Which Shared Background Traits Are Important to Underrepresented CS Students in Career-Transition Mentorship Programs?

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ABSTRACT

Mentoring programs are a valuable strategy employed by both educators and industry to improve retention, learning, and career outcomes; they can also play a crucial role in diversifying Computer Science. Although there has been much research into mentoring programs for early college students and mid-career professionals, less has been published about career-transition mentorship programs: programs with a focus on gaining knowledge and achieving short-term career objectives and little focus on belonging.

It is well documented that, for early college and mid-career mentorship programs, matching mentees with mentors of a similar social, economic, and demographic background is both very preferable to mentees and leads to better outcomes. This paper explores to what extent the same is true for career-transition mentoring. We report on student preferences for students enrolled in one of two mentoring programs which served primarily underrepresented students studying Computer Science at US Community and Technical Colleges (CTCs), who were close to graduating and planning to transition into a career. (n=369) The paper found that, the more mentorship focused on supporting specific specific knowledge gain, the less students preferred a mentor of similar background, that it had little effect on outcomes, and that some traits mattered more than others. These results may influence how similar programs prioritize mentor recruitment.

1 INTRODUCTION

Mentoring programs in higher education have gained remarkable popularity in recent years, becoming a pivotal part of the academic experience for many students. These programs are designed to facilitate personal and professional development by pairing students with experienced mentors, often faculty members, alumni, or industry professionals. The surge in their popularity is attributable to the increasing recognition of their value in enhancing student success. Mentors provide guidance, support, and valuable insights into academic and career pathways, making a significant impact on students' academic performance and future career prospects. Additionally, these programs foster a sense of community and belonging, which is crucial for student retention and satisfaction. The tailored support and advice offered through mentoring relationships help students navigate the complexities of higher education, build confidence, and develop essential skills for their professional lives. As a result, universities are increasingly investing in these programs, acknowledging their role in enriching the educational experience and preparing students for the challenges of the modern world.

To date, most academic mentoring programs have largely focused on helping students find belonging and navigate a new school or degree program, but there are also some mentoring programs which focus on an equally pivotal phase in the academic and professional journey of students – the transition from academia to industry. In 2020, the authors of this paper independently built two such mentoring programs for Computer Science students, with a particular focus on students attending Community and Technical Colleges (CTCs).

These programs, designed with the intention of aiding students who often lack representation in the tech industry, put considerable effort into recruiting mentors who mirrored the students' own backgrounds and demographics. This approach was rooted in the prevalent belief that shared experiences and backgrounds between mentors and mentees create a more relatable and effective mentoring relationship. When students were given the choice to select their mentors, however, students did not always prefer mentors of similar backgrounds. Furthermore, the end-of-year results showed no significant difference in outcomes between students who chose demographically similar mentors and those who did not.

This observation raises intriguing questions about the role of demographic matching in mentoring relationships, particularly in career-transition phases. The existing literature emphasizes the importance of such matching in early college and mid-career mentorship programs, highlighting its positive impact on both the preferences of mentees and the outcomes of the mentoring relationship.

Our initial data suggested there might be a gap in understanding when it comes to mentorship programs focused on helping students transition into a career, perhaps because these programs feature less of an emphasis on fostering a sense of belonging or long-term career development.

Our paper addresses this gap by exploring the extent to which social, economic, or demographic similarity between mentor and mentee is significant in career-transition mentoring programs. We examine student preferences and outcomes in two mentoring programs aimed at underrepresented students in Computer Science at US Community and Technical Colleges. Our study encompasses a diverse group of 369 students on the cusp of their professional journeys. The findings offer a nuanced view of the mentor-mentee dynamic in this context.

The insights gained from this research could have far-reaching implications for how mentoring programs, particularly those focused on career transitions in underrepresented groups, approach the recruitment and matching of mentors. By challenging the conventional wisdom around demographic matching in mentoring, this paper aims to contribute to a more effective and nuanced understanding of what makes mentoring relationships successful, particularly in the critical phase of transitioning from education to a professional career in fields like Computer Science.

2 BACKGROUND

Mentoring has been widely acknowledged as a valuable strategy for improving retention and developing a career. For early college students, research shows that mentoring relationships foster positive academic outcomes, including increased persistence and improved grades. [6, 7, 24, 41] In the business environment, mentoring can improve retention, career growth, and productivity for mid-career professionals.[5, 25, 39]

As educators and employers in Computer Science have been looking for initiatives to increase diversity, many have turned to these mentoring programs, because studies have found that they play a significant role in promoting social justice, particularly benefiting underrepresented and underrepresented and under-served groups such as female, [6, 15, 27] African American, [16, 21] Latina/o, [40] and low-income students. There is a growing body of evidence suggesting that mentoring programs can serve as an effective tool to enhance diversity in the science, technology, engineering, and math (STEM) workforce. [36]

2.1 Types of Mentorship

Broadly speaking, mentorship is a relationship between a more experienced person (mentor) and a less experienced person (mentee or protégé), where the mentor helps in the professional development of the mentee. [28] There are several ways to describe the type of mentorship: [13]

- **Type of Support:** Mentorship programs can provide emotional support; support in integrating into and navigating a career or degree program; support in gaining knowledge in a subject; and advocacy. [12, 18, 29] The type of support may vary from pair-to-pair within a mentoring program, or even change from meeting-to-meeting as the relationship develops. [18]
- **Type of Mentor:** Mentorship programs recruit mentors who are faculty, industry professionals, much older students, or near-peers. [38, 43]
- **Structure:** Mentorship relationships can be held one-on-one or in a group; in-person or online; and formal or informal.
- **Career Stage:** Most mentorship programs target students who are early college students [14] or mid-career professionals, but some target younger students, [23] or students who are about to transition into the workplace.

2.2 What Do Mentees Want From a Mentor?

Many studies have looked at what mentees desire in a mentor. They have found that mentors should:

- offer emotional support [31, 37]
- be good observers and listeners [1, 37, 38]
- demonstrate commitment and interest in the mentoring relationship [13, 33]
- clearly set high expectations [13, 35]
- help mentees problem-solve [1, 37, 38]
- be approachable and available [1, 38]
- be supportive and understanding [1, 37, 38]

Mentees tend to prefer in-person mentoring relationships, but there is no effect on the outcomes of mentoring. [8]

Culture may be important for mentors: one prior study found that a mentee's cultural values of collectivism and power distance influence what mentees want from their mentor. [9] For this and other reasons, mentor/mentee relationships are thought to be more desirable and effective when the pair share a similar background or demographics, particularly when the mentor and mentee are shared members of a group underrepresented in their field. [3, 4, 19, 30, 34, 42] To ensure the program is effective for a diverse population of students, therefore, many mentoring programs attempt to recruit a large proportion of mentors from underrepresented groups in STEM to improve the recruitment and retention of diverse students. [38] Despite this, other research suggests that well-trained mentors can make up for issues of diversity and creating pairs of mentors and mentees with similar backgrounds can be unnecessary in such a case. [10, 32]

There is no consensus in the literature about the best way to match mentors and mentees. Mentor programs have tried a variety of methods to match menetes and mentors, including assigning matches based on similar demographics or personalities [2, 17], technical solutions which allowed mentees and mentors to express their own preferences [20, 26], or by assigning mentors completely at random. [10]

3 CURRENT STUDY

Despite an increasing interest in mentoring, the literature is underdeveloped in many areas, including small sample sizes and a lack of consistent definitions. [11, 13, 22] A limitation that has been of particular interest to the authors is that most studies focus on either early college students or mid-career professionals, but relatively few studies focus on students transitioning from college to career. We refer to these types of programs as *career-transition mentorship programs*.

In 2020, the authors of this paper independently built two such mentoring programs: one providing career mentoring, and one providing skills mentoring. Both programs were aimed at underrepresented and under-served college students who were close to graduating from college with degrees in Computer Science and preparing to launch their careers. With the importance of shared backgrounds/demographics in mind, both expended significant effort to find many mentors with similar backgrounds and demographics to the students. However, after asking students to select a mentor, both programs were surprised to see lower than expected affinity for mentors from a similar background, and by the end of the year, there was no obvious difference in outcomes.

Consequentially, this paper seeks to answer the following:

- **RQ1:** do students in different career-transition mentorship programs have an affinity for mentors with similar social, economic, or demographic backgrounds?
- **RQ2:** do shared social, economic, or demographic backgrounds influence outcomes in different career-transition mentorship programs?

4 EMPIRICAL SETTING

The study uses data collected from two career-transition mentorship programs, for which an overview is provided in Table 1 and more details are presented below. Both programs serve juniors and seniors enrolled in Community and Technical Colleges (CTCs) who are pursuing a 4-year Bachelors of Science (BS) or Bachelors of Applied Science (BAS) in Computer Science. Both programs recruit mentors from the Computer Science industry, and students enroll into both programs with the goal of transitioning into a career in the software industry.

Table 1: Overview of Programs Providing Data

	CodeDay	MinT
Support	Subject Knowledge	Navigating Career
Mentor	Industry Professionals	Industry Professionals
Structure	One-on-One & Group	One-on-One
Stage	Workplace-Transition	Workplace-Transition

CodeDay Labs: CodeDay Labs is a program which helps students learn to work on computer science projects without detailed guidance, a skill which employers find is both important and lacking in new-grads. Students are matched with one mentor and work with 1-2 teammates to solve an open issue in an Open Source Software project. Students meet weekly with their team and mentor over the course of 9 weeks.

During the first weekly meeting, students review the resources they have discovered for their project (such as documentation and maintainer contacts) and their understanding of the codebase (including architecture diagrams and potential starting points). Mentors, who are not themselves experts on the codebase, provide feedback on how they would have answered the same questions. Similarly, in subsequent meetings, students present technical challenges they faced and their mentor provides feedback on how to solve the specific problems. The program is focused on helping students gain knowledge in identifying and narrowing-down problems, conducting independent research, experimentation, and verifying a solution.

Mentors in Tech (MinT): MinT is a program focused on helping students navigate the job search and hiring process in order to obtain a career. Students are matched with two mentors in either November or January, and expected to meet with each mentor virtually, once a month, until the end of the school year.

During each monthly meeting, students are provided with a suggested agenda which is based on the hiring calendars used by recruiters at technology companies, and the student and mentor choose to discuss one of a few different topic modules: "Tech Lay of the Land", "How Tech Hires", "Job Search", "Tech Interviews", "Your Network", "Culture and Conflict at Work", "Offers & Negotiation", "Working as an Employee", "Careers: Thinking Ahead", "Managing Money", "Final Commitments", and "LinkedIn and Resume".

5 METHODS

This study uses fully anonymized data from 3 total program sessions: CodeDay Labs July-August 2021, MinT School Year 2021-2022, and MinT School Year 2022-2023.

[1]Black or African American

Table 2: Demographics for CodeDay Labs students, n=163

	Asian	Black[1]	Hispanic/ Latinx	Native American	White
he/him	30.67%	4.60%	8.90%	12.88%	1.84%
she/her	30.06%	1.84%	3.37%	2.76%	3.07%

Table 3: Demographics for CodeDay Labs mentors, n=49

	Asian	Black[1]	Hispanic/ Latinx	Native American	White
he/him	24.49%	0%	12.24%	30.61%	14.29%
she/her	12.24%	0%	0%	0%	6.12%

Table 4: Demographics for MinT students, n=206

	Asian	Black[1]	Hispanic/ Latinx	Native American	White	N/A
he/him	14.12%	7.28%	6.43%	1.09%	35.24%	1.94%
she/her	9.14%	2.67%	5.74%	0.73%	9.14%	1.94%
they/them	0%	0%	0%	0%	3.40%	0%

Table 5: Demographics for MinT mentors, n=344

	Asian	Black[1]	Hispanic/ Latinx	Native American	White	N/A
he/him	24.99%	3.49%	2.76%	0.06%	42.09%	4.09%
she/her	8.92%	1.61%	2.49%	0.29%	9.21%	0%

Tables 2, 3, 4, and 5 present a breakdown of students and mentors grouped by gender and ethnicity. The heatmaps show that the traits we use to calculate our independent variables are distributed evenly throughout the dataset within each program.

We test our hypotheses using a set of measures constructed from the datasets. Our first independent variable is Pronouns, which is assigned 1 if a mentor and student both have the same pronouns or 0 if not. We code pronouns because they are a function of gender identity, and prior studies have suggested a link between gender rather than biological sex.

Our second independent variable is RaceEthnicity which is determined based on the symbolic list raceEthnicity in the dataset. It is set to 1 if *any* of a student's answers about their race and ethnicity match *any* of a mentor's answers and otherwise set to 0.

Similarly, our third independent variable is Background, which is determined based on the symbolic list marginalizedBackground, a list of marginalized backgrounds students and mentors may choose to identify with. The options presented were: first generation college student, first generation in a tech field, have a disability, parent, veteran, older college student, grew up in a rural area, first generation immigrant, struggled with poverty, came from a working class family/background, neurodiverse, and LGBTQ. The variable was set to 1 if *any* of the student's answers matched *any* of the mentor's answers.

Finally, our last variable is Any, which is set to 1 if either Pronouns, RaceEthnicity, or Background is set to 1.

To answer **RQ2**, we construct a dependent variable representing program outcomes as a measure of the percent of student-mentor pairings which conducted at least n meetings, where n is a number ranging from 1 to 8. The more successful the pairing, the greater the number of meetings.

6 RESULTS AND EVALUATION

6.1 Student Preferences

Figure 1: Likelihood of students choosing a mentor with a shared trait, as compared to random chance

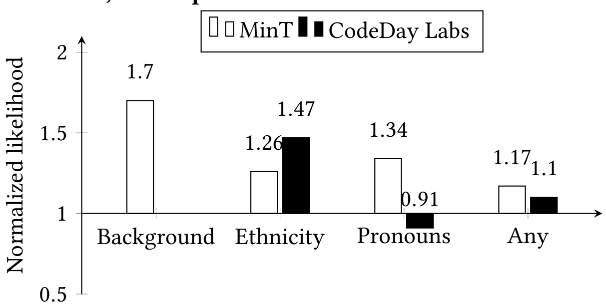


Table 6: Results of a chi-square test of independence on students picking a mentor with the same trait

	CodeDay $\chi^2(n = 107)$	**MinT** $\chi^2(n = 178)$
Background	n/a	52.42, p<.001
Ethnicity/Race	0.34, p=.55	3.49, p<.001
Pronouns	0.001, p=.96	29.55, p<.001
Any Trait	2.45, p=.11	20.24, p<.001

The study found that students' traits and their preferred mentor's traits significantly correlated in MinT students, but not CodeDay Labs students. (Fig. 1 and Table 6)

The study found that students from certain backgrounds had higher affinities for mentors of a similar background than others. Black or African American MinT students were more likely to pick Black or African American mentors, $\chi^2(1, N = 21) = 10.17, p = .001$. White and Asian students were both more likely to pick a mentor who shares a marginalized group. (White: $\chi^2(1, N = 93) = 26.73, p < .001$, Asian: $\chi^2(1, N = 44) = 13.82, p =< .001$)

6.2 Student Outcomes

Overall, the study found very little effect on student outcomes. (Fig. 2) A possible increase in student success was identified when the students and mentor are the same Ethnicity/Race, and a possible decrease in student success when the students and mentor come from different backgrounds, but both effects are within 2 standard deviations of the mean.

7 DISCUSSION

7.1 Research Question 1: Do students in different career-transition mentorship programs have an affinity for mentors with similar social,economic, or demographic backgrounds?

The study found student preferences differ depending on the type of mentoring support being offered by the program.

MinT, which focuses on providing students with career navigation support, (See 4) students showed a preference for a mentor with shared traits (Fig. 6). The most important trait to students was the background of their mentor (Fig. 1), and the least important was Ethnicity/Race.

CodeDay Labs, with it's focus on specific knowledge gain working on a clearly defined project (See 4), showed no significant student preference for a mentor with similar traits, on average.

The authors hypothesize that, the more general (i.e., the more emotional or sense-of-belonging support, as opposed to knowledge gain) the areas of support provided by the mentor, the stronger the student preference towards picking a mentor of similar background. We believe this trend to be present even when mentors are providing types of support not included by the programs analyzed in this study.

7.2 Research Question 2: Do shared social, economic, or demographic backgrounds influence outcomes in different career transition mentorship programs?

The study did not observe a strong correlation between shared backgrounds and program outcomes.

Fig. 2 weakly suggests that students with the same race or ethnicity as their mentor have better outcomes. This differs from analysis of other types of mentorship programs, which shows a significant positive correlation when students and mentors are of a shared Ethnicity/Race. Should such a correlation be shown to also exist in career-transition mentorships, the authors question why students preform best when matched with mentors of the trait least important to their preferences (Fig. 1).

The authors further pose that, trends may differ based on the goals and scope of the mentorship, similar to the variance seen in RQ1.

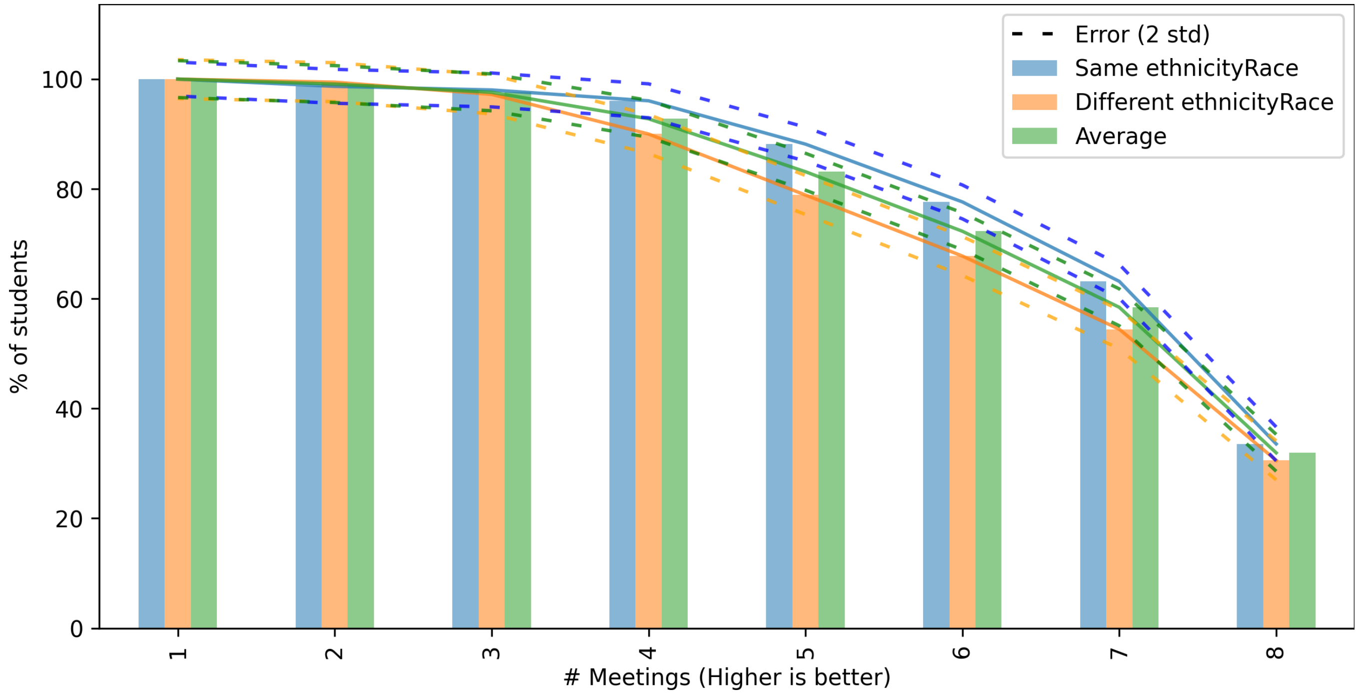
8 CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

The study examined whether students in career-transition mentorship programs had a preference for mentors with a similar social or demographic background. The study also examined whether any such background traits effected program outcomes when shared between a mentor and mentee. The study found students only prefer mentors of a similar background when the scope of a mentorship prioritizes "broad" areas. (Such as emotional or sense-of-belonging support, as opposed to specific knowledge gain)

Our results should be interpreted carefully. First, we do not claim that these results are true for all mentor programs; in particular, the literature suggests the opposite is true for mentoring programs which target early college or mid-career. Second, the number of mentees and mentors in certain social/demographic background traits was relatively small. Third, our analysis shows certain background traits (Such as Black or African American students, see 6.1) value a mentor with shared backgrounds more than students from other groups.

This work raises two important considerations for anyone building a mentoring program focused on career-transitional students.

Figure 2: MinT Student outcomes by shared ethnicity



First, when it comes to recruiting mentors, program builders may not particularly need to emphasize recruiting mentors with a similar social, economic, or diverse background to the mentees they plan to serve. Secondly, all program builders should consider letting students view a list of potential mentors and express their own preferences, ensuring to present mentors who are both very similar and very dissimilar in background from the student.

A key remaining question: How does the act of declaring preferences impact student outcomes? The study was unable to find significant correlations between shared traits and student outcome, even in MinT students, who showed a strong preference to pick mentors of similar backgrounds. This could suggest there is little to no positive benefit from being matched with the mentor they wanted, or even a mentor similar to their first choice.

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