counseling or psychological need I know where to call or go for help, 9: I know where to locate a lending library or study center for students like me, 10: I know where to receive emergency support from Slug Support, 11: I can locate my classes when I receive my class schedule.

The first 4 questions are directly relevant to the non-academic indicator categories (e.g., Peer Community, Resources, Sense of Belonging, etc.) that this paper studies. Therefore, this research compares sentiment scores of online and in-person responses for these 4 questions, imputing unanswered questions with a sentiment score of 0 (or neutral).

III. Results

A. RQ1: Program effect on students’ non-academic indicators

In testing whether the summer bridge program had a positive impact on a student’s outlook, there must exist some A/B test results that favor our first Alternative Hypothesis (“In the population, the post-program scores are *higher*, on average, than pre-program scores.”). Furthermore, to compare results between modalities, we compare the questions with statistically significant differences in each of the two modalities. In both tables, if the p-value for a particular question is less than 0.05, there is a statistically significant difference in pre versus post-mean scores.

In our comparisons, we check if a particular category is more affected by one modality versus the other, depending on the number of questions within the category that have statistically significant differences in their average pre- versus post-scores.

1) Online Modality Evaluation: Table IV shows the A/B test results (p-values) for all questions per category in the *online* version of the program (2020 and 2021). Results of A/B tests for Mathematics Self Concept (Q3 and Q8) and Programming Self Concept (Q3) indicate that post-scores are lower, on average, than pre-scores. Meanwhile, the results of Science Identity (Q2) and Resources (Q3, Q5, Q6, Q9, and Q11) reveal that post-scores are higher, on average, than pre-scores.

2) In-Person Modality Evaluation: Table V shows the A/B test results (p-values) for all questions per category in the *in-person* version of the program (2022 and 2023). In the in-person program offerings, there are no statistically significant differences for any question in the negative direction (post-score being less than pre-scores, on average). Additionally, results of Science Identity (Q2 and Q4) and *all* of the questions in Resources show that post scores are higher, on average than pre-scores for these questions.

B. RQ2: Difference between online and in-person modalities

Figure 1 shows the ratio plots for Science Identity Q4: "I have come to think of myself as a STEM scientist". The plot shows that the in-person distribution has a heavier right-skew around the $ratio = 1$ line than the online distribution. This indicates that there was a greater proportion of in-person students whose post-scores were greater than pre-scores for this category. The reason we include this visualization, instead of any of the other 67, is because in this question there is a positive and statistically significant change shown in the in-person program but not in the online program. Therefore, we expected the in-person distribution to be skewed more to the right, regardless of what the online distribution looked like. This supports the result of our A/B test.

Furthermore, akin to Figure 1, Figure 2 shows sub-plots corresponding to three selected questions from each category (29 sub-plots total because one category has two questions). The questions that were chosen to be displayed in Figure 2 had the most observable difference between the online and in-person distributions within their respective categories. In the majority of these output plots, the in-person histograms are slightly more skewed to the right than the online histograms. This indicates that a greater proportion of students demonstrate higher scores after the program than before. This shows that an in-person summer bridge program has more impact on the improvement of non-academic indicators of our underserved students.

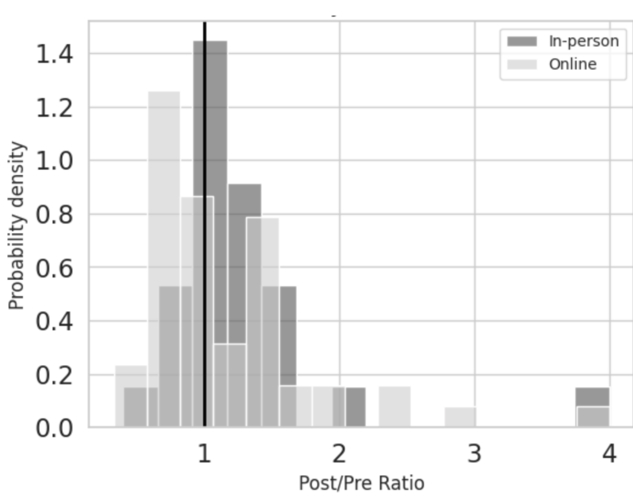


Fig. 1: Distributions of post versus pre-responses for Q4 in the Science Identity category. This question has a greater positive effect on the in-person program than on the online program. $ratio = 1$ is indicated by the black line.

C. RQ3: Analysis of students' attitudes via qualitative responses

a) Sentiment Analysis:

Each histogram in Figure 3(a) and Figure 3(b) represents the distribution for one of the following 4 questions:

Q24. How comfortable do you feel connecting with others (peers, staff, faculty) at BSOE? Do you have any concerns about forming connections?
Q26. How comfortable do you feel connecting with others (peers, staff, faculty) at UC Santa Cruz? Do you have any concerns about forming connections?
Q34. How do you feel about navigating social connections (with peers, staff, and faculty) in BSOE?
Q38. How do you feel about navigating social connections (with peers, staff, and faculty) at UC Santa Cruz more broadly?

When comparing the distributions, it's evident that the in-person distributions are more sharply left-skewed than the online ones, implying more positive responses to these questions for the in-person cohorts.

D. Discussion

Our analyses concluded that there are statistically significant differences between pre-program and post-program non-academic indicator scores and that the modality is an important factor to consider in being able to explain these differences.

1) Online: Students who participated in the program online (the 2020 and 2021 cohort) felt a greater sense of belonging to the STEM community and realized that they had access to useful resources than before the program, indicating that they felt more supported and included after the program. However, students did not have a positive attitude toward taking mathematics or programming classes in the future. Although this could be due to the administration of the program, it seems more likely that it is related to the specific technical concepts that were taught in the program. Incoming freshmen who are not underserved or those who do not go through such specially designed summer bridge programs may also share the same attitude about mathematics/programming after dabbling in university-level, sophisticated mathematics/programming concepts for the first time.

This result may also have been caused by differences in students' background preparation since this study did not control for it. Some students may have already been introduced to the kind of mathematics and programming questions taught in the bridge program, so they may have felt more well-equipped and confident from the very beginning. However, those who did not may have found it hard to grasp these concepts online for the first time, leading them to have a negative outlook toward taking programming/mathematics classes in the future.

Another possible source of bias is the fact that the program was held online during the COVID-19 pandemic. The pandemic may have affected many students' mental health

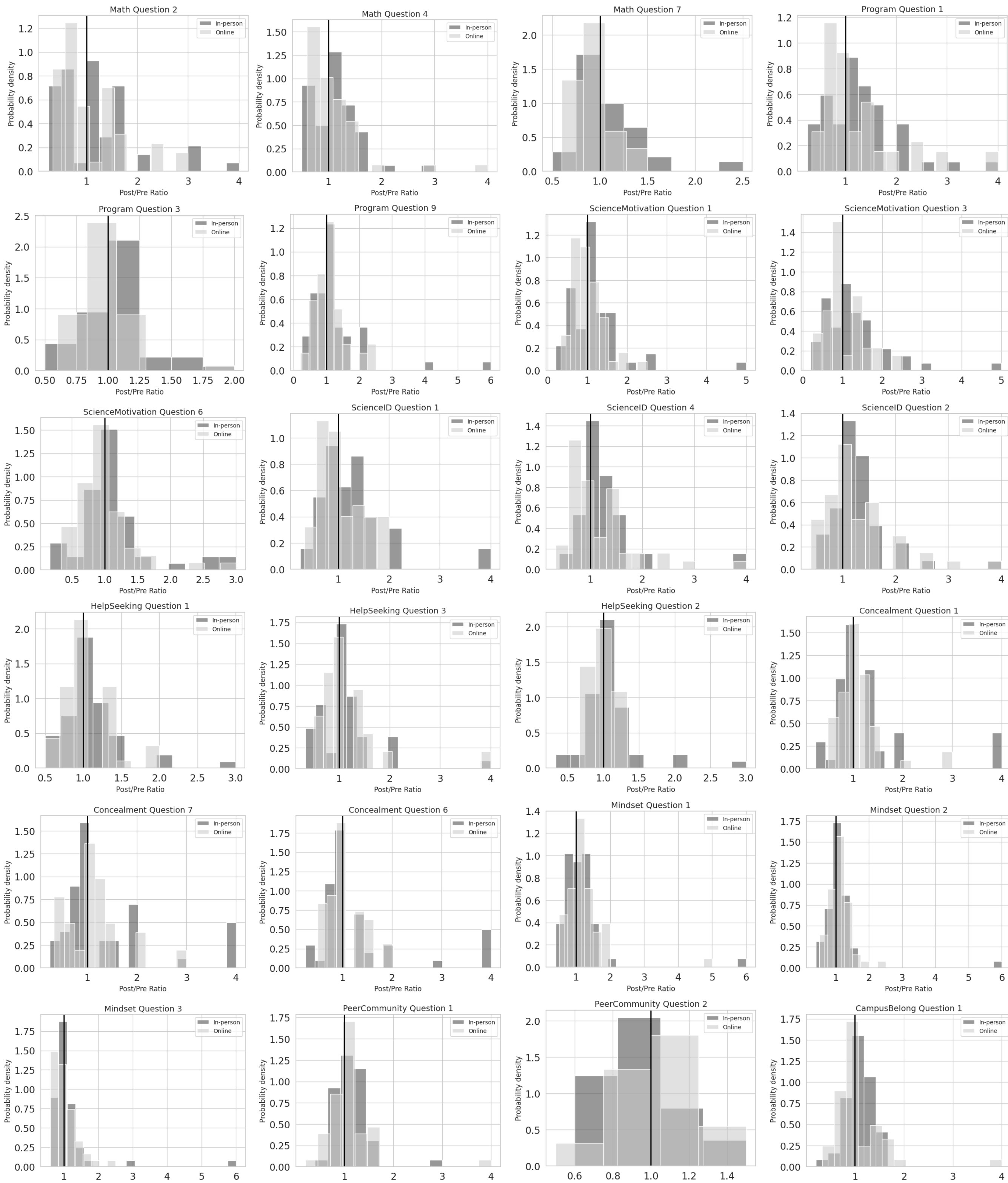


Fig. 2: Distributions of post- versus pre-scores for a selected number of 3 questions in each category. Each sub-figure shows an overlaid histogram of the distribution of responses from the online and in-person modalities.

TABLE IV: Online modality results - 2020 and 2021 data (* $p \leq 0.05$).

Indicators	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Mathematics self-concept	0.213	0.381	0.040*	0.421	0.111	0.398	0.090	0.040*	0.472	0.232	-	-
Programming self-concept	0.151	0.340	0.027*	0.276	0.471	0.237	0.303	0.276	0.278	0.441	-	-
Science motivation	0.232	0.284	0.124	0.309	0.203	0.057	0.390	0.307	0.058	0.201	0.350	0.441
Science identity	0.288	0.049*	0.188	0.308	-	-	-	-	-	-	-	-
Help-Seeking	0.259	0.060	0.415	0.131	0.124	-	-	-	-	-	-	-
Concealment	0.213	0.289	0.289	0.269	0.205	0.363	0.289	0.107	-	-	-	-
Growth mindset	0.167	0.376	0.396	-	-	-	-	-	-	-	-	-
Peer community	0.422	0.169	-	-	-	-	-	-	-	-	-	-
Campus belonging	0.354	0.141	0.393	-	-	-	-	-	-	-	-	-
Resources	0.308	0.309	0.050*	0.201	0.032*	0.021*	0.359	0.105	0.046*	0.199	0.013*	-

TABLE V: In-Person modality results- 2022 and 2023 data (* $p \leq 0.05$).

Indicators	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Mathematics self-concept	0.356	0.107	0.224	0.052	0.354	0.201	0.155	0.141	0.282	0.418	-	-
Programming self-concept	0.307	0.311	0.126	0.387	0.297	0.208	0.422	0.422	0.426	0.313	-	-
Science motivation	0.323	0.362	0.315	0.114	0.298	0.486	0.354	0.305	0.206	0.281	0.273	0.295
Science identity	0.155	0.010*	0.097	0.015*	-	-	-	-	-	-	-	-
Help-Seeking	0.317	0.129	0.501	0.404	0.120	-	-	-	-	-	-	-
Concealment	0.281	0.238	0.262	0.209	0.437	0.294	0.417	0.154	-	-	-	-
Growth mindset	0.413	0.427	0.250	-	-	-	-	-	-	-	-	-
Peer community	0.095	0.262	-	-	-	-	-	-	-	-	-	-
Campus belonging	0.378	0.133	0.176	-	-	-	-	-	-	-	-	-
Resources	0.000*	0.000*	0.005*	0.000*	0.000*	0.000*	0.000*	0.000*	0.004*	0.000*	0.000*	-

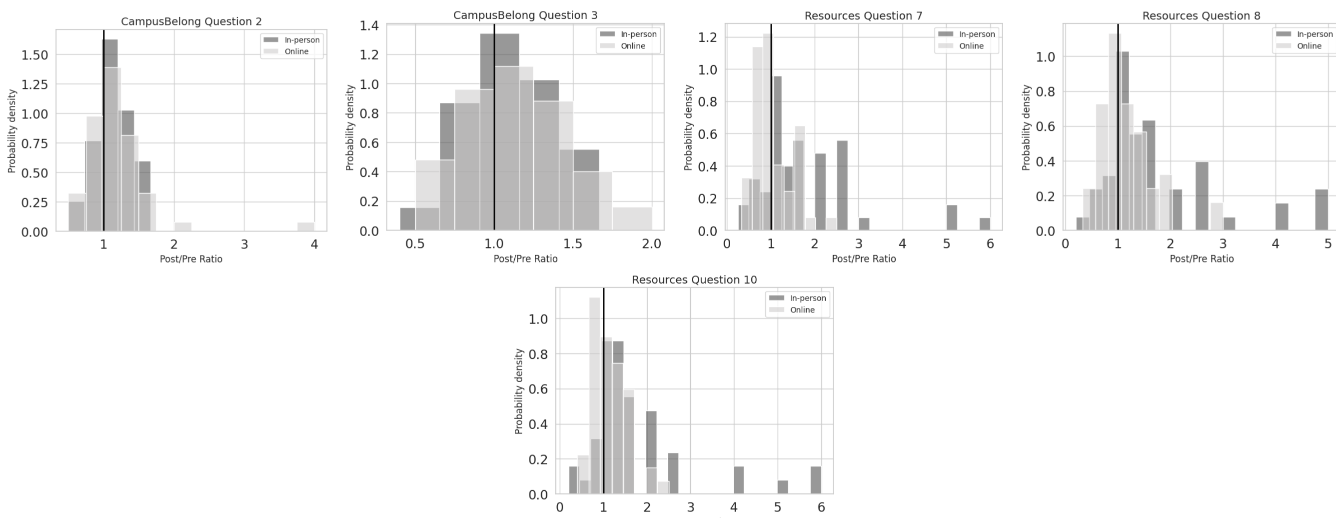


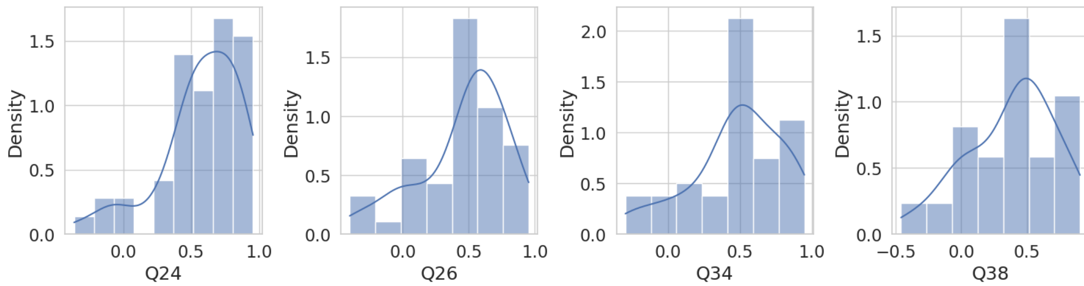
Fig. 2: (Continued)

and well-being negatively [25], [26]. Students may have had differing views on their upcoming mathematics and programming classes (especially in 2020) being held entirely online. However, even though the online summer bridge program may have lacked in piquing the interest of students in the context of academics, it has been shown to help underrepresented students find a community on campus with great knowledge of resource access [8].

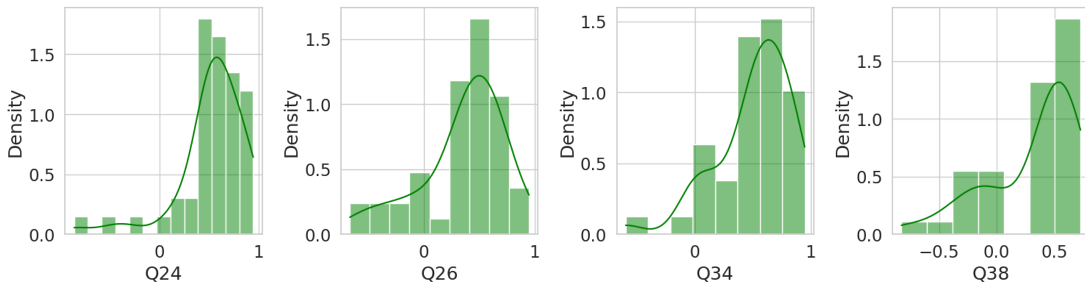
Overall, the online program was also helpful in developing social confidence for the participants, as the sentiment scores post-program were positive. This further supports the hypothesis that the program was helpful in increasing the non-academic indicators important for student success.

2) In-Person: Students indicated that they felt like they belonged to a community of STEM scientists and also that they started to see themselves as STEM scientists after the program. This is a very positive outcome because it shows that underrepresented students feel more confident in their career paths and optimistic about their professional lives as STEM students going forward.

Students also felt very well-equipped with resources after the program. They knew how to access campus services in case of any need, such as career advice, psychological counseling, emergency support, financial aid, etc. This is also a great indicator because these services enable students to feel more secure on campus and are, therefore, crucial to



(a): Online Sentiments



(b): In-Person Sentiments

Fig. 3: Comparison of Sentiment Scores: Online vs. In-person for 4 open-ended questions.

helping underrepresented students integrate better on campus with their peers.

Overall, across both modalities, the “Resources” category was the most positively affected category. This impact was also consistently positive over all the specific questions within each modality that had statistically significant differences between pre- and post-scores.

The sentiment analysis scores for the in-person program were significantly more positive compared to the online version, indicated by the left skew in Figure 4. This highlights the increased strength of social connection and community that in-person programs help develop.

IV. Future Work

Future work includes looking into post-program academic success indicators such as grades in introductory Computing and mathematics courses and identifying the impact of program content and post-program non-academic indicators on students’ course grades. Additionally, we will perform focus group studies to obtain more granular information on other factors that may have impacted students’ academic and non-academic indicators. Finally, we will propose a hybrid design for the summer bridge program to test its effectiveness against a purely online and in-person approach. After the hybrid design, we also anticipate that it would be worthwhile exploring ways to increase the number of participants to make this study more representative by replicating this study across other similar summer bridge programs in other R1 institutions.

V. Conclusion and Future Directions

This paper presents a quantitative analysis of a summer bridge program’s impact on non-academic indicators for underserved students in a Computing major. The study focuses on three key research questions:

RQ1) The overall effect of the program on students’ non-academic indicators.

RQ2) The differential impacts of online versus in-person program modalities.

RQ3) The differences in participants’ perceptions of online versus in-person program modalities.

Data was collected through pre- and post-program surveys over four years, with online programs conducted in 2020 and 2021 and in-person programs in 2022 and 2023. The surveys covered various non-academic indicators such as students’ sense of belonging, motivation in science, self-efficacy, and awareness of resources. The analysis used A/B testing and ratio analysis to assess changes in these indicators.

Our results indicate that the summer bridge program significantly improved students’ awareness of resources and increased their sense of belonging in the STEM Community. While both the online and in-person modalities were beneficial, the in-person program demonstrated a larger improvement in the positive changes in Resources and Science Identity.

Based on this, we conclude that both modalities of summer bridge programs are helpful, but due to the increased costs of an in-person program, it is reasonable to have a hybrid program where some of the curricular teachings are done online, and students are brought in-person only for a few days for cohort-building, mentoring, and introduction to campus resources. This is further supported by the results of the sentiment analysis, where the in-person program showed a substantially larger improvement in social confidence as compared to the online version.

Given the limited funding, this study underscores the importance of carefully considering the choice of program modality to maximize the impact on student outcomes. Future work will explore the program's impact on academic performance and design a hybrid model that combines the strengths of both online and in-person approaches.

VI. Acknowledgement

We want to thank Prof. Covorubias and their team for designing the survey that served as the foundation for this study. We are also grateful to Dr. Carmen Robinson for her exceptional leadership in the logistics and planning of the program on which this evaluation is based. This research was made possible by the support of the National Science Foundation (NSF) under grant CNS-2245904. We appreciate their funding and commitment to advancing scientific research.

References

[1] Dina Ghazzawi, Donna Pattison, and Catherine Horn. Persistence of underrepresented minorities in stem fields: Are summer bridge programs sufficient? In *Frontiers in education*, volume 6, page 630529. Frontiers Media SA, 2021.

[2] Anna Brady and Dorinda Gallant. Stem bridge program. *Journal of College Science Teaching*, 50(6):57–62, 2021.

[3] Sarah R Cohodes, Helen Ho, and Silvia C Robles. Stem summer programs for underrepresented youth increase stem degrees. Technical report, National Bureau of Economic Research, 2022.

[4] Michael Ashley, Katelyn M Cooper, Jacqueline M Cala, and Sara E Brownell. Building better bridges into stem: A synthesis of 25 years of literature on stem summer bridge programs. *CBE—Life Sciences Education*, 16(4):es3, 2017.

[5] Kylan Stewart, Bruce Debruhl, and Zoe Wood. An equity-minded assessment of belonging among computing students. In *2022 ASEE Annual Conference & Exposition*, 2022.

[6] Anita L Campbell, Inês Direito, and Mashudu Mokhithi. Developing growth mindsets in engineering students: a systematic literature review of interventions. *European Journal of Engineering Education*, 46(4):503–527, 2021.

[7] Veronica A. Lotkowski, Steven B. Robbins, and Richard J. Noeth. The role of academic and non-academic factors in improving college retention. act policy report. 2004.

[8] David L. Tomaskoa, Judy S. Ridgwaya, Susan V. Olesika, Rocquel J. Wallera, Minnie M. McGeea, Lisa A. Barclaya, Kathleen T. Harkina, and Jan Upton. Impact of summer bridge programs on stem retention at the ohio state university. *American Society for Engineering Education*, 2013.

[9] Narges Norouzi, Hamidreza Habibi, Carmen Robinson, and Anna Sher. An equity-minded multi-dimensional framework for exploring the dynamics of sense of belonging in an introductory cs course. In *Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education V. 1*, pages 131–137, 2023.

[10] Larrabee Tracy, Norouzi Narges, Robinson Carmen, and Quynn Jenny. Successful interventions to eliminate achievement gaps in stem courses. In *2020 Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)*, volume 1, pages 1–4. IEEE, 2020.

[11] Raj Chetty, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. Mobility report cards: The role of colleges in intergenerational mobility. *National Bureau of Economic Research*, 2017.

[12] Jennifer Ma, Matea Pender, and Meredith Welch. Trends in higher education series, education pays. 2019.

[13] Narges Norouzi and Carmen Robinson. Evaluation of the impact of modality for equity program. In *Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 2*, pages 1335–1335, 2022.

[14] Narges Norouzi, Carmen Robinson, Rebecca Covarrubias, Ruby Hernandez, Danay Weldegabriel, Gwynn Benner, Wenjuan Sang, and Rafael Espericueta. Baskin engineering excellence scholars bridge program: Planning, implementation, and evaluation. In *2021 IEEE Frontiers in Education Conference (FIE)*, pages 1–8. IEEE, 2021.

[15] Hsiao-Lin Tuan, Chi-Chin Chin, and Shyang-Horng Shieh. The development of a questionnaire to measure students' motivation towards science learning. *International Journal of Science Education*, 27:639–654, 2011.

[16] Matthew Jackson, Gino Galvez, Isidro Landa, Paul Buonora, and Dustin Thoman. Science that matters: The importance of a cultural connection in underrepresented students' science pursuit. *CBE Life Sciences Education*, 2016.

[17] Gwen Marchand and Ellen A. Skinner. Motivational dynamics of children's academic help-seeking and concealment. *Journal of Educational Psychology*, 2007.

[18] D. Da Fonseca, S. Schiano-Lomoriello, F. Cury, F. Poinso, M. Rufo, and P. Therme. Validation study of the implicit theories of intelligence scale. *L'encephale*, 2007.

[19] Carol Dweck. Mindset: The new psychology of success. 2008.

[20] ——. Self-theories: Their role in motivation, personality, and development. 2013.

[21] Danielle M. Young, Laurie A. Rudman, Helen M. Buettner, and Meghan C. McLean. The influence of female role models on women's implicit science cognitions. *Psychology of Women Quarterly*, 2013.

[22] Martin M. Chemers, Eileen L. Zurbriggen, Moin Syed, Barbara K. Goza, and Steve Bearman. The role of efficacy and identity in science career commitment among underrepresented minority students. *Journal of Social Issues*, 2011.

[23] Leonard A. Jason, Ed Stevens, and Daphna Ram. Development of a three-factor psychological sense of community scale. *Journal of community psychology*, 2015.

[24] Sylvia Hurtado and Deborah F. Carter. Effects of college transition and perceptions of the campus racial climate on latino college students' sense of belonging. *Sociology of Education*, 1997.

[25] Changwon Son, Sudeep Hegde, Alec Smith, Xiaomei Wang, and Farzan Sasangohar. Effects of covid-19 on college students' mental health in the united states: Interview survey study. *Journal of Medicanl Internet Research*, 2020.

[26] Jad A. Elharake, Faris Akbar, Walter Malik, Amyn A.and Gilliam, and Saad B. Omer. Mental health impact of covid-19 among children and college students: A systematic review. *Child Psychiatry Hum Dev*, 2022.