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Encouraging STEM Careers among Minoritized High School Students: The Interplay between Socio-Environmental Factors and Other Social Cognitive Career Constructs

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Abstract (paper type: ERM) -- Performance in math, particularly algebra, is a major barrier to student success and participation in STEM among under-represented minoritized students, particularly Black U.S. high school students. This research applies Social Cognitive Career Theory (SCCT) to measure impacts of an afterschool algebra-for-engineering program on math self-efficacy and interest in STEM among high school students in a large urban district. To study the program's effects, a mixed methods research design was used where schools were assigned to either treatment or control conditions. Students in treatment schools accessed algebra-for-engineering modules, STEM-professional role model videos, and field trips, while students in control schools accessed role model videos and field trips only. Surveys measuring math self-efficacy, and STEM interest, outcome expectations, and choice goals were completed by participants in both conditions at the beginning and end of two separate program years, 2021-22 and 2022-23. Across both years, quantitative results suggest some positive effects of BOAST participation, particularly for STEM choice goals, but benefits depend upon student participation levels. Qualitative data offer student voice around prior experiences in math and science and the development of postsecondary plans in STEM. In combination, the results suggest that for students who do not initially identify as STEM career-bound, afterschool programming may not necessarily promote preparation for STEM careers due to an accumulation of weak math and science school experiences and other socio-environmental influences.

Index terms: engineering, high school, math self-efficacy, minoritized students, urban education

I. INTRODUCTION

Performance in math, particularly algebra, is a major barrier to student participation, enthusiasm, and success in STEM among minoritized[4] students in U.S. high schools. Furthermore, the transition between middle school and high school is a liminal and tumultuous time for adolescents, and it coincides with the time during which students typically undertake algebra. For too many students, algebra is not the gateway to mathematical literacy, but a

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[4] Minoritized students encompass African Americans/Blacks, Hispanic/Latinx, Native Americans, students with dis(abilities), students in poverty, girls, trans, and non-binary students [1]. Given the demographics of City Schools, this paper focuses specifically on racially minoritized students, including African American/Black and Hispanic youth who compose 71% and 18.6% of the district's student population, respectively.

gatekeeper. Algebra is foundational to formal mathematics, so supporting students in this subject specifically is a key lever to promoting rich postsecondary opportunities [2],[3],[4],[5].

In Baltimore City Public Schools (City Schools), high school math has persistently posed challenges to students' state assessment performance, on-time graduation, as well as access to credit-bearing courses once enrolled in college. For instance, in 2023 just 5% of City Schools 8th graders were proficient on the math state assessment. Among students taking the algebra state assessment at the end of their Algebra I course in 2023, only 6.5% were deemed proficient [6]. A study of Baltimore graduates who enrolled in college found that approximately 90% of the class of 2011 were assessed to need remedial coursework, most often in math; graduates' SAT math score was, on average, 380 [7]. Gaps in equitable access, instruction, and resources across the district contribute to lower mathematics achievement. City Schools suffers from chronic underfunding; statewide, as the percentage of minoritized students increases, the gap between funding targets and actual funding gets worse [8]. Moreover, teacher shortages and high turnover impact math instruction. In 2018-2019, only 18% of 6th grade teachers were certified in math [9].

Several studies have tested the efficacy of strengthening students' math skills by using expanded opportunities for algebra in high school [10], [11], [12], [13]. While a strategy of extended learning time in algebra has primarily been implemented for the purpose of reducing course failures, its proven effectiveness in bolstering math course pass rates by adding increased instructional time holds promise for bolstering students with an interest in STEM, but who have not mastered algebra skills. For example, students in Chicago Public Schools who received double-dose algebra achieved significantly higher algebra assessment scores, relative to students with only a single dose [12]. Further, the long-run effects of double-dose algebra included a higher number of credits earned in high school, a higher probability of graduation, and higher likelihood of college enrollment [10], [11].

Ensuring students' mastery and confidence in algebra is crucial, since math proficiency and self-efficacy have been identified as key moderators of student persistence in STEM pathways [14]. Self-efficacy is belief about one's capabilities for success on a given outcome [15], [16], and self-efficacy in math specifically pertains to individuals' confidence in their approach to performing mathematical tasks and solving math problems successfully [17]. Research demonstrates that math self-efficacy is predicted by successful math performance [18], and in particular, experiences where students have the opportunity to show mastery have been found to be a particularly powerful mechanism to increase students' feelings of math efficacy [19]. Notably, math self-efficacy has been shown to mediate the effects of gender, and maintain independent effects on long-term achievement outcomes, as well as postsecondary matriculation [17], [20], [21]. Thus, strengthening students' math self-efficacy helps ensure they are psychologically equipped to succeed in advanced math coursework and satisfy prerequisites to enter engineering career pathways in college, as well as maintain STEM interests and career goals.

Social Cognitive Career Theory (SCCT) offers a framework to explore the mechanisms involved in students forming and maintaining goals to pursue engineering career pathways. SCCT posits that developing a career identity is a long, cumulative process, effected recursively by interests, self-efficacy, barriers, and relevant experiences [22]. Yet, more recent applications of SCCT highlight the importance of socio-environmental factors [23], such as ethnic identity and family influences among youth from lower socioeconomic (SES) backgrounds [24].

Specifically, Ali et al. [25] found that sibling and peer support for educational goals accounted for most of the explained variance in low-income ninth graders' vocational and educational self-efficacy, whereas perceived barriers were not significantly predictive. This suggests that social supports are more impactful to self-efficacy than challenges among this subpopulation. Ali et al. [25] further found that educational/vocational self-efficacy was the only significant predictor of outcome expectations, when tested against family and peer supports and perceived barriers. Studying low-income high school students' academic engagement and vocational outcome expectations, Kantamneni et al. [26] found a positive relationship between ethnic identity and both self-efficacy and outcome expectations; they also identified a positive association between mothers' support and academic engagement, and a positive association between fathers' support and self-efficacy. They also found self-efficacy to be strongly predictive of outcome expectations, which supports the SCCT model. Surprisingly, Kantamneni et al. [26] also found a positive association between perceived barriers and self-efficacy among their low-income population. Their findings imply that low-income students' self-efficacy may be sourced in ways that are different from students with more socioeconomic resources.

According to SCCT [27], opportunities to experience mastery, learn with peers from nurturing teachers, and apply math standards to practical demonstrations could promote higher self-efficacy, interest and goal-setting in related careers. However, research on educational self-efficacy among students of color and low-income populations is still emerging, and thus, the current study will contribute to the literature in considering how a predominantly Black and relatively low-income high school population's experiences – in the program and in school -- impact STEM career development.

A. Program Description

BOAST, an eight-month afterschool engineering program for high school students, was offered to two cohorts in a large urban school district in school years 2021-22 and 2022-23. The program's curriculum entailed a series of online modules with math/algebra (reinforcement) lessons as applied to engineering challenges. Most students participated in a hybrid format, attending weekly afterschool meet-ups with an in-person instructor, and students could work on modules asynchronously if needed. Instructors were also available for regularly-scheduled virtual office hours and communicated with students via email. Field trips to the sponsoring university's campus and high-quality videos of interviews with diverse STEM professionals were also key program components.

Six modules covering a range of relevant and engaging engineering topics were developed. Each module was divided into four sections, including an introductory session (i.e., an icebreaker activity and time to view a video of a professional STEM role model sharing about their career trajectory); a 'play' session in which students could experiment with materials; a 'learn' session where students reviewed and practiced relevant algebra standards; and finally a 'build' component where students built a design using the algebra skills reinforced during the learning component. The engineering topics covered included a general introduction to BOAST, technical rescue, machine learning, soundproofing, business optimization, and urban heat islands.

In-person instructors were hired by the sponsoring university and chosen based on their proven ability to work with minoritized students and general demeanor as a caring, nurturing teacher. Ten role model videos 5-10 minutes in length were created that featured predominantly minoritized professionals describing their work in a range of STEM careers, including electrical, optical, computer, cyber security, mechanical, systems and civil engineering. Professionals shared stories about how their career interests developed, challenges they encountered, and their experiences in high school and college, including ways that mentors, friends, and family had helped them persist in the face of social or educational obstacles.

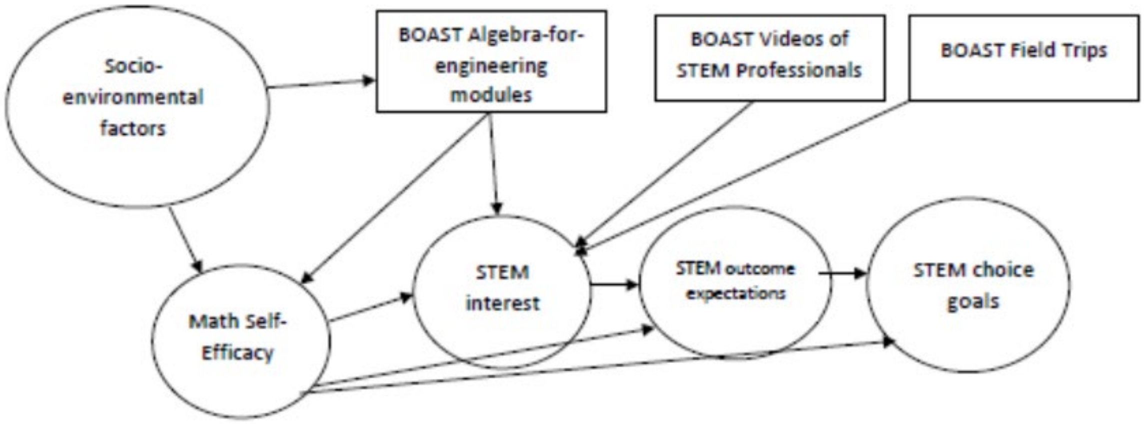
B) Program Recruitment

Students were recruited to participate in the BOAST program during August-September before the beginning of the school years in several ways. First, information about the program and how to apply was disseminated on a university website and using brochures, small posters, and a local radio station announcement. Materials were shared by university staff with school leaders, with the request that they would share it with teachers, parents, and students. University staff also went to the high schools during lunch periods to recruit applicant students directly. Interested students, whether self-nominating or encouraged by another, indicated their interest in participation by completing an online application. The only requirements for participation were having already completed Algebra I with a final report card grade of C- or better, and being enrolled in a high school that had agreed to host the program.

II. METHODS

The theory of change for the current study was adapted from Lent et al. [27] and based on SCCT. Our model hypothesizes that the BOAST program components impact career goals through students' math self-efficacy, STEM interests, and their interdependence with socio-environmental factors. This model is illustrated in Fig. 1.

Fig. 1. Conceptual Model. Adapted from [27]



A) Data

To measure exposure to algebra-for-engineering modules, data were collected passively from students from the online learning management system (LMS). These data detail the number of hours students spent in each module throughout the year. In addition, the LMS data captured the number of role model videos students viewed. Field trip participation data were captured separately. Students' math self-efficacy was measured both at the beginning (pre) and end of the program year (post) using a previously validated self-administered online survey [28]. Data on students' interest, outcome expectations, and choice goals in STEM were also collected from participants pre- and post-program year using an instrument that prior research had suggested was valid [29].

Finally, qualitative one-on-one interview data from 14 students were also collected over the course of both program years using a semi-structured protocol to capture the influence of socio-environmental factors. Students were asked about their reasoning for electing to participate in BOAST; barriers to participation (e.g., scheduling challenges, technology issues that prevented module completion); reactions to the role model videos and field trips; their experiences in math and science classes; their post-high school plans including career goals and potential obstacles to reaching them; and sources of social support (i.e., family members and friends) for preparing for college and/or career.

B) Research Design

This study employed a convergent parallel mixed methods research design, where schools were assigned to either treatment or control conditions. As a first step, all eligible high schools in the district (n=28), excluding alternative schools for students with intense academic needs) were paired *a priori* based on student characteristics, including whether the school had academic entrance criteria, school enrollment size, percent Black, percent Hispanic, percent English learner, graduation rate, and percent of students proficient on the Algebra I state assessment the prior year. This resulted in 14 high school groupings in which each pair was as similar as possible on key factors. The principal of each school per pair was approached by a member of the BOAST program team to gauge interest in hosting the BOAST program, either as a treatment or a control school. Principals of schools in the treatment condition were informed that their eligible student applicants would receive the algebra-for-engineering afterschool lesson meetups along with all other program components (i.e., STEM role model videos, field trips). Conversely, students in schools in the control condition would have access to the STEM role model videos and field trips only. Quantitative and qualitative data were collected simultaneously during both program years, and the data collected depended upon their school's experimental condition. Specifically, LMS module participation, pre/post survey, and student interview data were collected from students in treatment schools, while pre/post survey and role model video views only were collected from students in control schools. Field trip participation data was collected for students in both conditions.

Although random assignment of schools to an experimental condition would offer the most robust method to identify causal effects of program participation, randomization was infeasible. School leaders expressed strong concerns about encouraging their students to apply for the BOAST program without knowing ahead of time what participation would mean for students in terms of time and effort commitment; therefore, randomization of schools with applicants was decided to be ethically questionable. As a result, analysis to create like-school-pairs was performed to approximate random assignment to reduce the potential for unobserved variable bias. Of particular concern were differences between treatment and control groups in student interest in STEM; thus, the opportunity was similarly advertised at schools in both conditions as a set of STEM-focused activities occurring outside regular school hours. It is unknown the extent to which student applicants were aware of which condition their school had been assigned.

C) Analysis

Quantitative analysis entailed statistical bivariate comparisons and multivariate regression estimating changes in math self-efficacy, STEM career interests, outcome expectations, and choice goals based on BOAST participation and other student characteristics. Regressions were estimated in Stata v. 18 with robust standard errors to account for student clustering within schools.

Qualitative data were analyzed using a deductive approach. In particular, the researcher read transcripts several times and then began coding with a set of expected categories based on the theoretical framework of SCCT. These initial codes represented topics including 'barriers to

BOAST participation,' 'educational and career goals' 'interest in STEM,' 'prior experiences with math,' 'prior experiences with science,' 'plans after high school,' and 'social supports.' Secondarily, the researcher further coded the data within each category using an inductive approach to capture greater nuance. For instance, within social supports, codes were created to identify sources of 'peer support' and 'family support' for particular domains such as college planning and career planning. The findings are organized according to the themes identified from the secondary set of codes.

III. Findings

A) *Sample Descriptives*

Data were collected during two program years (2021-22 and 2022-23) for 89 students in ninth through eleventh grade, of whom 60 were in treatment and 27 in control schools (refer to Table I). Approximately 81% of the sample identified as Black and 9% as White Hispanic. The remainder were either White non-Hispanic or Asian. Most participants were either high school sophomores (35%) or juniors (35%) and the majority identified as female (70%).[5]

TABLE I
BOAST STUDENT CHARACTERISTICS BY EXPERIMENTAL CONDITION

	Treatment	Control
Entering grade		
Grade 9	.26 (.44)	.37 (.49)
Grade 10	.38 (.49)	.26 (.45)
Grade 11	.34 (.48)	.37 (.49)
Demographic characteristics		
Female	.73 (.45)	.63 (.49)
Male	.27 (.45)	.37 (.49)
Black	.83 (.38)	.78 (.42)
Hispanic, White	.07 (.25)	.15 (.36)
White or Asian, non-Hispanic	.10 (.30)	.07 (.27)
Special education	.10 (.30)	0
English learner	.02 (.13)	.04 (.19)
Academic characteristics		
Algebra I grade (4-point scale)	3.07 (.77)	2.89 (1.05)
School day attendance rate, year before treatment	92.3 (.09)*	83.4 (17.32)
School day chronic absence, year before treatment	24.6 (.43)*	55.6 (50.6)

[5] Demographic characteristics reflect students' district administrative records; in Maryland students may identify their gender as non-binary and as more than one race. Ethnicity is recorded separately from race.

n	60	27

Note. Means (and standard deviations) presented.
* Group difference significant, p<.05

Among students in treatment schools, 10% received special education services and 2% received EL services, whereas no students in the control group received special education and slightly more (4%) were EL. Final Algebra I report card grades were slightly higher for treatment than control students (3.07 vs. 2.89).

Baseline comparability between students in treatment and control schools was tested (refer to Table I). Statistically significant differences between treatment and control groups were evident only for students' prior year's school-day attendance. The average daily attendance rate of students in the treatment group was 9 points higher than those in the control group (92.3 vs. 83.4). Similarly, students in the control group had much higher levels of chronic absenteeism (i.e., being absent 10% or more of total days on roll) than those in the treatment group (55.6% vs. 24.6%). As context, chronic absence levels among all high school students in the district are troublingly high in recent years. In 2022-23, approximately 46% missed 20 days of school or more [6].

Regarding baseline comparability on the SCCT constructs (refer to Table II), the mean for each scale collected during the pre-year survey administration was comparable between students in treatment and control groups. Though students in the treatment group had slightly higher responses for STEM interests (4.12 vs. 3.97), this difference was not statistically significant, nor were any other comparisons on these baseline measures.

TABLE II
BASELINE COMPARISONS OF SCCT CONSTRUCTS

SCCT construct	Treatment	Control
Math self-efficacy	3.87 (.51)	3.69 (.51)
STEM interest	4.12 (.62)	3.97 (.61)
STEM outcome expectations	3.72 (.62)	3.76 (.76)
STEM choice goals	3.86 (.72)	3.81 (.78)

Note. No mean differences were statistically significant (α=.05).

Data on the three forms of BOAST participation are presented in Table III. On average, participants in the treatment group spent 3.77 hours working on modules within the LMS. This measure does not capture other ways that students could interact with the BOAST material, which may not have been logged during in-person afterschool meetup sessions where the instructor could have used the whiteboard, material demonstrations, and peers may have worked together in real time. In analyses not shown, the length of total time students spent inside the

LMS learning modules during the year varied considerably, with the median time 0.50 hours and the 90% percentile 9.02 hours. Because of the dedicated time in each module to view the videos of STEM professionals, time spent watching them was slightly higher for students in the treatment group (0.46 vs. 0.39 hours), though the difference is not statistically significant. Field trip attendance was significantly higher among students in the treatment group (1.6 vs. 0.95 trips).

It is also notable that school-day attendance patterns during the program year differed substantially between treatment and control groups; these differences were also statistically significant. Students in treatment schools had higher average daily attendance rates than in control schools (90.3 vs. 81.6) and lower levels of chronic absence (34.4% vs. 66.7%). However, further analyses did not suggest an association between daily attendance and LMS participation for students in the treatment group (r = .19, p=.08).

TABLE III
BOAST PARTICIPATION LEVELS

	Treatment	Control
Total LMS hours†	3.77 (7.64)	na
Total video viewing hours	.46 (.74)	.39 (.46)
Number of field trips attended	1.60 (1.21)*	.95 (.22)
School day attendance		
Average daily attendance rate	90.3 (8.3)*	81.6 (17.1)
% Chronically absent	34.4 (47.9)*	66.7 (48.0)
n	60	27

Note. Means (and standard deviations) presented. School day attendance is presented to provide context on student participation in BOAST's out-of-school time components.
* Group difference significant, p<.05
†LMS hours do not capture in-person exposure to algebra-for-engineering content.

B) *Quantitative Findings*

At the beginning and end of the program year, students in both the treatment and control groups were asked to complete a 15-minute survey that measured their math self-efficacy, and STEM interest, outcome expectations and choice goals. All survey constructs at each time point were determined to be reliable using Cronbach's alpha analysis (refer to Appendix I). As a first step, relationships between the pre-survey constructs were tested based on the hypothesized conceptual model, where math self-efficacy is thought to positively impact STEM interest, which in turn, impacts STEM outcome expectations and choice goals.

TABLE IV
RELATIONSHIPS AMONG SOCIAL COGNITIVE CAREER THEORY CONSTRUCTS, PRE-SURVEY RESPONSES

	STEM interest	STEM outcome expectations	STEM choice goals
Math self-efficacy	NS	NS	NS
STEM interest	--	.50**	.65***
STEM outcome expectations	--	--	.60***

Note. Standardized betas presented.
NS: not statistically significant
***p<.001 **p<.01

Standardized estimates from bivariate regression analyses show that math self-efficacy is unassociated with STEM interest, outcome expectations, and choice goals. However, STEM interest and outcome expectations were strongly related (β=.50, p=.001). STEM choice goals were also strongly associated with both STEM interest (β=.65, p<.001) and outcome expectations (β=.60, p<.001).

Next, we examined the extent to which participation in the BOAST program was associated with pre-to-post change in the SCCT constructs. A summary of regression analyses predicting change scores for each construct is provided in Table V (the full set of estimates is provided in Appendix II). Results shown for Model 1 represent the estimate for number of hours spent on BOAST material in the LMS. Though small, positive effects on math self-efficacy, STEM interest and STEM outcome expectations were statistically significant.

TABLE V
TREATMENT EFFECTS

Outcomes (pre/post delta)	Model 1	Model 2	Model 3
Math self-efficacy	.02 (.01)*	.19 (.12)	-.11 (.16)
STEM interest	.03 (.01)**	.08 (.16)	.29 (.19)
STEM outcome expectations	.03 (.01)*	.30 (.51)	.46 (.75)
STEM choice goals	.01 (.01)	.18 (.22)	.59 (.16)*

Note. Treatment group coefficients and robust SEs presented.
Model 1 includes only treatment effects where ‘treatment’ estimate is for LMS hours.
Model 2 controls for demographic characteristics.
Model 3 controls for demographic and prior academic characteristics.
**p<.01 *p<.05

Models 2 and 3 (Table V) present estimates for the indicator of experimental group membership; we find that whether controlling for levels of exposure to the BOAST components, demographic characteristics, Algebra I grades, or school attendance rate, there were no significantly differences between treatment and control groups in change in math self-efficacy, STEM interest, or STEM outcome expectations. However, students in the treatment group had STEM choice goals that increased, on average, by 0.59 points relative to the control group (p=.01), but only when accounting for demographic and academic characteristics. This finding is unexpected given the null effects of LMS hours for STEM choice goals.

C) *Qualitative Findings*

Interviews with students in the treatment group were collected to gain insights into how students were thinking about their educational and career plans, their perceptions of what might be required to reach them, and what they believed might help or hinder during that process.

1) *Developing Postsecondary Interests:* Most students interviewed described some level of interest in a STEM-related career. However, participant responses ranged considerably between firm, bourgeoning, and vague plans. For example, Renee, who appeared to be relatively firm in her plans said, “[I want to] get my bachelor's degree like my sister has before . . . I want to major in engineering. It's engineering. I don't know what type exactly yet. But it's engineering.” Another student, Nivea, shared her plan along with a specific college: “Johns Hopkins is actually one of my first choices . . . I would say software engineering, or computer science is my top two [choice of majors].”

In contrast, some students seemed to have doubts about their emergent plans. A male sophomore, Jean-Paul, shared:

> I would like to go to college to get my engineering degree or computer engineering degree because that's what I wanted to do. Right now I'm just having second thoughts . . . When I first came [to this country], my plan was just computer engineering . . . But right now, I'm just having second thoughts about how everything's working out and how to get to everything. I'm just having doubts about myself being good enough to do the job that I'm supposed to be doing . . . I may have good grades, but I don't think rationally like everybody else. I don't think clear. I mostly learn things from just watching.

Similarly, Vivian, expressed her plans in vague terms but expressed confidence about her interests:

> I know I want to enroll to a four-year college . . . I do want to do something in STEM. I don't really like politics or history. I love science, I love math. I think more, I love engineering, but I don't really know if I would really want to major in that. I really like

> astronomy and physics. I could spend hours reading, and from abstract papers, research papers, Stephen Hawking, you know, all of those. I really love learning about that.

Two other students – Marla, who responded to how she was preparing for college and Darwin, responding to what is career at age 30 might be -- appeared to have what might be considered unrealistic goals. Their responses reflect ideas that may have formed without appropriate consideration of timing before graduation or prior experiences that would shed light onto what a STEM professional's workday entails:

> Marla: I want to play college sports . . . I was thinking for my senior year in high school, I would try to do some sports to see which ones I'm really interested in and try to get a scholarship from them.

> Darwin: The plan is to join the Navy, and after joining the Navy to finish my degree or start my degree in a business course and also in marine biology. . . . I see myself maybe seven in the morning getting up, going and boat out to one of our research places, doing a little research, diving to check on some of our sharks that we have in the research lab. And then coming home, stopping by my house, showering up and heading out to prepare for the nightclub that I will own in the future.

While Marla and Darwin's ambitions are admirable, Marla's expectation of gaining an athletic scholarship without years of training and Darwin's plan to be a marine biologist and own a nightclub by age 30, highlight a need for practitioners in the career preparation space to offer students more information about the requirements for both postsecondary access and particular careers.

Indeed, participants' responses to questions about their plans corresponded with the experiences they shared about how school, family, and peers might be supporting (or not supporting) their educational goals and career interests. Ways that each of these factors potentially influenced students' goals are illustrated next.

2) *Social Supports:* Renee and Nivea, who had very clear plans, attended a selective high school that offered pathways of study in STEM. Describing opportunities she had that are helping her prepare, Renee explained, "I've done multiple internships and I have one right now at John [sic] Hopkins where I studied greenhouse gas emissions and I'm comparing them to Baltimore to see what Baltimore could do better to lower their greenhouse gas emissions." When asked why she applied to the BOAST program, Nivea stated:

> Nivea: It was actually one of my teachers recommended me to join. It was my engineering teacher. And also I'm just really interested in engineering. And I heard that BOAST had algebra and engineering combined. So that's also why I wanted to do it, and I thought that it would help me with my algebra, which it actually does.

Nivea also shared ways her school was connecting her with experiences that were connected to her interests and goals:

> Nivea: We've actually done some things in school where we actually choose our major or have some ideas for what we want to do when we're older. . . I've been trying to just try to join as many programs as I can, especially STEM related programs. . . . I'm in engineering and this is my third year in engineering. I'm also in BOAST, obviously. I'm trying to do [an engineering internship] in the summer, which is a Johns Hopkins program. So that's probably what might help me decide what I want to do.

Other participants attended schools where such concerted efforts did not appear to occur. For instance, Marla, who was waiting until senior year to think about sports participation that would lead to a scholarship, was asked if she'd had any conversations with adults in her school about career options. She responded, "Nope. Not that I know of." Darwin, whose intentions of being both a marine biologist and a club owner, described a situation that appeared to reflect haphazard support:

> Darwin: I've not really heard much about STEM, so I never really thought of entering any field in STEM . . . I currently don't have any science classes or engineering classes… I've never took engineering classes and right now, they just put me on some courses to get my schedule filled. I haven't really had much say in it.

Some participants, particularly those with uncertain or nascent ideas about a desired career, also shared frustrating educational experiences. For example, Maliah described an interest in nursing, saying, "My goal is to become a traveling nurse. . . But I always wanted to travel, so it's like me being a traveling nurse, I can go experience stuff and still do what I want." Yet, Maliah also described recent disappointments in her math class:

> Maliah: I used to enjoy math, but once COVID started, I guess, me being at home for three years . . . I guess that chunk away from school really knocked me off of really being a good student in math . . . When I went back in person this year, it was a big struggle for me to get adjusted back to a math class, actually any of my classes. And once we got to school, we didn't really have teachers. We still don't. And then our math teacher is actually gone . . . So I'm just in a math class sitting there every day . . . We have subs there, but they're different every day and they just keep telling us to get on something called Imagine Math but that really doesn't help me. And because I don't have a teacher, I can't ask questions the way I want to. I'm not really feeling math anymore.

This vignette from Maliah emphasizes how negative school experiences, not to mention COVID-related school closures, can potentially derail interest in particular subjects. To succeed in pursuing a nursing career, this student will need to maintain subject matter self-efficacy, and this example seems to suggest that self-efficacy and interest in math (i.e., "feeling" it) are interdependent.

Concerning how family members informed students' interests and goals, it is notable that Renee couched her goal of getting a bachelor's degree as "like [my] sister has before." Other participants also relayed how their families and others encouraged them. Jean-Paul, who expressed a goal of becoming a computer engineer but with emerging doubts, said that his brother was supportive. Yet, the lack of specific ways that his brother would help mirrored the hesitancy of his goals:

> Jean-Paul: I told my brother about what I wanted to pursue. He just said he would help me get it and all that. He would just be there to help me get it and he would just get me the program that I needed and then get me the things I need to get it.

Jean-Paul also shared that his friends had similar interests and goals, but his emphasis on "trying to do online things" and lack of resources potentially resonate with his prior expression of inadequacies to achieve his goal:

> Jean-Paul: Most of [my friends] want to be an engineer as well. I talk to them about engineering. We go over some things about it. We try to do online things. We try to do NFTs and stuff, but we just don't have the resources for that.

Two male participants, Richie and Jonas, could be categorized as having nascent plans. For instance, Richie' goals were to be a lawyer or investment banker. When Richie was asked how he and his friends talked about plans after high school, he stated, "I just don't talk to them about the future . . . Most them not trying to go to college anyway." Concerning his mother's support for his plans, he shared:

> Richie: My mom's kind of really religious, and she says all lawyers are heartless, soulless. They sell their soul. And she was freaked out when I said I wanted be lawyer so switched over to investment banking and I learned about it, and it's okay.

Richie' explanation of his change in career plans points to the key influence of parents; Richie also described his goals as a contrast to those of his peers, as though they need protecting from negative influences.

In describing his postsecondary planning, Jonas, attending the same school as Richie, stated, "I would really love to go to college. Same time, I would love to start doing gigs and promoting what I do after school." Following up, he explained that after school he did video editing. When asked how he felt about taking math coursework in college, he shared, "Math is just like a brain stimulant. I love it." But later when responding to a question about his experiences in high school math class, he said:

Jonas: Math classes are usually very boring. And it's as if I'm being stilled with the learning . . . I usually do really well in math, but when I'm feeling like the class is really slow, my assignments or the grades would go down.

Jonas' comment indicates a strong connection between competency and interest, and his impressions may reflect varying experiences of engaging math instruction. Sentiments such as his suggest that self-efficacy and bourgeoning interests in STEM subjects may be precarious for minoritized and low-income students. When the researcher asked Jonas if he'd had the opportunity to talk to anyone at the school about what he might do after high school, he replied:

Jonas: No. They said that we could reach out to them. They've talked to students as a whole group . . . about things and plans we can do after high school and then college. But the message altogether, I don't feel like it's hitting 80% of the classes, especially since nobody really cares. They [students] don't really care for their futures. They're okay with being on the streets, selling drugs and all that. Or just working at McDonald's. They don't really care for future problems or any of that.

Jonas' response illustrates how a lack of deliberate guidance, in combination with negative peer influences and unengaging classes, may be especially detrimental to productive career ideation among this population of high school students.

D) *Mixed Methods Findings*

In combination, the quantitative and qualitative results offer unique insights into the development of self-efficacy, interest, and career goals. Although not all participants expressed interest in STEM necessarily, their data remain relevant to understanding the complex interplay of socio-environmental factors and the other constructs featured in the SCCT model among minoritized, low-income high school students. Fig. 2 offers a joint display of findings from both strands in terms of how social supports and barriers relate to the outcomes of interest.

Fig. 2. Joint Display

Socio-environmental factors	**Math self-efficacy**	**STEM interest**	**STEM outcome expectations**	**STEM choice goals**
·Weak school support · Unengaging instruction ·Negative peer influences	· Math self-efficacy conditional on positive classroom experiences	· Interest is positively associated with self-efficacy	· Weak connections between key steps and reaching goals	- Nascent or tenuous postsecondary goals

· High-resource schools · Deliberate school guidance · Positive family role models	· Math self-efficacy reinforced by supportive school adults and experiences	· Interest cultivated and sustained by relevant opportunities	· Steps toward goals are apparent and perceived as actionable	· Concrete postsecondary and career goals

Among students with nascent or uncertain postsecondary goals, whether they concern STEM or non-STEM careers, the data suggest that an accumulation of disappointing educational experiences and other negative social influences had left some students with a weak understanding of the concrete steps needed to achieve their individual goals. Their schools did not appear to be organized in deliberate ways around ensuring each student had clear postsecondary interests and goals, and that the curriculum or set of experiences on offer were perceived by students as outside of their control and/or less than optimal. Conversely, students with clearer plans had benefited from a range of beneficial enrichment opportunities, more engaging coursework in STEM, and the adults in their school and at home were reportedly helping them to achieve their goals. Notably, further quantitative analysis (not shown) found enrollment in a particular school explained approximately 20% of the variance in STEM interest, 23% in STEM outcome expectations, and 33% of math self-efficacy at baseline.

These results also shed light on some of the surprising quantitative findings regarding the impact of BOAST. While participation in the BOAST program had no significant effect on math self-efficacy, STEM interest, or STEM outcome expectations, students accessing all components of the program had significantly higher levels of STEM choice goals. This is consistent with SCCT research in demographically similar samples. For example, one study used SCCT to predict the math/science goal intentions of low-income prospective first-generation college students (n = 305); contrary to hypotheses, the relationship between barriers and goals was mediated neither by self-efficacy nor interests [30]. We surmise that BOAST participation helps maintain pre-existing math self-efficacy and STEM interests, and that participants who are engaging with the BOAST curriculum were already quite high in these domains. However, concerning the significant boost in STEM choice goals associated with BOAST, we argue that through BOAST, participants gained an increased desire to learn new STEM-related skills and take steps to pursue STEM careers.

IV. CONCLUSION

The current research investigated the extent to which a STEM-focused afterschool program was associated with improved math self-efficacy, STEM interests, outcome expectations, and choice goals. Through the lens of the SCCT framework among a low-income, predominantly Black high school student population, we found that socio-environmental factors are particularly salient to how students' postsecondary plans develop, or fail to. Our findings also echo existing studies employing SCCT, particularly those employing samples of minoritized, low-income populations. While it was surprising that math self-efficacy appears to be unrelated to other SCCT constructs, Garriott et al. [30] also found no effects of self-efficacy on choice goals. However, our findings confirm previously identified associations in more heterogeneous samples regarding relationships between interest and outcome expectations and choice goals, as well as between choice goals and outcome expectations [24], [27], [30].

Members of our sample who benefited from a greater number of STEM-focused opportunities in school, positive family role models, and concerted coordination of interest-based opportunities had clearer, firmer plans for what they would do after graduation. On the other hand, our sample included many students who did not benefit from well-resourced schools, were subject to haphazard curriculum, under-staffing, and questionable peer influences. These students expressed far less certainty about their goals, or had stated goals that appeared to be less well-informed.

The results of this study offer promising evidence that BOAST has beneficial impacts on some of the psychological constructs associated with productive career planning, though the effects were weaker than expected. Yet, like other school-embedded programs, student engagement with BOAST is influenced by many external factors. Of special importance was the high degree of variation in students' completion of the algebra-for-engineering modules and STEM role model videos. This variation is a reflection of the many competing opportunities that this population of students confronts. It may be that an afterschool program, in comparison to the larger set of academic, social, and environment influences to which students are subject, is too negligible to produce strong effects. The BOAST program is currently being delivered to a third cohort in 2023-24, and additional forthcoming data is anticipated to offer greater statistical power and student voice regarding its potential impacts.

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Appendix I

CRONBACH ALPHA RELIABILITY TESTS FOR SCCT CONSTRUCTS, PRE- AND POST-SURVEY

Construct (N items)	Pre-survey	Post-survey
Math self-efficacy (24)	.918	.941
STEM interest (6)	.711	.730
STEM outcome expectations (6)	.648	.757
STEM choice goals (6)	.786	.779

Appendix II

REGRESSION OF MATH SELF-EFFICACY CHANGE ON BOAST PARTICIPATION LEVELS AND STUDENT CHARACTERISTICS

	Model 1	Model 2	Model 3
Intercept	.04 (.24)	-.01 (.16)	-.48 (1.21)
BOAST participation			
Treatment group (vs. control)		-.19 (.12)	-.11 (.16)
Total LMS hours	.02 (.01)*		
Role model video hours	.31 (.21)		
Numb. field trips	-.19 (.10)		
Demographics			
Male		-.65 (.12)**	-.58 (.07)**
Black [a]		.02 (.20)	-.06 (.29)
Hispanic [a]		1.23 (.26)**	1.24 (.17)**
Academics			
Algebra I final grade			-.16 (.15)
School-day attendance rate			1.04 (1.83)
R^2	.16	.59	.71

Note. Coefficients and robust SEs presented.
[a] Reference group is White or Asian
**p<.01 *p<.05

REGRESSION OF STEM INTEREST CHANGE ON BOAST PARTICIPATION LEVELS AND STUDENT CHARACTERISTICS

	Model 1	Model 2	Model 3
Intercept	.19 (.18)	-.16 (.12)	-1.23 (1.41)
BOAST participation			
Treatment group (vs. control)		.08 (.16)	.29 (.19)
Total LMS hours	.03 (.01)**		
Role model video hours	-.26 (.07)**		
Numb. field trips	-.10 (.08)		
Demographics			
Male		-.38 (.39)	-.70 (.52)
Black [a]		.07 (.04)	.12 (.11)
Hispanic [a]		.39 (.52)	.56 (.61)
Academics			
Algebra I final grade			-.03 (.10)
School-day attendance rate			-1.11 (1.54)
R^2	.48	.17	.41

Note. Coefficients and robust SEs presented.
[a] Reference group is White or Asian
**p<.01 *p<.05

REGRESSION OF STEM OUTCOME EXPECTATIONS CHANGE ON BOAST PARTICIPATION LEVELS AND STUDENT CHARACTERISTICS

	Model 1	Model 2	Model 3
Intercept	.20 (.66)	-.26 (.61)	2.55 (3.07)
BOAST participation			
Treatment group (vs. control)		.30 (.51)	.46 (.74)
Total LMS hours	.03 (.01)*		
Role model video hours	.07 (.52)		
Numb. field trips	-.16 (.31)		
Demographics			
Male		.49 (.42)	.19 (.53)
Black [a]		-.01 (.44)	-.31 (.87)
Hispanic [a]		.05 (.29)	-.09 (.54)
Academics			
Algebra I final grade			-.13 (.32)
School-day attendance rate			-2.54 (3.82)
R^2	.07	.12	.19

Note. Coefficients and robust SEs presented.
[a] Reference group is White or Asian
**p<.01 *p<.05

REGRESSION OF STEM CHOICE GOALS CHANGE ON BOAST PARTICIPATION LEVELS AND STUDENT CHARACTERISTICS

	Model 1	Model 2	Model 3
Intercept	-.14 (.26)	-.28 (.30)	.52 (1.17)
BOAST participation			
Treatment group (vs. control)		.18 (.22)	.55 (.10)*
Total LMS hours	.01 (.01)		
Role model video hours	-.20 (.20)		
Numb. field trips	.16 (.15)		
Demographics			
Male		-.35 (.20)	-.67 (.11)**
Black [a]		.25 (.28)	.49 (.14)*
Hispanic [a]		.69 (.32)	.88 (.15)**
Academics			
Algebra I final grade			-.09 (.05)

School-day attendance rate			-.77 (1.36)
R^2	.14	.19	.71

Note. Coefficients and robust SEs presented.

[a] Reference group is White or Asian

**p<.01 *p<.05