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ABSTRACT

Programming is a highly demanded skill in both STEM research and the broader economy. Although many life sciences majors are interested in learning how to code, they are nervous to learn and have not been warmly invited into computational fields. While there is much research on entry into computer science broadly, there is limited research on the unique barriers facing life sciences majors as they are introduced to programming. To address this gap, we sought to understand students' motivations to take a new introductory coding class in biology. We conducted focus group interviews with 22 students that revealed a range of motivations for taking the course, ranging from social and career motivation to the ability to be creative or analyze biological datasets. In addition, we probed the expectations for students taking the course, finding a wide range that varied depending on students' progression through college and prior experiences of pursuing opportunities to learn programming skills. Our findings elucidate the reasons students choose to take a discipline-based programming class and have implications of practices for inviting these students into these spaces.

CCS CONCEPTS

• **Social and professional topics → Computing education**; **CS1**; *Computing literacy*; • **Applied computing → Life and medical sciences**.

KEYWORDS

CS1, Applied coding, Student motivation, Social cognitive career theory

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1 INTRODUCTION

With the expansion of computer and data science sectors over the past few decades, coding has become a highly demanded skill in the growing workforce. Computational skills such as modeling and analyzing large data sets have become increasingly important in other fields outside of computer science, including the life sciences [1, 4, 16, 20, 26]. In response to these needs, many educators have developed discipline-specific coding modules or even full courses dedicated to teaching coding to non-CS students in the context of other fields [13, 14, 19, 29]. However, we do not yet understand the motivational dispositions of non-CS students who choose to participate in such discipline-specific coding experiences. Such insights would inform how we can recruit and retain non-CS students in computational paths in biology.

1.1 STUDENT MOTIVATIONS & IMPLICATIONS FOR EQUITY

As educators continue to develop interdisciplinary and innovative curricula, we also must ask who is taking advantage of it and why. Specifically, it is important to understand what motivational factors influence non-CS students' decisions to pursue CS curricular experiences, as well as how these motivational factors can shape or be shaped by expectations of course outcomes and accessibility.

Motivation describes how and why effort is directed toward a specific goal, which can be influenced by a suite of contextual, intrinsic, and interpersonal factors, with learning outcomes often associated with the extent to which students perceive they have clear direction and expectations [21]. An understanding of motivational factors can elucidate how non-CS biology students initiate their computational learning trajectories and how participation may be enabled or constrained by their expectations. Investigating the reasons behind students' decisions to engage with this type of curricular experience can inform how we invite non-CS students into programming opportunities and can identify the characteristics of students who are and are not participating in these experiences.

1.2 GOALS OF THE PRESENT STUDY

The potential career mobility and salary increases that come from acquiring programming skills relates to issues of equity in outcomes for students who do not have access to these skill sets. While there are known instances of disciplinary courses that have been created to teach non-CS students programming skills in ways that are interesting and relevant to their discipline of study [7, 10, 13, 15, 28, 31–33], these courses continue to be an exception rather than the norm. A direct investigation of non-CS students' motivations and expectations for pursuing opportunities to learn programming is essential for informing the development of curricular interventions that students perceive as accessible, relevant, and meaningful for their academic and professional development. Using an introductory coding course for biology students as a study site, the research questions addressed in this study are:

- Q1. What motivates non-CS students to learn how to code? Relatedly, is the utility of coding clear to non-CS students?
- Q2. What are students' expectations of an introductory programming course in biology?

1.3 THEORETICAL FRAMING

This study uses social cognitive career theory (SCCT) as a theoretical framework to guide our methodology for exploring students' motivations and expectations for learning programming in biology contexts. SCCT is derived from social cognitive theory, which posits that an individual's knowledge or skill acquisition is derived from complex interplay between an individual's experiences, social interactions, and the environment [5]. SCCT accounts for multiple personal, psychosocial, and environmental factors that can affect an individual's motivation, goal orientation, and behavior when forming career goals and actions.

A salient model of SCCT is the choice model, which examines individual cognitive variables (self-efficacy and outcome expectations), as well as environmental supports and barriers that influence choice making [22]. This model of SCCT has been used in prior studies that have examined undergraduate students' choices for pursuing computer science, primarily for CS majors [2, 23]. For example, a previous study applied the self-efficacy and outcome expectations dimensions of the SCCT framework to study undergraduate computer science students' motivations for learning how to code [2]. This study also examined two additional environmental factors that influenced students' academic and career choices: prior experiences and social support. Together, these factors holistically describe how personal and contextual factors can directly and indirectly affect professional motivations and decisions. Here we leverage these interrelated factors to examine students' motivations and expectations toward programming in a novel study population focused on programming in biological contexts.

2 METHODS

2.1 Participants

This study took place at a large research-intensive (R1) public institution where CS1 course enrollments are typically in the hundreds. The course in focus here, "Introduction to Python for Biologists" has been offered three times in the past two years (2022-2023), with 42, 80, and 90 students in each offering. This course covered fundamentals of Python, with a specific focus on data visualization and teaching common algorithms for analyzing biological data. No prerequisites or prior coding experience was required to enroll. While this course focused on teaching applications of Python in biology, students were not required to be enrolled as biology majors (about half were, and many others were in chemistry/biochemistry, environmental systems, or cognitive science). A detailed breakdown of focus group participants' majors and class years (which are representative of the course as a whole) can be seen in Table 1.

Table 1: Participant demographics.

	Group	Frequency
Gender	Female	16
	Male	6
Class Standing	Senior	9
	Junior	7
	Sophomore	6
Major	Biological Sciences	11
	Cognitive Science	3
	Environmental Systems	2
	Bioengineering	2
	Biochemistry	2
	Social Sciences	2

2.2 Focus Group Protocol

We conducted a total of six one-hour focus groups with 3-5 students each in week 8 of a 10 week class, totaling 22 students across 3 quarters (representing about 10% of enrolled students). An email invitation to participate in these sessions was made available to all students in the course two weeks prior. All interested students were recruited from an online sign-up form and were assigned a session based on their availability. The focus groups were conducted by the first author, who had no prior interactions with the participants or involvement in the course. This work was conducted under IRB Protocols #170886 and #804991.

This paper presents qualitative findings from a larger mixed-methods study of student perspectives, which included pre- and post-surveys. The focus group questions were grounded in SCCT, which explored students' expectations about coding, overall affect toward coding, perceptions of utility of coding, and social influences in learning to code. Our analysis and results here focus on responses that probe students' motivations and expectations for the course.

Transcripts were first iteratively read to create analytical memos on salient ideas emerging within each respective focus group session. They were then coded using a decontextualized approach where each question was treated as an isolated segment of the interview transcript, allowing data across all focus groups to be merged. Coding in this decontextualized phase was performed by two separate coders. The coders each generated their own set of preliminary inductive codes and would then meet regularly to resolve disagreements and consolidate codes and definitions through dialogic consensus [27]. The consensus codes were organized into a codebook, and broader categories were generated inductively by grouping codes together.

3 SOCIAL SUPPORT AND INFLUENCE

Using this approach, we asked why non-CS students chose to take a coding class. We identified several categories that aligned strongly

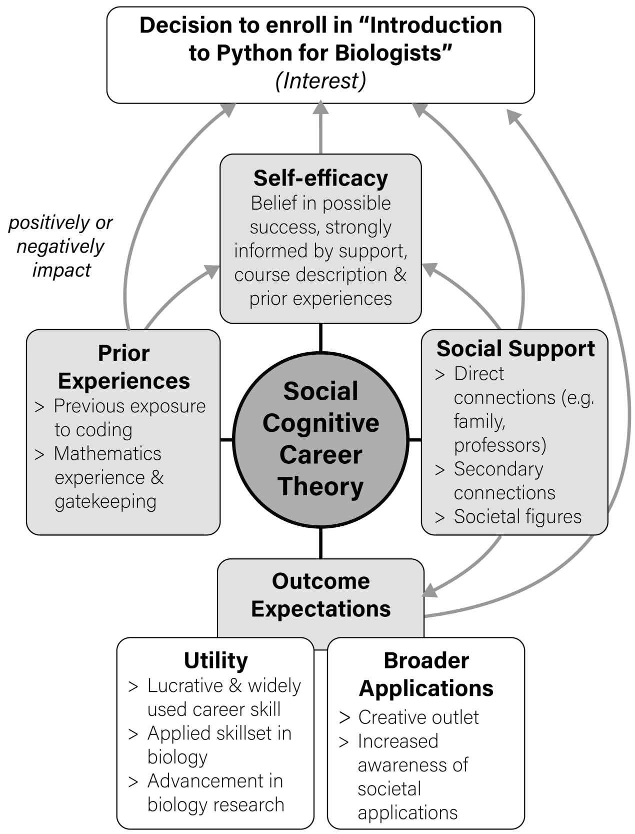

Figure 1: Our observations as framed by social cognitive career theory.

with the facets of SCCT (Figure 1). Arguably the most common motivating factor in our interviews was social and societal influence.

All participants were able to describe at least one figure who they perceived was influential, especially individuals who reinforced the potential financial and growth opportunities of pursuing a career that included programming. These influences most often included peers with programming experience, professors or former teachers, research advisors, and family members. These direct influences were often discussed in a positive light, with the participants perceiving these influences as being inspirational role models who they wanted to emulate by pursuing an introductory coding class. For example, one participant described their admiration for the personal and professional fulfillment of close peers in CS:

> I'm still in touch with my friends from high school, and they all went out to pick up Comp Sci majors or some sort of related field. Seeing how much they're enjoying it, or what they could do with it, and how most of them are even planning to work after college really influenced my decision for taking this class.

Due to the direct personal connection and shared values, the perspectives and experiences of peers had strong weight as the participants sought their own opportunities to gain programming experience. Likewise, family relatives were salient sources of authority – participants often described feeling pressured to develop programming skills by relatives who understood the growing demand for these skills in the economy and recognized that these were skills for having greater career mobility:

> My parents pushed me to get involved in coding, or something related to that, because, like it is the future. And you don't want to be left behind per se. So like my parents want me to kind of have those skills as a backup, so they also kind of piqued my interest in you know, taking coding at some point in college.

Beyond personal connections such as family and friends, some participants also described direct professional influences who had influenced their decision to code. Because this was a course focused on applied programming in biology contexts, participants who worked in faculty research laboratories felt compelled to take this course due to direct cues from their advisors on the relevance of developing this skill set. For example, one participant described how their research advisor emphasized that coding is a widely coveted and transferable skill in biology.

> My [research principal investigator] influenced me just because she told me from the beginning that I was going to do coding and she told me it might be something that you might encounter if you're going to a lab or another field that you're interested in. So I think it was a good opportunity for me to grow professionally and also just expand my interest.

While many participants described direct influence from personal connections who helped them recognize the importance of programming, some also described indirect influences with whom they had no personal connection. These influences were often societal figures who either implicitly or explicitly reinforced the discourse on the importance of coding for innovation and advancement, such as "people on YouTube that also do coding [that] do some interesting things" or "big figures that have made it in technology [who] show that it's possible, that there's a real foothold here."

4 OUTCOME EXPECTATIONS

4.1 THE UTILITY OF CODING IN BIOLOGY RESEARCH & COURSEWORK

As many participants were biology majors, it is no surprise that the opportunity to learn about coding in biology contexts was a frequent motivating factor. For several participants who were working in research laboratories, firsthand experience allowed them to recognize that more researchers with coding experience could prevent computational knowledge from becoming siloed:

> In research, a lot of coding is involved, and in my lab, there's a data science major that's responsible for all the coding and stuff. But I think it'll be more useful for everyone to kind of know what's going on, so instead of having one person being responsible for coding 100% and the bio majors knowing all the bio stuff.

This motivation to learn programming for application in a research setting was often reinforced by a shared sentiment that "there's a lot of pressure to learn coding in the biology field." Many students reiterated the increasing size of datasets in biology, especially in genomics, a point that was made by at least one instructor early in the class. Within biology research settings, they recognized that coding has not only enhanced how data analysis is performed but has improved reproducibility and accuracy in the research process:

> I think a lot of bio research is ultimately data in whatever forms of data there are... coding and technology allow scientists to process this biological data much quicker and much more efficiently, much more accurately. And also, I think it's easier for other people to follow and reproduce for other scientists in this case, so I think it's kind of the next big thing in biology.

Outside formalized biological applications in research settings, participants also perceived intrinsic value in the opportunity to develop a more tangible and practical skill that could expand beyond the content knowledge acquired in their biology courses. Many of our life sciences students are overloaded with coursework that is deeply content-driven, requiring memorization. In light of this, several students noted that it was refreshing to take a course that was so explicitly skills based, both for the utility of coding beyond the class and for a sense of seeing their own progress:

> For me, biology just feels like there's just this giant assortment of facts to learn from. Coding feels like you really have something to measure yourself with. Like, here's how I'm getting better. Here's a project I can do. Here's what I can, you know, actually go and put on a resume.

Similarly, another student said, "It's been a really different process from learning something in a biology class or a chemistry class. It's required just a lot more trial and error. And I think that that has been a really good skill."

Overall, recognizing coding as a tangible skill that can be leveraged into concrete applications in both formal biology research settings and informal independent projects was a salient motivating factor for students to enroll and persist in this class.

4.2 A LUCRATIVE CAREER SKILL

While many of the participants were motivated by the use of programming in biology, they also described it more generally as a valuable skill that could confer greater mobility in their careers. Although some of these participants did not have a clear vision of a trajectory for how they would use coding in their respective career pathways, they were generally interested in at least gaining some exposure. As one participant reflected:

> My goal was to get to know coding and just have a general idea of what it entails, because I know that it's very common knowledge that you know coding, Computer Science, is a very lucrative industry and I was just curious whether this was something I was also interested in because I am a bio major but also being able to code and being interested in that field, I think, would be a great a big plus in my skill set.

The recognition of coding as a 'very lucrative industry' implies an understanding of the potential higher salaries, advancement, and career mobility that are associated with pursuing careers that involve coding. Other participants saw it not as a supplemental skill but as a necessary one, acknowledging that "we're reaching a point where coding is almost kind of like a basic [skill] at this point, and it's much more beneficial to at least have some kind of basic knowledge of coding than not to."

4.2.1 Expectations by career stage. We found that the above expectations lie on a continuum, ranging from more general expectations about potential applications and utility to more concrete goals about how coding could be leveraged in their future careers.

Participants who were at earlier stages in their undergraduate education typically discussed the more general importance of coding based on their exposure to direct social or indirect societal discourses that emphasized the lucrative nature of careers involving coding and the omnipresence of coding applications in many different facets of everyday life. As described by one sophomore participant, literacy in coding can be beneficial regardless of the field one ultimately pursues:

> Coding is directly involved in everything nowadays, you know, from our computers to this Zoom session that we're taking part in right now. Yeah, so being literate is going to help us regardless of whatever field we're going into.

Similarly, another sophomore stated more generally, "I think, especially now we are noticing a trend where people who have coding jobs or some kind of careers that require coding skills tend to make more money." In contrast, students who were more advanced in their undergraduate education described more concretely their motivation and perceived pressure to learn coding to prepare for their more imminent career path. For example, a participant who was in their final year at the university described computational applications as an increasingly important part of the career they're progressing toward:

> I want to eventually work towards a job relating to genetics, so I feel like in that case you need some basic software here and there to analyze some stuff, especially if you're trying to discover certain genes that tend to lead to certain diseases. So, I definitely could see myself using it in the future that's for certain and, just in case that's why I do want to develop my Python skills.

While students in later stages also recognized the wide applicability and general value in learning to code, their expectations and motivations for pursuing the course tended to be more grounded in established career plans or ongoing goals.

4.3 AN OUTLET FOR CREATIVITY AND BROADER SOCIAL AWARENESS

Beyond the expectations that coding would be beneficial professionally, some participants recognized that familiarity with coding could enable creative outlets that enrich other personal aspirations, as well as contribute to their development as a more socially aware citizen who understands the many applications of coding in everyday life. Similar to the notion that coding allows for more tangible practical applications in biology and the development of measurable project goals, some participants expressed excitement about coding because they perceived it as a constructive process that allowed them to take creative ownership of a project. In particular, many of the participants described coding as a tool that can be used in different creative avenues, as the process of building code is to "make something tangible," as one participant articulated:

> I view coding as kind of like making art because it's like you're making something tangible or like technically physical and it can be functional and do something or it's already customized and be creative as much as you want.

In addition to using coding to pursue individual interests, the participants described knowledge of coding as important for awareness of social issues, as coding is involved in nearly all sectors of society in some capacity: "it actually affects every single aspect of our life to the point where like even critical things, like an ambulance getting to work on time." The participants asserted that even if one is not proficient, basic exposure to coding would be beneficial to helping them navigate and understand the impact of coding in many different facets of everyday life.

5 PRIOR EXPERIENCES

Although no previous coding experience was required to enroll, some participants described prior learning experiences as motivational factors in their decision to take the course. For example, one participant described a positive experience in a high school summer immersion program that inspired them to seek additional opportunities to learn coding in their postsecondary education.

> I did a program called Girls Who Code in high school, a summer immersion program [that] was like 10 weeks. And people basically, like taught us how to code like, introductory. And so there, I was, like, really interested in it, I could see the things that you could do, the innovations you can bring. So then I just thought, like, why not continue it here.

In contrast, several participants described that the decision to take the course was grounded by their motivation to overcome negative prior experiences with coding. For example, one participant stated that they had been struggling with deciding to pursue biology or computer science and had initially left their computer science major. They enjoyed the creative opportunities that coding allowed, but ultimately felt that they did not have the "right personality" to become a computer scientist. They articulated that this class was another chance to explore whether coding was right for them:

> I'm a third year and so now I'm trying it again, it's just- it's kind of hard for me to decide, because I mean, I think it's interesting the code like it's- it's fun, I get to be creative and make new things, but I don't know if I have the right personality, because I get too anxious and frustrated when I get like some kind of error.

5.1 CONFLATION WITH MATH SKILLS

Participants overall valued and recognized that this introductory course was intended to be a low stress learning experience that was aimed at exposing non-CS majors to basic applications of coding. However, some participants expressed that they were initially nervous about taking the course because they perceived they lacked math proficiency, which they felt would limit the tasks they could engage in. For example, one participant stated that "I feel like coding is really presented as math heavy and so I was under the impression I was going to be at a disadvantage by not really liking math that much." Reflecting on their prior experiences, another participant articulated that not having a math background had previously been a structural barrier for them to pursue other programming based courses, stating that, "I feel like there's a lot of pressure to know coding now in the biology field, and because I didn't take the right math in lower divs, I couldn't take any of the data science majors or any other coding class." The conflation of mathematical and computing skills instilled a sense of hesitation regarding the accessibility of the course, yet participants were still motivated to participate given the potential long-term benefits of attaining fundamental programming skills.

6 AN UNDERTONE OF SELF-EFFICACY

While our methodological approach and findings are grounded in SCCT, this paper's focus on motivational factors and expectations does not fully account for the self-efficacy construct. Self-efficacy is indirectly manifested in the other constructs; for example, several participants described how their affective dispositions resulting from prior experiences had influenced their motivation to take the course. However, because articulation of one's self-efficacy often depends on an experiential frame of reference to judge their abilities, this construct may not have been as salient on motivations and expectations given that this course required no prior programming experiences. As this work is part of a larger mixed-methods study, self-efficacy will be more directly probed as we examine how attitudes toward coding evolved as students gained concrete learning experiences to reference as they progressed through the course.

Nonetheless, the categories emerging from our analysis in this current study offer important considerations for the development and adaptations of discipline-based programming classes for non-CS students. Specifically, our findings have implications for increasing the accessibility and attraction of these courses, including plausible strategies for addressing issues of equity and inclusion.

7 THREATS TO VALIDITY

There are several threats to validity that should be accounted for when interpreting the findings. First, focus group participants represent a small proportion of the class, which could introduce selection bias. We acknowledge that a broader sample of students may reveal a fuller range of perspectives. Nonetheless, we identified variations in the emerging categories, indicating participants were not homogeneous in their perspectives and experiences.

Second, we acknowledge that interpretations of qualitative data can be highly subjective and influenced by researcher bias. To counteract this bias, the coding analysis was completed primarily by the authors who had no prior involvement with the students or course. Interpretations were discussed as a research team and disagreements were resolved. Continually refining emerging categories against the data challenged the research team to continually test conjectures about how the emerging categories fit the data.

8 DISCUSSION

Our observations contain insights that can inform the development of discipline-based coding classes and recruitment to such opportunities. First, we note variations in expectations from students in different academic stages, with those at earlier stages tending to describe more fluid goals than later stage students, who described more specific needs for pursuing the course. To be inclusive to non-CS students interested in learning programming skills, it is therefore important to recognize the differing needs and motivations of students at different educational stages when crafting the curriculum. Instructors can survey students' interests and goals at the beginning of the course in order to adapt the curriculum to include relevant and useful disciplinary applications for students with various academic and career backgrounds and goals.

Second, beyond the utility of coding in biology, participants articulated that programming could be a creative outlet as well as a ubiquitous feature of everyday life. Students' interest in understanding how coding plays a role in creative and social applications suggests that it may be worthwhile to highlight these applications as part of the curriculum. Connecting disciplinary practices to student values has been shown to be especially important for students from backgrounds not well represented in science [18]. Explicitly highlighting these connections in introductory courses, such as through project-based work that addresses issues relevant to students' career goals and values, could be a valuable intervention for developing meaningful outcome expectations. Future work may also need to investigate whether students perceive computing in the context of biology as equivalent to more traditional CS education.

Third, social networks are an important source of motivation for students to engage in curricular opportunities in higher education, especially as these support networks have been shown to mediate self-efficacy and outcome expectations [2, 11, 30, 34]. *All* participants were able to describe a social influence in their decisions to pursue this course, with many participants describing direct influences who conveyed the importance of coding for conferring career mobility. Some students had the necessary social capital to orient them toward curricular opportunities in programming. Students without these social networks may be less likely to engage in these curricular experiences, especially if students do not have prior programming experiences to serve as a frame of reference. Expanding equitable access to programming opportunities for non-CS students may therefore necessitate students accessing positive role models earlier in their education. It is vital that departments and universities consider ways to increase student awareness of the potential utility of coding and make opportunities for non-CS coding education more widely advertised and accessible, as well as increase the visibility of individuals who can serve as positive role models that inspire students to pursue such opportunities.

Fourth, our data here shows that participation in extracurricular laboratory experiences may directly expose students to the growing importance of computational skills in biology research. An ongoing conversation in biology curricular reform initiatives is the importance of democratizing undergraduate research experiences, yet there are many barriers that prevent equitable inclusion in these opportunities for undergraduates [6, 24]. As several students in this study described their participation in research as a significant influence in their motivation for learning to code, the barriers to pursuing opportunities in research may also block an essential source of navigational capital that can orient them toward computational learning experiences. Therefore, efforts to expand undergraduate research opportunities must also integrate conversations and opportunities for students to learn computational skills and provide tangible resources and support networks that can orient them toward these opportunities.

Finally, when reflecting on expectations and prior experiences, several participants noted a linkage between coding and mathematics, with an expectation that an underdeveloped mathematics background would be a disadvantage for taking the course. This perceived linkage between coding and mathematics can still lead to feelings of doubt that undermine students' motivation and perceptions of their ability to learn how to code. This finding is consistent with previous research demonstrating that biology students recognize the importance of mathematical skills, with attitudes toward mathematics and computer science often being positively correlated [3, 8]. While advanced computational work typically benefits from proficient mathematics skills, basic programming may not. The universal conflation of programming and computational skills may gatekeep non-CS students from pursuing opportunities to learn programming. Thus, efforts to explicitly dismantle this perception may be necessary to increase the attraction to programming skill development for students from all mathematical backgrounds.

8.1 FUTURE WORK ON AFFECT & LEARNING

While this study focuses on the motivational factors that orient students toward a discipline-based programming course, attitudinal dispositionshave been shown to impact students' motivation to learn and achievement in CS courses [9, 12, 17]. While we did not directly probe for self-efficacy in the current study, we speculate that students' prior experiences and social supports influence feelings of self-efficacy [23]. Increased feelings of self-efficacy can then in turn influence students' interests in computing and decision to take a computing course (Figure 1). An investigation into the evolution of affect throughout the course can identify the elements of the learning and social environment within the course that may positively or negatively impact student attitudes. Understanding how attitudes shift can be informative for the development of interventions that increase students' sense of self-efficacy in non-CS programming courses [25]. Furthermore, triangulating these affective dispositions with measures of learning can provide a more comprehensive understanding of the extent to which discipline-based programming courses equip students with fundamental skills relative to traditional introductory CS courses. By examining the intersection of learning and affect, we can better understand how to warmly invite non-CS students into computational fields and equip them with the computational skills that are becoming increasingly demanded in the STEM workforce.

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