Applying the Communal Goal Congruity Perspective to Enhance Diversity and Inclusion in Undergraduate Computing Degrees

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ABSTRACT

The lack of diversity in the tech industry is a widely remarked phenomenon. The majority of workers in tech roles are either white or Asian men, with all other groups being under-represented.

Some authors point to cultural factors influencing self-efficacy, leading to a lack of diversity at the start of the “pipeline” of IT talent. Others point to toxic workplace culture that can lead skilled tech workers to drop out of the industry.

While these effects are very real and important, this paper focuses on a third concept contributing to lack of diversity, communal goal congruity. We present a growing body of evidence suggesting that working with others, and in the service of others, are important career goals that many believe tech careers lack. We describe prior work that shows that these beliefs also have a significant impact on the pipeline of tech talent.

We then report on the first pieces of data out of the first long-term intervention designed with this communal goal congruity perspective in mind. We have created a cohort-based service-learning program in computer science, computer engineering, electrical engineering, and software engineering. The result is a program with 26.3% women and 31.6% African American and/or Hispanic students, including 15.8% African American and/or Hispanic women, at an institution that has never previously seen this level of diversity in its computing majors.

Keywords

service learning; diversity;

1. INTRODUCTION

The lack of diversity in the computing professions has been widely remarked. Many people are working on trying to make computing a more diverse and more inclusive

field, but not always with great success. U.S. Department of Education data show (see Figure 1) that the share of degrees in computing fields earned by women is less than 20%. Even more puzzling, this is down from a high of 37% in the early 1980s. While other STEM (Science, Technology, Engineering, and Math) fields have shown increasing participation by women over the past 40 years, computing has regressed.

Figure 1: Percentage share of bachelors degrees earned by women, over time, in various STEM fields. Data from: NCES Digest of Education Statistics[23]

Participation rates for most ethnic groups (all groups other than non-Hispanic whites and Asians) are also much lower than those groups’ overall share of the U.S. population. These disparities have attracted intense interest from equal rights activists, and caused major tech companies (Yahoo!, Google, LinkedIn, and others) to regularly publish diversity information. Even so, the tech roles at these companies are mostly filled by white and Asian men. Indeed, roughly 80% in tech roles are men, and about 90% are either white or Asian[14, 15, 25]. These figures do not vary much between major tech companies.

In what follows we will first summarize the most well-known explanations for the lack of diversity in tech, which are cultural undermining of self-efficacy and workplace hostility. We will then describe a less well-known, but potentially useful, concept called communal goal congruity. We conclude with a description of how we used communal goal affordance theory to design a new scholarship program at

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our institution, and the impressive increase in diversity, at least in initial enrollment, that resulted as a byproduct.

In our review of the literature we found that the computer science education community has not yet started to use and benefit from the communal goal affordance perspective. We consider introducing it to the field one of the main contributions of this paper.

2. LOOKING FOR EXPLANATIONS

Throughout most of what follows we will focus on lack of gender diversity in tech, touching on racial and ethnic diversity wherever we know of research that addresses it.

It is well known that women have now surpassed men in earning college degrees, earning 57.5% of all bachelors degrees in the U.S. [23]. How then do we explain why women earn such a small share of the bachelors degrees in computing and engineering?

2.1 Perceived self-efficacy

In his ground-breaking work on the topic, Albert Bandura argues that the choice of which actions we attempt is influenced by our own expectations of efficacy — whether we have the ability to do what needs to be done in the given situation [1]. He argues that the various types of interventions used in psychological treatments (verbal persuasion, emotional arousal, vicarious experience, and performance accomplishments), though apparently very different, all work by affecting one’s perceived self-efficacy.

Much previous work on under-representation of women in computing has focused on computer self-efficacy. We will only mention a few illustrative examples here, as the literature is voluminous. For example, men tend to show higher computer self-efficacy than women [2], and underlying gender differences in computer self-efficacy predict gender differences in signing up for computing courses [17].

More recently, Vekiri and Chronaki found that parental support was the strongest predictor of a child developing computer self-efficacy [24]. What emerges is a theoretical model that argues that low participation by women in computing is due in part to parental and peer discouragement leading to poor self-perceived self-efficacy, resulting in decreased interest in computing.

There have not been many studies on links between race or ethnic identity and computer self-efficacy. Post et al. [20] studied math self-efficacy of black college freshmen. They found that the career considerations of their male subjects were mostly driven by self-efficacy and confidence, while the career considerations of their female subjects were mostly driven by interest. Crisp et al. [7] found no link between racial/ethnic identity, the decision to declare a STEM major, or success in a STEM major. They found that gender, high school preparation, and first-semester success were the main predictors of interest in STEM majors.

Variation in computing self-efficacy thus provides some explanation for gender (but not ethnicity) differences in pursuing computing degrees. Understanding what might motivate female students to engage in computing experiences and thus gain greater self-efficacy remains a key question.

2.2 It’s Not (Only) a Pipeline Problem

Another factor discouraging diversity at various points in the tech pipeline is hostility — whether overt or subtle — to individuals who are “outsiders” to tech culture (those who

are not white or Asian males).

Our work, as well as the previously mentioned work on self-efficacy, tends to explain the lack of diversity using a pipeline metaphor. As students move through school, at each step along the way, a few more women and students of color leak away, with the result being that very few select tech majors in college. Many commentators believe this ignores a bigger problem, which is a workplace culture that is toxic for women and under-represented minorities. It is perhaps not surprising that academic researchers tend to focus on the pipeline leading to college, since this is what ensures that we have plenty of students to teach.

Jon Evans called this a “trapdoor” problem [12], by which they mean that those that *do* enter the industry tend to find hostile work environments, and drop out again. In an NPR story by Rachel Martin, Laura Gómez (CEO of Atipica, a startup that does job applicant tracking systems) goes as far as to say that “It is not a pipeline issue whatsoever” [16].

Cohoon et al. [5] had slightly more nuanced findings. In a longitudinal study of women in the Computing Research Association’s Graduate Cohort program they found that women in CSE doctoral degrees reported less experiences of sexism than “women in other settings report.” At the same time, experiences of sexism had a significant impact on thoughts of leaving, and on actual departures, from doctoral degree programs.

Of course it has been well established that implicit bias and stereotyping both play roles in driving women out of computing and engineering. The AAUW book “Solving the Equation” [6] provides quite a bit of evidence, and we refer the interested reader to that work. Chapter 3, for example, summarizes the famous “name” study of Moss-Racusin et al. [18], where science faculty members were given a job application to evaluate. Some managers had an applicant named “John” and some an applicant named “Jennifer,” but the applications were otherwise identical. Managers consistently rated the “John” applicant as more competent and more hireable. Another study by Reuben et al. [21] described in the report showed that employers tend to overestimate the mathematical competence of men, while underestimating for women. Implicit biases that associate men with math and science emerge as early as seven [8], and can influence a range of decisions, including college major choice [19].

In addition, “stereotype threat” affects the performance of under-represented groups (including women) in both school and the workplace [22]. Stereotype threat is the fear that one will confirm a negative stereotype of one’s group by performing badly. This fear can lead to decreased risk taking and increased anxiety, resulting in worse performance over the long term.

2.3 Is That All?

While we certainly agree that both self-efficacy and workplace climate play key roles in whether a person chooses a computing major, recent research suggests that these differences are not sufficient to completely account for the lack of diversity in some STEM fields.

For example, Eccles surveyed results on gender differences in math self-efficacy. She found that, on the balance, differences in math self-efficacy did *not* predict “gender differences in math course enrollment; the perceived value of the math course did” [11].

Similarly, prejudice may have, at one time, resulted in

girls being discouraged from doing well in math, and have led to women having less math training and ability as a result. Ceci, Williams, and Barnett [3] have studied this question extensively, and argue that this is no longer the case, at least as it applies to selection of college major. They looked at the far right tail of the distribution of standardized math test scores, presumably the group that is prepared for college in a math-related field, and found that women are well represented in that group. They also summarize a body of work that suggests that overt discrimination is unlikely to be the main culprit, though implicit bias and stereotyping are not ruled out.

All of these authors point to women's preferences and choices as having a crucial role in the process. But here we most emphatically *do not* speak of a simple "women do not like computing" explanation for why women are under-represented in computing! Rather, we need to understand how these preferences are formed, through stereotyping, socialization, and other processes. When Eccles says "the value of the course" determined a woman's interest in taking a math course, this leaves open how that "value" was socially constructed. Similarly, if a woman prefers a particular social role that precludes the possibility of pursuing a STEM career ... how was that social role constructed, and how/when/why was her preference formed?

These issues have been studied by many authors. Ferriman et al. [13], for example, found gender difference in social role preferences and life priorities. These differences intensified over time, and were most pronounced in parents as compared to childless individuals. Cheryan [4] argues that math-related careers are stereotyped as masculine, and that the work involved in math-related careers is stereotyped as incompatible with typical feminine stereotyped life and career goals.

This line of work frames the act of choosing a particular career or college major as opting into a particular social role. What we believe about a particular social role, and whether or not that social role fulfills our personal life goals and preferences, determines whether we pursue it. Our understandings of the available social roles are complicated by stereotyping, leading to systemic perpetuation of the gender divide in these fields.

3. THE COMMUNAL GOAL CONGRUITY PERSPECTIVE

How exactly does this stereotyping of social roles function? What types of career goals are most gender linked? Many of the goals that people have can be classified as either agentic or communal in nature. The communal goal congruity perspective argues that communal goals in particular influence STEM decisions [9]. A communal goal is one that focuses on working with, or in the service of, others, with an altruistic or outward focus. Agentic goals, by contrast, focus on the self, self-efficacy, working with things (instead of people), and so on.

Some examples of agentic career goals/experiences:

1. I want to work with the fastest supercomputers in the world
2. I want a job where I'm always learning
3. I love the recognition I get for jumping into a failing project, and rescuing it

Compare these to some communal career goals:

1. I love being part of a team, doing something that we'd never be able to do on our own
2. I want a job where my work has a long-term impact on society
3. I like knowing that, because of my code, people that badly need kidneys are getting them

Using a survey study of 333 undergraduate students from a variety of majors, Diekman et al. [9] showed that there was a strong stereotype that STEM careers do not afford opportunities for pursuit of communal goals, even worse than "male stereotypic" professions as a whole. Students who were particularly interested in communal career goals were particularly disinterested in STEM. Even when controlling for self-efficacy, communal goal affordances still have a significant impact on interest in STEM.

They also found that gender predicted interest in communal goals, and interest in communal goals predicted disinterest in STEM; "the relationship between gender and STEM interest decreased when controlling for communal goal endorsement" [9].

This has motivated a variety of experimental interventions that focus on communal goal affordances in STEM. Diekman (with a different set of co-authors) went on to show that changing beliefs about the communal affordances of a career lead to changes in interest in that career [10]. Subjects (241 undergraduate students) "read about the typical day of an entry-level scientist whose daily activities were framed to be either highly collaborative or highly independent" [10]. While all types of students tended to prefer the "collaborative" version, the effect was much stronger for women than men.

This all points towards a possible path forward: Design programs and messaging that support communal goal affordances in computing professions. One example: Yowell and Sullivan [26], though likely not aware of the communal goal congruity perspective, reported success in increasing diversity in their program using materials from the National Academy of Engineering's (NAE) "Changing the Conversation" campaign — a major component of which emphasizes how engineering "makes a difference."

Another notable success is at Harvey Mudd College. In 2009 their percentage of female computer science majors was 14%, roughly the national average. They then introduced some interventions, and the percentage has risen to about 35-40%, where it has held steady for four years. As reported in "Solving the Equation" [6], Harvey Mudd made three major changes:

- Redesigned their intro course to provide a track for those with no prior experience in programming, and to emphasize real-world uses of programming
- Increased opportunities for participation in research
- Supported female students to attend the Grace Hopper Conference

These last two items, both of which are strongly but not exclusively communal in nature, appear to have had a disproportionately positive impact on women, and their decisions of whether or not to major in computer science.

In this work we report on the first major long-term intervention designed to leverage the communal goal congruity

perspective. Ours is a cohort-based service learning program for our computing majors, funded by the NSF S-STEM program. In the next section we describe the design of the program, how the goal congruity perspective influenced the design, and the surprising impact it has had on our student diversity.

4. PREACH SERVICE, REACH DIVERSITY

One of our alumni went to work for a major political campaign. When we asked how he found the job, he said that he had lucked into it. Despite a longstanding interest in politics and political activism it had simply not occurred to him that computer scientists could do that kind of work. He had assumed that his career would consist of working at startups or tech giants, and that he would have to pursue political action in his free time.

This perspective is somewhat depressing, because it illustrates just how bad a job we, as a society, are doing at communicating the impact that computing professionals have on the world. It also illustrates that there are students with communal career goals that are not being satisfied by our current curriculum and messaging. On the other hand, this experience illuminates an avenue for change if these opportunities to integrate service with computing are made visible.

4.1 Service Learning

In what follows it will be useful to the reader to know our definition of service learning. By *service learning* we refer to a very specific type of pedagogy in which neither service nor learning dominates. Students learn through service, and serve through learning. We partner with a local non-profit to fulfill a real community need, and the time spent fulfilling this need allows students to advance towards achieving their course learning outcomes, just as if they had spent that time on reading or homework instead.

We do not, for example, send CS1 students to serve soup at a soup kitchen. Instead, we send them to elementary schools to teach coding clubs, teaching CS1 concepts. Students in a databases course might design and code some new database queries needed by a non-profit that has an existing database.

Our first cohort is currently finishing their first semester, taking our CS1 course. For their service learning, we partnered with Kode2Learn, a student club that delivers hands-on coding experiences before and after school one day a week at three local elementary schools. Our Office of Service Learning handles much of the administrative work: Transportation to and from placements, background checks, liability insurance, etc. We hired an undergraduate to be the Service Learning Coordinator for the class. She worked with the school district to identify the time and place of the clubs, and tracked student attendance. Each student was required to attend five club sessions throughout the 14 week semester.

4.2 Designing a Scholarship Program Around Communal Preferences

We designed a communal goal oriented program within our computer engineering, computer science, electrical engineering, and software engineering majors. What follows is a brief survey of the main elements of the program, some novel, many tried-and-tested by others before us.

- The program is called “Electronics and Computing Ser-

vice Scholars,” and is advertised as a program where students learn “to work together with others to make a difference.”

- Students in the first year of the program live together in the dormitory, and have two courses in common during their first semester, to aid in cohort building and cohesion.
- Students apply to the program via essay, and are selected based on merit as demonstrated through the essay. Merit is defined as “evidence of passion for and/or experience with leadership in service.”
- Admitted students were awarded scholarships of up to \$10,000 per year for 4 years, based solely on financial need.
- Students are required to participate in at least one service activity per year, though this is intended to be satisfied by taking existing service learning designated courses.
- A service learning section of our introductory programming course was created, partnering with a local non-profit that provides coding clubs at local elementary schools.
- A dedicated study space has been allocated where students in the program can meet with each other, peer advisors, and teaching assistants.
- We will supplement our already strong career counseling with additional information about careers in government, non-profits, and B-corporations.
- We will provide guest speakers from government agencies and non-profits to aid in role modeling and career networking.

Our hypothesis is that our program will be more attractive to women than the “normal” computing programs, because the design and messaging of our program clearly communicates a focus on communal career goals.

One important lesson learned from prior S-STEM efforts at our institution is, in advertising, to de-emphasize the scholarship money. Many programs have reported that most students that apply only want the scholarship money, and do not participate in the other support programs. In our advertising and marketing we focus on selling the parts of the program that communicate a communal focus: cohort dorm living, courses in common, peer advisors, service projects, dedicated group study space, and so on. We also required students to describe, in their application form, which of the support services they were most excited about, or would find most helpful. Our hope is that this exercise will help them to initiate the use of the support services.

Though we are just getting started, our results are somewhat startling.

4.3 Results

It is important to note that race, ethnicity and gender were *not* used to select students for the program, or as input in setting scholarship amounts. National Science Foundation guidelines indicate that only merit and need should be used in the selection process.

In Table 1 we report the demographics of our first entering cohort in the Electronics and Computing Service Scholars, and compare it to school and industry norms. Of the 19 scholars in the cohort, all provided self-described gender

(free text entry), and 17 of 19 provided self-identified racial and ethnic information using the U.S. federal government categories. Note that “UR/E” denotes under-represented race and/or ethnicity.

The “Baseline” row presents data for students at our institution majoring in computer engineering, computer science, electrical engineering, and software engineering and starting in either August 2014 or August 2015. The “Tech giants” row presents data for employees in tech roles at Yahoo!, Google, and LinkedIn, based on their published 2014 diversity numbers [14, 15, 25]. Because the numbers at the three companies are very similar, we chose to average them together to give a composite for comparison. The other three rows present data for the Electronics and Computing Service Scholars at the three key stages in the admission process. Furthermore, women that self-identify as at least one

Table 1: Diversity of Service Scholars Compared to Industry Norms

Population	% female	% UR/E
Baseline	12.3%	12.7%
Tech giants	16.7%	6.7%
EaCSS applied	19.2%	21.3%
EaCSS admitted	25.0%	25.0%
EaCSS matriculated	26.3%	31.6%

of black, African American, or Hispanic make up 15.8% of the matriculating EaCSS cohort.

From the data one can see that the demographics of the group that chose to apply to the program were already significantly more diverse than the baseline population.

In the decision of whether or not to admit, students were ranked based on whether their career goals and/or service experiences were aligned with the program¹, and then we selected the top 32 students to admit. This number was based on available capacity in the program. Many applicants, for example, wrote about their academic achievements, and their desire to start a company or work for a tech giant, but did not address the service aspects of the program at all. It seems likely that some applicants simply re-submitted their standard college essays, without revising them to fit the program criteria. This particular mistake was only made by one female applicant, which at least partly explains the increased percentage of women in the admitted pool compared to the application pool.

The fact that the matriculated pool is even more diverse than the admitted pool is also very interesting. This is the point where we expected the scholarship money to have the biggest impact on whether or not students matriculated at our institution, but the data seem to contradict this. Of the students that received no scholarship money (due to no financial need), 47% still matriculated into the program. Among those that were offered awards, 63% matriculated.

Scholarship sizes were set based on the student’s FAFSA data, so that students with higher unmet need received larger awards. There was surprisingly little correlation between the size of the award and whether or not the student matriculated into the program (Pearson’s r of 0.206 for the overall sample, 0.202 if restricted to students with financial need).

¹Students could have been disqualified for having insufficient high school grades and coursework, but no such students applied for the program.

Though far from conclusive, these early results suggest that students are selecting the program in large part for reasons *other* than the scholarship money. In future research we will investigate the matriculated students’ reasons for choosing the program, their career goal preferences (whether agentic or communal), and their sense of belonging. But the fact that there is not a clear connection between the scholarships and matriculation is a good sign that students might have chosen the program based on their goals and values, not on purely financial grounds.

4.4 Missteps and Lessons

By far the biggest challenge has been advertising the program. Though the program provides tremendous value to participants, it is surprisingly hard to get students or parents to open an email or read a flier, even when you are offering up to \$10k in scholarship money. We tried a variety of ways to reach our target audience. Rather than trying to recruit students that had already expressed an interest in STEM, our goal was to reach students that had expressed an interest in service, and to educate them about the ways that computing can lead to a career of service. A few things we tried:

- Email contact with *all* high school principals in our state. Email open rate was 21.9% and the click rate was 2.3%. We asked that scholarship info be passed on to guidance counselors, students, and/or PTA groups. We see no evidence that this happened.
- Word-of-mouth contact through our alumni, and speaking with students that came for campus visits in the fall. This resulted in 3 applications.
- Email contact in mid-November with *all* high school seniors that submitted a Request For Information to our institution. This resulted in 2 applications.
- Email contact in mid-February with all accepted students to our College of Engineering and Computing. This resulted in 20 applications.
- Email contact in late May with all students that confirmed their admission to our College of Engineering and Computing. This resulted in 28 applications.

This tells a pretty clear story. Students first select which school they will attend, and then look into programs and scholarships after that decision is made.

We argue, therefore, that a broad national campaign is needed to change student attitudes and stereotypes about engineering and computing careers. Intervening during the college selection process is unlikely to work, because the student’s focus is on “which college,” and little else. We applaud the many organizations are already engaged in this work (e.g. Code for America, Code.org, and the previously mentioned NAE “Changing the Conversation” project).

5. CONCLUSIONS AND FUTURE WORK

The communal goal congruity perspective provides a fresh lens for understanding the lack of diversity in computing, and designing mitigating interventions. We believe that many teachers, scholars, and authors are already making the turn towards increasing service and civic engagement in college curricula, and the communal goal congruity perspective helps provide a theoretical explanation for why this is a good idea.

Our own work, so far, has been much more successful than we expected. Without at any point explicitly focusing on diversity, we have managed to achieve diversity in our S-STEM program simply by designing and marketing the program around communal goal affordances.

Of course the data we have so far is small, and only tells us that our group is diverse. It does not tell us why this is the case, or get at the root causes of the difference between our Service Scholars and the baseline student body in these majors. Over the coming year we will be comparing the students in our service learning CS1 section with students in an honors section of CS1 and a “normal” section of CS1 to investigate how these variations affect belonging, self-efficacy, and other indicators of persistence and retention.

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