A Holistic Approach to Building Resilient Computer Science Pathways: Exploring Gender, Engagement, and Attrition in Computer Science from Academia to Industry

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Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Engineering Education

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June 3, 2025
Blacksburg, VA

Keywords: computer science, attrition, women

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ABSTRACT

In today's technology-driven society, computing knowledge and expertise are increasingly essential, yet the field of computer science (CS) continues to struggle with high attrition rates in both academia and industry. This persistent issue contributes to a growing shortage of qualified professionals, with millions of computer science positions in the U.S. remaining unfilled. Compounding this challenge is one of the widest gender disparities among STEM disciplines. This dissertation investigates factors contributing to both the gender gap and high attrition rates in computer science through three interconnected manuscripts. Manuscripts 1 and 2 examine why high-performing non-CS majors choose not to pursue a computer science minor, focusing separately on the experiences of women and men. Using thematic analysis of interview data framed by Ecological Systems Theory, these studies reveal significant gender-based differences in how students navigate various system layers to ultimately disengage from the field. Manuscript 3 explores the use of generative AI for large-scale thematic analysis of social media posts, identifying reasons individuals leave computer science across four stages of departure. Contextualized through Social Cognitive Career Theory, this study identifies six recurring themes present at every stage of disengagement. Collectively, these manuscripts offer a comprehensive view of the factors driving disengagement from computer science, amplifying underrepresented perspectives and generating actionable recommendations for both research and practice.

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In today's technology-driven society, computing knowledge and expertise are increasingly essential, yet the field of computer science (CS) continues to struggle with high attrition rates in both academia and industry. This persistent issue contributes to a growing shortage of qualified professionals, with millions of computer science positions in the U.S. remaining unfilled. Compounding this challenge is one of the widest gender disparities among STEM disciplines. This dissertation investigates factors contributing to both the gender gap and high attrition rates in computer science through three interconnected manuscripts. Manuscripts 1 and 2 examine why high-performing non-CS majors choose not to pursue a computer science minor, focusing separately on the experiences of women and men. By analyzing interview, these studies reveal significant gender-based differences in how students navigate classroom experiences and university policies to ultimately disengage from the field. Manuscript 3 explores the use of generative AI for large-scale analysis of social media posts, identifying reasons individuals leave computer science across four stages of departure. This study identifies six recurring reasons for leaving present at every stage of disengagement. Collectively, these manuscripts offer a comprehensive view of the factors driving disengagement from computer science, amplifying underrepresented perspectives and generating actionable recommendations for both research and practice.

To all the women in STEM who have ever felt like outsiders, questioned their worth, or been told they did not belong—
You do.
You are capable.
You are needed

ACKNOWLEDGEMENTS

I would like to thank my advisors, Andrew Katz and Sara Hooshangi, for their unwavering support and guidance throughout my graduate journey. Their willingness to work together has been a major influence shaping my academic work and allowing me to explore my cross-disciplinary interests.

Additionally I want to thank my committee members, Holly Matusovich and David Knight. Their thoughtful feedback and mentorship have been crucial in helping me finish my dissertation, and their guidance has extended to all aspects of graduate school. A special shout-out to Holly, for always providing a safe space to cry and talk things through, more times than I can count.

I am also incredibly grateful to the ENGE faculty, whose contributions have shaped me into both a successful graduate student and a lifelong learner. I want to specifically thank Sarah Rodriguez for her time on my committee and her influence on how I approached my dissertation work.

To my friends, who have been my emotional anchors and academic sounding boards. Malini and Hannah, thank you for your constant support, your invaluable feedback, and for all the fun activities that gave me the breaks I desperately needed. Olivia, you have been my rock, and I am endlessly grateful for your patience, your listening ear, and your unwavering support. You were always there, whether it was for a much needed vent, a long yap session, or a good cry.

To Jacob, whose encouragement and support have meant the world to me. I knew you were a keeper when you were there for me during my prelim. Thank you for being there in ways I didn't even know I needed.

To Dad and Meg, who have always been my pillars of strength. Whether near or far, your unwavering belief in me has been a constant source of reassurance when things got hard. You've always been there for me, and I have felt your love and support every step of the way. To Zack, thank you for encouraging me to step outside of academia and to stay grounded. Your coaching has been crucial to maintaining my mental and physical well-being.

To Mom, my greatest role model and inspiration. You've shown me that women can not only succeed in STEM but truly thrive in it. You've always believed in me, even when I doubted myself, and you have been my biggest guide and mentor throughout my educational journey.

And finally, to Remy, who has been a constant source of comfort and sanity. You made sure I took breaks, got outside, and always provided the best snuggles when I needed them. Your unconditional love reminds me that there's more to life than work and academia.

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Chapter 1: Introduction

1.1 Motivation

The demand for computing knowledge in the workplace is rapidly increasing. Job growth projections reflect this trend, with computer and information systems managers expected to grow by 17%, software developers by 18%, and information security analysts by 33% over the next decade (Bureau of Labor Statistics, n.d.). Overall, the industry anticipates a 14.6% growth rate from 2021 to 2031, which would add approximately 682,800 new jobs in those ten years (Krutsch, 2022). However, the rapid rise of generative artificial intelligence (AI) technologies introduces important nuances to these projections. While AI is expected to automate certain programming tasks, particularly those involving routine, foundational skills, the need for computing professionals capable of higher-order problem-solving, interdisciplinary integration, and ethical decision-making is unlikely to diminish. In fact, this evolution in the job market underscores the importance of cultivating a workforce equipped not only with technical knowledge but also with the adaptability and critical thinking required to navigate an AI-influenced landscape.

This shifting landscape reinforces the relevance of computer science education pathways, especially for students pursuing minors the pave paths into interdisciplinary computing opportunities. But these programs often emphasize fundamental programming skills, the very skills most susceptible to automation, and as a result students may begin to question the utility of these pathways. Yet they also serve as a critical gateway to deeper, applied, and creative computing competencies that remain in high demand.

High attrition rates in computer science also pose a significant challenge to meeting workforce needs. Computer science having the highest college dropout rate among university majors (Winograd, 2024). Roughly 15% of students enrolled in a computer science major drop the major within their first year (*Persistence & Retention | National Student Clearinghouse Research Center*, n.d.). As a result, industry may struggle to meet workforce demands, hindering economic growth and emphasizing the need for a larger pool of individuals with computing expertise.

Furthermore, the field of computer science not only requires more professionals overall but specifically needs greater gender diversity. Since the mid-1990s, women's representation in several STEM disciplines, such as mathematics, chemistry, and biology, has increased at the bachelor's level (Cheryan et al., 2017; Sax & Newhouse, 2018). However, their representation in computer science has remained consistently low. Although women make up over 59% of all college enrollments in the United States (*National Center for Education Statistics*, n.d.), they account for only 20% of computer science enrollments (Engineering and Engineering Technology by the Numbers, 2022). Computer science is the only STEM field where women's representation has declined over the past 35 years, and it currently has the lowest proportion of women among STEM disciplines of biological and biomedical sciences, mathematics and statistics, physical sciences, and engineering (Sax & Newhouse, 2018). This trend continues into degree completion, with women comprising just 15% of computer science graduates despite representing 20% of enrollees (Engineering and Engineering Technology by the Numbers, 2022).

Attrition challenges also extend into industry, where turnover rates in computer science-related occupations reach 12.9% (Lewis, 2022). Gender disparities persist at this level as well. Although women make up about 47% of the general workforce, they constitute only 28% of computing occupations ("Women In Technology Statistics," 2022). This underrepresentation has implications beyond numbers. Since women make up half of technology users, their absence in product development can lead to gender-biased products, such as voice recognition systems that struggle to recognize women's voices (Loiacono et al., 2016) and Amazon's recruiting tool that inadvertently discriminated against women applicants (Teodorescu et al., 2021). Therefore, addressing the gender gap and high attrition rates in computer science is not only crucial for meeting workforce demands but also essential for ensuring equitable technology solutions that meet the needs of all users.Taken together, these workforce shifts, attrition challenges, and gender disparities highlight the need for research that investigates how students navigate computer science pathways, particularly minors and introductory experiences that act as critical entry points into the field. Understanding the factors that contribute to persistence and attrition in these programs is essential for developing educational strategies that not only broaden participation but also prepare students for a rapidly evolving technological workforce.

1.2 Background

1.2.1 Attrition in Computer Science

Extensive research has explored why students leave computer science programs, revealing a complex range of social, emotional, and practical factors. Studies indicate that isolation, limited social connections, heavy workloads, and unclear career pathways significantly contribute to attrition (Biggers et al., 2008; Giannakos et al., 2017; Peteranetz, Flanigan, et al., 2018). Academic challenges also impact persistence, with students further along in their studies more likely to continue, while those facing high demands or lower-than-expected grades are more likely to leave (Pappas et al., 2016). Additional factors, including financial difficulties, health issues, family obligations, and class attendance, are often cited as primary reasons for dropping out (Setosta et al., 2017). Broader analyses, such as Xenos et al. (2002), categorize dropout reasons into professional, academic, family, health-related, and personal domains, illustrating the diverse challenges students face. Notably, many students decide to stay or leave within their first two years, often while taking introductory courses (Huang & Brainard, 2001; Pappas et al., 2016).

Another cause of student attrition in computer science is negative perceptions about the field, which are often shaped not only within academic settings but also by media portrayals (Rosson et al., 2011). Media frequently reinforces stereotypes, painting computer scientists as technology-focused individuals with a strong interest in programming and electronics (Cheryan et al., 2011; Margolis & Fisher, 2002; Spieler et al., 2020) and little interest in people or collaborative work (V. A. Clarke & Joy Teague, 1996; Diekman et al., 2010). Additional stereotypes suggest that computer scientists are solely focused on programming, lack diverse interests, and often engage in hobbies associated with men's interests, such as science fiction or gaming, leading to the misconception that computer scientists are predominantly male (Beyer et al., 2003; Cheryan et al., 2009). Furthermore, computer scientists are often depicted as highly intelligent "nerds" or "geeks," which contributes to a stereotype of social awkwardness and poor interpersonal skills (Beyer et al., 2003; Kendall, 2011; Mercier et al., 2006). These stereotypes can deter students who do not identify with these narrow portrayals, contributing to attrition in the field.

Other research has identified several factors that encourage students to stay in computer science. Key influences include a clear understanding of the degree's practical value (Giannakos et al., 2017), strong social integration within the program (McGrath Cohoon & Asprey, 2006; Rosson et al., 2011; Weng et al., 2010; Xenos et al., 2002), and supportive learning environments (Tan, 2015). Additional positive factors are the perceived value, quality, and relevance of the curriculum (Pereira et al., 2015) and having prior programming experience alongside high self-efficacy (LeBlanc et al., 2020). Research suggests that retention can be enhanced by courses that build self-efficacy and foster effective learning skills (Takács et al., 2022), by creating robust social support networks (Rosson et al., 2011), and by offering engaging opportunities such as undergraduate research (Peckham et al., 2007).

Research on computer science attrition has largely focused on students early in their pathway, leaving significant gaps in understanding why individuals exit the field later in their pathway. Existing studies indicate that employees often leave computing roles seeking higher pay, reduced work hours, or more fulfilling job responsibilities (Bao et al., 2017; J. Davis & Kuhn, 2003; Lewis, 2022). However, no research has explored why computer science graduates who complete their degrees may choose not to enter computing careers. While knowledge of attrition among computer science students has expanded, insights into career exits at other stages of their professional pathway remain limited.

1.2.2 Women in Computer Science

Another large body of literature has investigated the gender gap persistent within computer science. Research shows that men and women exhibit equal aptitude in mathematics and science (Ceci et al., 2009), but that attitudes, stereotypes, and expectations often shape career choices more than ability alone (Ceci et al., 2014; Spelke, 2005). Studies find that women, on average, show less interest in introductory computing courses than men (Beyer, 2014), and have a lower sense of belonging in these spaces (Sax, Lehman, Jacobs, et al., 2017) due to gendered stereotypes linking computing to men (Corbett & Hill, 2015; Main & Schimpf, 2017; Yücel & Rızvanoğlu, 2019) and biased learning environments (Eagly et al., 2000; Riegle-Crumb et al., 2019). As a result, women's computing self-efficacy often remains low, even when they perform well (Beyer, 2014; Lehman et al., 2020). Despite frequently earning higher grades than men peers (Woodfield, 2012), women are more likely than men to find course pace and workload challenging (Barker et al., 2009). Additionally, studies identify sexist barriers, such as needing to prove competence before receiving support, men dominating discussions, and discriminatory remarks from instructors, as further deterrents for women's persistence in computing fields (Blackburn, 2017; Falkner et al., 2015; Giannakos et al., 2017; Lapan & Smith, 2023). Together, these factors contribute to a lower retention rate of women in computing fields, pointing to the need for more inclusive educational and professional environments.

The literature on women in computing reveals a gap in understanding why women who initially express interest in computing, particularly those outside the traditional computer science major pathway (non-CS majors), eventually disengage. Few studies examine why these nonmajors students decide to leave the field. Additionally, while much of the research on the gender gap in computer science focuses on women's experiences, there is limited exploration of men's perspectives. The gender gap in computer science arises not only from the low number of women entering the field but also from the high number of men choosing to pursue it. Men's decisions contribute significantly to the gender imbalance, yet few studies consider nonmajor men students. Examining both populations together allows us to distinguish between factors that are gender-specific and those that are more broadly associated with the field.

1.3 Purpose

The purpose of this dissertation is to address the gender gap and high attrition rates in computer science by examining different understudied perspectives and scales of engagement. In doing so, I answered the following overarching research question: Why do individuals disengage from the computer science field?

Manuscript 1 focuses on high-achieving women who are non-CS majors and who show initial interest, but ultimately decide not to pursue the field further. This study fills a crucial gap by investigating factors that influence women outside the traditional computing pathway, whose reasons for disengagement may differ from those already pursuing a computer science degree. Manuscript 2 builds on Manuscript 1 by examining the men non-CS major perspective, which is often overlooked in discussions of computer science gender disparities. However, understanding the choices of high-performing men who also choose to leave computer science is crucial for a holistic picture of attrition. By comparing the experiences of men and women, this dissertation reveals which factors influencing disengagement are specific to women and which are shared across genders. Manuscript 3 addresses the broader landscape of attrition in computer science by analyzing why individuals across multiple stages, including students, graduates, and professionals, decide to leave the field. This large-scale qualitative study extends the scope of previous qualitative studies, offering a generalizable perspective on computer science departure. Additionally, this study captures the understudied population of graduates and professionals, offering insights into the attrition problem at previously understudied stages of computer science career development.

Together, these studies offer complementary insights into the gender gap and attrition in computer science. Manuscript 1 highlights the experiences of women and reasons for their disengagement. Manuscript 2 broadens the perspective in order to compare men's and women's disengagement. And Manuscript 3 scales up the analysis to include diverse stages and contexts, providing a comprehensive overview of the reasons behind computer science departure. Collectively, they provide a multi-layered understanding of attrition, from early academic experiences to workforce dynamics, and can inform strategies for improving the gender balance and retention across the entire computer science pathway.

1.4 Terminology

Field of Computer Science: The computing field encompasses various disciplines, as illustrated in Figure 1.1. Each of my studies focuses on individuals who leave the field of computer science, though the definition of this field varies across manuscripts. In Manuscripts 1 and 2, the definition is narrow, referring exclusively to individuals who major or minor in computer science. In this context, being part of the computer science field is limited to those pursuing a formal academic credential in computer science. In contrast, Manuscript 3 adopts a broader definition due to its focus on both industry professionals and academics. Here, the field of computer science is not limited to degree programs but also includes the types of jobs typically associated with a computer science background. As shown in Figure 1.1, this encompasses all domains except hardware. At the industry level, this includes fields such as software development, cybersecurity, IT platforms and infrastructure, and digital transformation and intelligence. However, at the academic level, the focus remains on individuals within computer science degree programs.

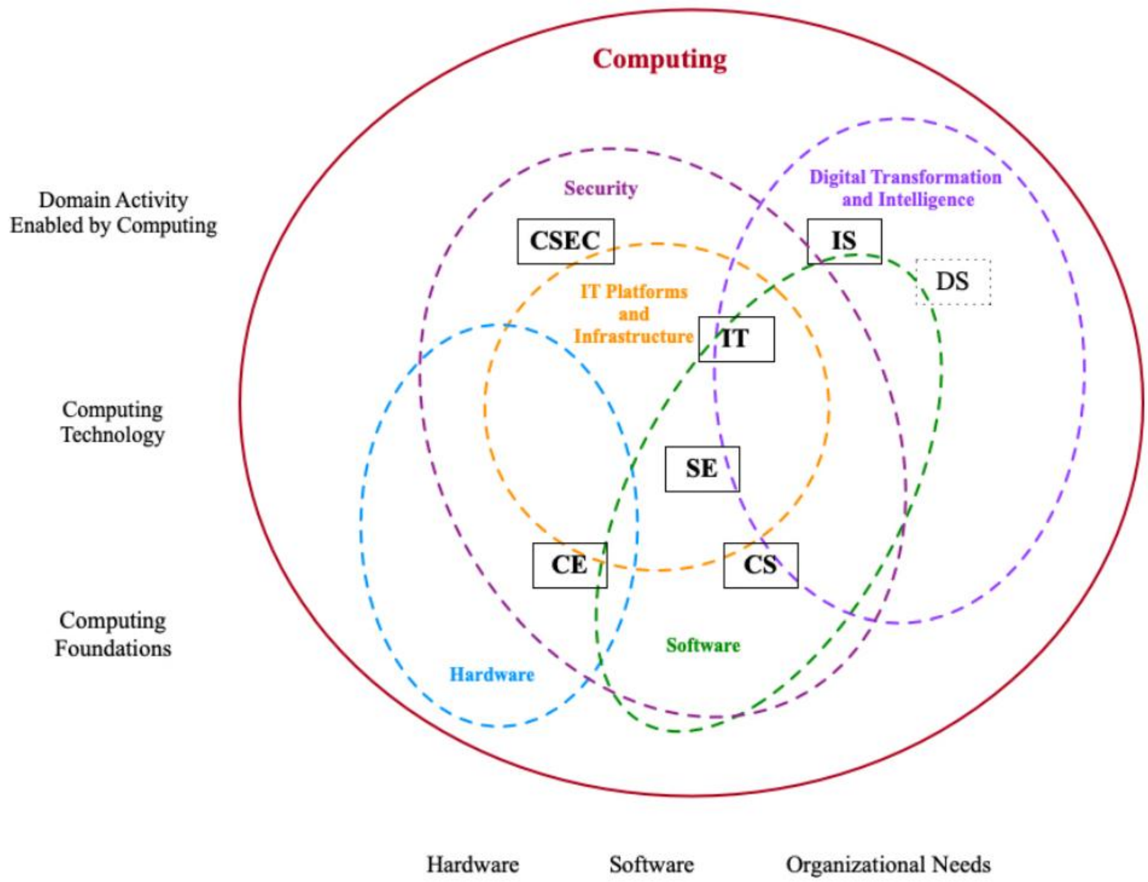


Figure 1.1. Landscape of the Computing Field (Cc2020 Task Force, 2020). The available computing degrees are represented by the black rectangles (CSEC=cyber security, CE=computer engineering, SE=software engineering, IT=information technology, CS=computer science, IS=information systems, DS=data science). The dotted lines represent the different subfields within computing. The computing degrees overlap with subfields if an individual with that degree is qualified to perform work within that subfield.

Gender: In this study, gender is defined as a self-identified construct, distinct from biological sex. For manuscripts 1 and 2, participants were given the option to self-identify their gender by selecting from the following categories: female, male, nonbinary, prefer not to say, or other. Throughout the studies, the terms 'woman' and 'female' are used interchangeably, reflecting the terminology used by authors in prior literature. However, in our study's methods and results, we use the terms 'women' and 'men’. This approach acknowledges the diversity of gender identities and aligns with the study's focus on gender as a social and personal identity rather than a biological or assigned category.

1.5 Project Overview

Manuscripts 1 and 2 were developed as part of the research activities funded by NSF Grant 2225314, which was designed to address the persistent gender gap in computer science. This grant specifically focuses on women who are outside the traditional computer science pipeline, namely those who are not majoring in computer science. The overarching aim of the project is to investigate the factors influencing these students' engagement with computer science and to identify strategies that can enhance diversity and inclusion within the field.

Both Manuscripts 1 and 2 are a result of this larger research project and represent primary research endeavors, with data collected explicitly to address their respective research questions. Each manuscript is aligned with the objectives of the grant, offering empirical evidence that contributes to a deeper understanding of the gender gap in computer science and providing actionable recommendations for educational institutions seeking to foster more inclusive learning environments. Manuscript 3 is not associated with this NSF grant and was conducted as an unfunded project.

1.6 Overview of Manuscript 1

Despite extensive research on women’s experiences in computer science and an improved understanding of the gender gap, the persistence of this gap signals the need for new approaches. This manuscript addresses this issue by examining an understudied group: women who are outside the traditional computing pathway (i.e. non-CS majors), who show some initial interest in the field, but ultimately disengage. Specifically, we adopt an asset-based approach, examining high-achieving women who earned an A or B in their introductory computing courses. Our focus is on how these women's interactions with their environments shape their decisions to leave the field, emphasizing their choice to disengage rather than viewing it as a lack of ability to succeed. This shift in perspective highlights ways the field can improve, rather than placing fault on individuals.

Guided by Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979) this study explores the following research question: Why do women who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor? To answer this question, semi-structured interviews were conducted with seven women at Virginia Tech who had taken an introductory computing course but had not declared a computer science major or minor. The interview protocol was developed using Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979) and asked participants about their experiences with each system layer. These interviews were then analyzed thematically to uncover factors contributing to their decisions. Results showed that participants chose not to pursue a minor in computer science due to negative classroom experiences, stronger interest in other fields, and a lack of belonging within the discipline.

Table 1.1. Manuscript 1 Overview

Population	High performing women who are non-CS majors but took an introductory computer science class for non-CS majors
Context	Introductory computer science classes for non-CS majors at VT
Theoretical	Bronfenbrenner's Ecological Systems (Bronfenbrenner, 1979)

Framework	
Research Questions	Why do women who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor?
Data Collection	Semi-structured Zoom interviews with 7 participants
Data Analysis	Thematic Analysis

1.7 Overview of Manuscript 2

The second manuscript complements and builds on Manuscript 1 to allow for later comparisons across genders. This manuscript takes another unique approach and looks at a second understudied population: men who are outside the traditional computing pathway (i.e. non-CS majors), who show some initial interest in the field, but ultimately disengage. This study also adopts an asset-based approach, utilizing high-achieving men and thus focusing on these men's choice to disengage rather than framing it as a lack of ability to succeed.

Guided by Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979), this study explores the following research questions: Why do men who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor? To answer this question, semi-structured interviews, utilizing the same interview protocol as in Manuscript 1, were conducted with six men at Virginia Tech who had taken an introductory computing course for non-CS majors but had not declared a computer science major or minor. These interviews were then analyzed thematically to uncover factors contributing to their decisions, and later, results were compared to those from Manuscript 1. Results showed that men chose not to pursue a minor in computer science due to critical perceptions of their introductory course, stronger interests in other fields, and a lack of desire to belong within the computer science community.

Table 1.2. Manuscript 2 Overview

Population	High performing men who are non-CS majors but took an introductory computer science class for non-CS majors
Context	Introductory computer science classes for non-CS majors at VT
Theoretical Framework	Bronfenbrenner's Ecological Systems (Bronfenbrenner, 1979)
Research Questions	Why do men who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor?
Data Collection	Semi-structured Zoom interviews with 6 participants
Data Analysis	Thematic Analysis

1.8 Overview of Manuscript 3

The third manuscript is a large-scale qualitative study that looks at computer science attrition across all career development stages. It focuses on a third understudied population: computer science graduates and professionals who leave the field, capturing both early-stage attrition (while earning their degree) and later-stage departures (in their careers). The study's broad design draws data from a wide range of contexts, rather than a single case, which enhances the generalizability of insights into the factors contributing to computer science attrition.

Guided by Social Cognitive Career Theory (SCCT) (R. W. Lent et al., 1994), this study explores the following three research questions: (1) What are the primary reasons individuals choose to leave the field of computer science and (2) What external or contextual factors influence the decision-making process for individuals considering leaving the field of computer science? To answer these questions, Reddit posts were thematically analyzed using a modified version of the previously tested generative AI method, Generative AI-enabled Theme Organization and Structuring (GATOS) (A. Katz et al., 2024). A human-in-the-loop step was added to the GATOS method to ensure result accuracy and to make sense of the AI generated themes using SCCT. Results revealed six major reasons for leaving the field of computer science that persisted across all stages of departure: job dissatisfaction, interest in other fields, psychological and emotional challenges, health and well-being concerns, and industry-related issues. Additionally, several factors influenced the decision to leave at every stage, though a distinct pattern emerged when comparing exits from academia versus industry. These factors included the nature of the alternative field, transition requirements, individual background and preparation, and personal circumstances.

Table 1.3. Manuscript 3 Overview

Population	Individuals in computer science (earning degree or working in industry) who want to or decide to leave the computer science field (change major or find job outside computer science field in industry)
Context	Unknown, but assumed diverse
Theoretical Framework	Social Cognitive Career Theory (R. W. Lent et al., 1994)

Research Questions	RQ1: What are the primary reasons individuals choose to leave the field of computer science across various departure stages? RQ2: What external or contextual factors influence the decision-making process for individuals considering leaving the field of computer science across various departure stages?
Data Collection	Reddit posts from individuals who are in computer science but who have decided or are considering leaving the computer science field
Data Analysis	Thematic analysis using generative AI GATOS method (A. Katz et al., 2024) with an added human-in-the-loop step

1.9 Significance and Implications

The results of this dissertation make several important contributions to the broader literature and the field of computer science attrition. First, by comparing the findings from Manuscripts 1 and 2, this work offers a fresh perspective on Bronfenbrenner's Ecological Systems Theory (1979), shedding light on how individuals interact with various system layers and how these interactions differ by gender. Second, it expands our understanding of career decision making in computer science by exploring how students decide to pursue minors, an area largely overlooked in existing research, which has traditionally focused on majors. Third, this study identifies new departure points along students' computer science pathways, offering insight into previously unexamined stages of disengagement. Finally, it makes a methodological contribution by demonstrating novel applications of generative AI for qualitative data analysis.

The results of this research also offer actionable guidance for creating more inclusive and supportive environments that can improve retention in computer science, particularly for women and individuals who are not fully immersed in the field. At the individual level, the three manuscripts highlight strategies for building resilience, fostering confidence, and promoting low-stakes exposure to computer science. For educators, peers, and family members, the findings emphasize the importance of creating environments that validate diverse experiences and pathways into the field, recognizing that even small, everyday interactions can significantly influence a person's sense of belonging and decision to persist.

At a broader systems level, the studies demonstrate how academic and industry structures can either support or hinder engagement in computer science. Elements such as course design, community-building, mental health support, and flexible program pathways play a critical role in student and employee persistence. Additionally, institutional policies and cultural narratives must evolve to reflect the full diversity and wide-ranging relevance of computer science careers. By addressing attrition across these interconnected levels, change at every level in the system can help reduce the high attrition rates across the field.

1.10 Contributions

This dissertation comprises three manuscripts, each developed with contributions from multiple collaborators. The specific contributions for each manuscript are as follows:

Manuscript 1: The study design was developed by Dr. Hooshangi, the Principal Investigator (PI) of the NSF project. The participant recruitment surveys and interview protocol were designed by Khushi Parajuli. Interviews were conducted as follows: two by Khushi and Dr. Hooshangi, two by Khushi and myself, and the remaining three by myself. I developed the final codebook used for analysis; however, the resulting themes were informed by prior thematic development by Dr. Hooshangi, Khushi, and myself.

Manuscript 2: The study design, which follows the framework established in Manuscript 1, was developed by Dr. Hooshangi. The participant recruitment surveys and interview protocol, also adapted from Manuscript 1, were designed by Khushi P. I conducted all participant interviews and was solely responsible for developing the codebook and conducting the data analysis.

Manuscript 3: I was responsible for the study design, data collection, and analysis. The data analysis was conducted using a generative AI framework primarily developed by Dr. Katz. While I contributed by engaging in discussions on how the framework could be developed for qualitative analysis and applied to this study, the computational code itself was developed through multiple iterations based on Dr. Katz's work. My role focused on managing the human-in-the-loop aspect of the analysis, ensuring that the AI-generated results were accurate, and themes were interpreted and refined within the context of the research.

Chapter 2: Manuscript 1

2.1 Introduction

Although women make up over 59% of all college enrollments in the United States (*National Center for Education Statistics*, n.d.), they account for only 20% of enrollments in computer science (Engineering and Engineering Technology by the Numbers, 2022). Similarly, while women represent about half of the overall workforce (47%), their representation in computing occupations remains low at just 28% ("Women In Technology Statistics," 2022). This lack of representation in the educational pathway has implications beyond workforce participation. Since half of all technology users are women, underrepresentation in education and, subsequently, in the workforce, can lead to the development of products and services with unintended gender biases (Loiacono et al., 2016). For example, voice recognition systems have struggled to recognize women's voices (Loiacono et al., 2016), and Amazon's automated recruiting tool discriminated against women applicants (Teodorescu et al., 2021).

Within the literature on women in computing, there is a gap for lessons learned from the experiences of women students who have a peripheral interest in computing but who are not formally in the computer science pathway. Most of the literature focuses on the persistence and retention of women students already in the computing pathway, i.e., those who have chosen computer science as their field of study (Amelink et al., 2018; Blackburn, 2017; Cheryan et al., 2009; Sinclair & Kalvala, 2015). Other work has focused on K-12 education and psychological and social factors that contribute to young girls' loss of interest in math and science (Alvarado et al., 2018; Gunderson et al., 2012; Master et al., 2016). But these studies do not directly address the following question: what happens to high achieving women with some interest in computer science who disengage?

Enrollment in introductory computer science courses is at an all-time high (Zweben & Bizot, 2023). Many universities now offer multiple versions of these introductory courses to cater to a large and diverse audience. However, what happens to women who perform well in these courses but ultimately choose not to pursue further studies or careers in computing? Additionally, what insights can we gain from the experiences of these students to inform best practices for creating a welcoming and supportive environment—one that encourages a greater number of these individuals to continue in their computer science pathway? This paper aims to address these questions.

2.2 Background

2.2.1 Lack of Representation of Women in Computing

While women's representation in many STEM disciplines at the bachelor's level has increased since the mid-1990s, the proportion of computer science bachelor's degrees awarded to women has consistently remained low (Cheryan et al., 2017; Sax & Newhouse, 2018). A substantial body of research seeks to understand the factors contributing to this gender disparity. Studies on cognitive development from early childhood through adulthood indicate that men and women demonstrate equal talent in mathematics and science (Ceci et al., 2009). However, attitudes and expectations often have a stronger impact on career trajectories (Ceci et al., 2014; Spelke, 2005), with women generally showing lower interest in introductory computing courses than men (Beyer, 2014). Gendered preferences for computing may arise from girls' later exposure to computing activities (Lehman et al., 2020; Smith & Gayles, 2018), pervasive stereotypes that link computing with boys and men (Corbett & Hill, 2015; Main & Schimpf, 2017; Yücel & Rızvanoğlu, 2019), and biases within the learning environment, which can reduce women's sense of belonging (Sax, Lehman, Jacobs, et al., 2017) and ultimately deter their interest and persistence in computing fields (Buse et al., 2013).

In addition to shaping interest, similar factors also influence women's persistence and retention in completing computer science degrees. Recent studies highlight stereotypes, biases, masculine classroom cultures (Eagly et al., 2000; Riegle-Crumb et al., 2019), lack of computer self-efficacy, and an uncertain sense of belonging (Beyer, 2008, 2014; Good et al., 2012; Lehman et al., 2016) as barriers to both successful degree completion and career entry for women in computing (Blackburn, 2017; Cheryan et al., 2017). When examining why women leave the computing pathway, research has identified factors such as masculine cultures, stereotyping, an unstable sense of belonging in classroom environments (Cheryan et al., 2009, 2013), and limited early exposure to the field (Mullan, 2018; Sevin & DeCamp, 2016). Conversely, early exposure to computing has been shown to foster greater computer self-efficacy (Correll, 2001; He & Freeman, 2010; Master et al., 2017) and to cultivate more positive stereotypes associated with the tech field (Cheryan et al., 2013).

Women often struggle with computing confidence, even when they perform well in computer science courses. Although women tend to earn higher grades than their men counterparts in computing courses (Woodfield, 2012), they frequently rate their own abilities lower than men do (Lehman et al., 2016), which contributes to lower computing self-efficacy (Beyer, 2014). Additionally, women are more likely to perceive the course pace and workload as challenging compared to men (Barker et al., 2009). Consequently, this perception of lower computer self-efficacy affects their expectations for success in the technology field (Beyer, 2014; Dempsey et al., 2015; Rosson et al., 2011).

Most current research focuses on the negative aspects of women's experiences in computing classrooms, including issues with confidence and self-efficacy. This often paints a bleak picture of women's ability to excel and thrive in computing, which is not necessarily accurate (Woodfield, 2012). However, the literature is less comprehensive regarding other factors influencing disengagement, such as women's interest in other fields or their sense that being part of the computing community is unnecessary. Women have choices, and many women are fully capable of excelling in computer science courses and careers, yet they simply choose not to pursue this path. This study adopts an asset-based approach to examining the lack of women's representation in computer science, centering on an understanding of why these capable individuals make this choice.

2.2.2 How People Choose Majors

To understand why women may or may not choose computer science as a major, it is helpful to first consider how students select college majors more broadly. Numerous theories have sought to explain the factors behind students' choices of fields of study. McCrae and Costa Jr. (Costa & McCrae, 1999) developed the Five-Factor Model, which suggests that decisions are shaped by an individual's basic tendencies, characteristic adaptations, self-concept, objective biography, and external influences. This model includes five personality traits—extraversion, agreeableness, conscientiousness, neuroticism, and openness—that capture variations in personality. Studies have shown that college students in different majors often exhibit specific personality profiles, indicating that personality plays a significant role in students' choice of major (Balsamo et al., 2012).

Additionally, Holland's Theory of Personality and Vocational Choice (Holland, 1959) posits that six personality types—realistic, investigative, artistic, social, enterprising, and conventional—guide individuals toward particular career paths. This model has also been found to influence STEM major selection, with students displaying strong investigative traits more likely to choose STEM fields over those with more artistic traits (Chen & Simpson, 2015). Finally, Bandura's Social Cognitive Theory (Bandura, 1986), adapted as Social Cognitive Career Theory (SCCT) (R. W. Lent et al., 1994) for career choice, emphasizes that personal, behavioral, and environmental factors shape individuals' interests, goals, and actions. SCCT research has shown that social support, career opportunities, and the potential to make a positive societal impact are significant factors influencing students' decisions to major in computer science (Alshahrani et al., 2018).

When choosing a major or career field, women face additional sociocultural barriers and stereotype threats that can deter them from pursuing STEM majors (Williams et al., 2016). Specifically, self-efficacy, math anxiety, and interest have been identified as three significant factors that limit career path choices. Stereotypes conveyed by parents, peers, and role models, along with parental support and with learning experiences, can also influence women's decisions to pursue a STEM major (Bieri Buschor et al., 2014; Szelényi et al., 2013), persist within that major (Perez-Felkner et al., 2014), and ultimately shape their career goals in the STEM field (Leaper & Starr, 2019).

2.2.3 Fields Where Women Are Highly Represented

While women are underrepresented in computer science, this trend does not hold true across all STEM fields. In fact, women earn more than half of all undergraduate degrees in biology, chemistry, and mathematics in the U.S. (Cheryan et al., 2017). This raises the question: what empowers women to pursue these majors at much higher rates than in computer science? Prior research has sought to identify why women excel in some STEM fields while remaining disproportionately underrepresented in others (Cheryan et al., 2017). This underrepresentation begins even before college, with women comprising only 31% of Advanced Placement (AP) computer science students (College Board, 2023). In contrast, girls represent the majority of test takers for the AP Biology exam, and they make up roughly half of the test takers for AP Chemistry, Statistics, and Calculus AB exams (College Board, 2023). A literature review on this topic (Cheryan et al., 2017) identified three main factors contributing to the relative success of women in certain STEM fields compared to their underrepresentation in computer science: (1) the masculine culture of computer science, which leads to a lower sense of belonging for women; (2) a lack of early educational exposure to computer science; and (3) larger gender gaps in self-efficacy.

The first factor, masculine cultures, comprises three components: stereotypes that conflict with how women view themselves, negative stereotypes and perceived discrimination within the field, and a scarcity of women role models (Cheryan et al., 2017). In computer science, prevailing stereotypes are often seen as more masculine and incompatible with women's self-identification. These stereotypes include a higher male-to-female ratio (Matskewich & Cheryan, 2016) and the perception of computer scientists as socially awkward individuals with little interest outside of technology (Beyer et al., 2005; Cheryan et al., 2009, 2013; Schott & Selwyn, 2000). In contrast, fields such as biology, chemistry, and mathematics are associated with less masculine traits, such as discovery (Chambers, 1983), innovation (Board, 2012), positive classroom interactions, such as smiling (Rock & Shaw, 2000), and exhibit a smaller male-to-female ratio (Matskewich & Cheryan, 2016). These stereotypes have a significant impact, as women with stronger implicit male-science biases are less likely to identify with the field and develop weaker career aspirations related to it (Cheryan et al., 2017; Cundiff et al., 2013; Lane et al., 2012).

Stereotypes regarding women's abilities to succeed in various STEM fields also play a significant role in their experiences. In fields like computer science, where the male-to-female ratio is higher, women are more likely to encounter stereotype threat (Inzlicht & Ben-Zeev, 2000; Murphy et al., 2007; Sekaquaptewa & Thompson, 2003; Shaffer et al., 2013). They may perceive that men and women students receive different treatment (Heyman et al., 2002) and often view the environment as less welcoming (Morris & Daniel, 2008). In contrast, women in fields with a more balanced gender ratio, such as biology, chemistry, or mathematics, generally face less gender discrimination (Robnett, 2016) and are more likely to have role models (Lyons, 2013) who can support their persistence in these fields (Griffith, 2010).

Fields in which women are more represented coincide with fields to which women are more exposed in early education (Cheryan et al., 2017). Computer science courses are less likely to be offered to K-12 students (Google & Gallup, 2015b), and when it is available to students, still fewer students take these courses due to the fact that no schools make these courses a requirement (Zinth, 2007). Compared to biology, chemistry, and math, which are offered in most high schools in the US (United States Departments of Education, 2014). Not only that, but all high schools require a minimum level of math, 40% of schools require at least one biology course, and a handful require chemistry (Zinth, 2007). In addition to the limited freedom and availability of course offerings, there exists a gender gap in who takes what courses. Women are less likely to take computing courses before college compared to men (Barron, 2004; Nord et al., 2011), where as more women take biology and chemistry courses in high school than men (Burkam, Lee, & Smerdon, 1997; Schreuders, Mannon, & Rutherford, 2009).

Finally, both undergraduate and high school women report lower self-efficacy and self-perceptions in computer science compared to their men counterparts (Cheryan & Plaut, 2010; Rosson et al., 2011). Notably, this gender disparity in self-assessment is smallest in the field of biology (Matskewich & Cheryan, 2016). The prevalence of negative stereotypes in computer science, compared to fields like biology, chemistry, and mathematics, helps explain the observed differences in gender gaps. Fields that are associated with negative stereotypes tend to exhibit larger gender gaps in self-efficacy (Correll, 2001).

2.3 Research Purpose and Questions

While our understanding of the reasons behind the gender gap in computing has improved, the persistent lack of sustained success in addressing this imbalance indicates that further work is needed (Smith & Lapan, 2021; Yates & Plagnol, 2021). Unfortunately, despite 20 years of research and discussion, the graduation rate for women in computer science remains at only 20% nationwide. Researchers have advocated for a more holistic approach to understanding the lived experiences of women students, with a focus on in-depth qualitative analysis that captures the nuanced complexities of students' lived experiences (Blackburn, 2017; Riegle-Crumb et al., 2019; Sinclair & Kalvala, 2015).

The purpose of this study is to address the gap in the literature regarding women who are outside the traditional computer science pathway who express some interest in the field by enrolling in at least one introductory computer science course, perform well, but ultimately choose not to pursue a formal qualification in the field. Specifically, we aim to answer the following research question: Why do women who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor?

2.4 Theoretical Framework

This study is guided by Bronfenbrenner's ecological systems theory (Bronfenbrenner, 1979), which situates an individual and their decision-making within multiple interrelated contextual spheres of influence. This framework takes into account both personal settings and relationships, as well as various levels of external contexts, regardless of whether an individual is a direct participant in the system. The framework comprises four distinct layers of systems:

1. **Microsystems:** settings and relationships experienced directly by the individual. In our study, this included students' families, friends, peers, academic advisors, and instructors.

2. **Mesosystems:** interconnections between the microsystems. In our study, classroom settings, study groups and project teams, friend groups, and extra curricular groups are included in this system level due to how pieces of the microsystem interact with one another.

3. **Exosystems:** settings in which the individual is not directly involved, yet influences the microsystems. For example, students' experiences with their microsystem could be affected by the media, family and friends' jobs, admission processes, college or K-12 policies and resources, government policies, or instructor priorities/education.

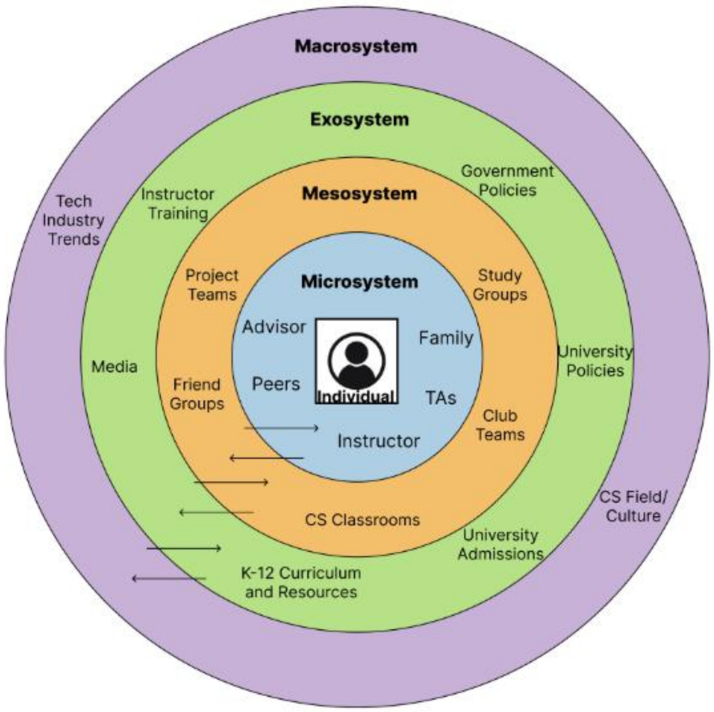
4. **Macrosystem:** overarching culture that influences the actors, including industry trends, department and university vibes, and the overall culture of computer science in the United States.

Figure 2.1 shows these different systems, and how each lower-level system is contained within the higher-level systems, with the individual at the center. With this layout, Bronfenbrenner's framework places the focus on the role of the environment. For our context, it allows for individual variation while emphasizing the influence of multiple agents in academic decisions and potential transitions—factors often overlooked by more individual-focused frameworks.

Ecological transitions, such as selecting or changing an undergraduate major, lie at the heart of this approach. These transitions are crucial developmental phases that necessitate changes in one's perceptions and/or settings, typically leading to behavioral adaptations. By applying ecological models, scholars recognize that various layers of students' environments can influence their postsecondary choices. While traditional college choice models may consider aspects of social context to varying degrees, ecological models require a comprehensive focus on the ecosystems surrounding the individual to fully understand their postsecondary decision-making processes.

Previous studies utilizing Bronfenbrenner's theory have examined various aspects of decision-making in educational contexts. For instance, research has explored women engineering students' sense of belonging and their intentions to persist in engineering (Glisson, 2023), students' major decision-making processes (Ma, 2011), the influence of public narratives on college choice (Hallmark & Ardoin, 2021), and the factors that lead first-generation Appalachian female students to choose education as a major (Gannoe, 2013). Additionally, other studies have employed theories derived from Bronfenbrenner's work to analyze women's choices in STEM majors (McKinney et al., 2021) and the decision-making processes of engineering students regarding their major (Ngambeki, 2012). We chose this framework to guide our study because of its established effectiveness in examining decision-making, particularly concerning major choice and persistence, as well as its relevance in a gender-focused context within engineering.

Figure 2.1. Adapted Bronfenbrenner's Ecological Systems Theory



Additionally, because we are interested in non-CS students who do well, the phenomenon we are concerned with is less one of deficit or a lack of self-efficacy and more about the environment and interactions with the computer science culture and community. In other words, we approach this phenomenon from an asset-based, anti-deficit perspective (Ramos Montañez, 2023). Given the impact of stereotyping and negative cultural norms identified by prior research (Corbett & Hill, 2015; Main & Schimpf, 2017; Yücel & Rızvanoğlu, 2019), Bronfenbrenner's theory allows us to take an asset-based approach and focus on the environmental factors that influence students' major choice. In doing so, it puts emphasis on the layers of the various system levels and the connection between these layers as they influence the overall decision making of the individual.

We utilized this framework to guide the design of our interview protocol, crafting questions that addressed each level of the various system layers. For instance, when exploring the microsystem, we asked participants about their interactions with classmates and instructors/TAs, as well as the influences they experienced from friends and family. To investigate the mesosystem, we inquired about their classroom experiences. Regarding the macrosystem, we focused on participants' future plans and their perceptions of the larger computer science community. The full interview protocol is provided in the Appendix.

We chose not to pose direct questions about the exosystem, as this layer involves elements that students are not directly engaged with and are therefore less likely to consciously recognize in relation to their experiences. However, we remained attentive to this aspect of Bronfenbrenner's theory during the interviews and posed follow-up questions whenever participants mentioned policies, processes, or other components of the exosystem that influenced their experiences. For example, when discussing their motivation for taking the course, all participants noted that it was a requirement for graduation. This prompted us to ask follow-up questions to gain deeper insights into specific graduation requirements and the options available to fulfill them.

2.5 Methods

2.5.1 Sampling

The study population comprised non-CS women undergraduate students who had taken an introductory computer science course designed for non-CS majors at Virginia Tech. During the spring and fall semesters of 2023, we distributed a survey via email to all students enrolled in one of the five introductory computing courses offered for non-CS majors. This survey included questions regarding students' demographic information, their performance in the course, their intentions to pursue a computer science minor, and their willingness to participate in a 30-minute interview for a $20 Amazon gift card.

From the survey responses, we selected seven students who self-identified as women, based on their self-reported high performance in the course (earning an A or a B) and their intention not to pursue a minor in computer science. These seven students were chosen one by one until we reached a point of data saturation, where no new themes or significant insights were emerging from subsequent interviews. This indicates that the sample size was sufficient to capture a range of relevant experiences and perspectives aligned with the aims of the study. When selecting these students iteratively, we primarily aimed to ensure a diverse representation of majors within our sample and secondly to have a diverse representation of race/ethnicity and prior programming experience if available. Table 2.1 provides a breakdown of our participant demographics.

Table 2.1. Participant Demographics

Pseudonym	**Race/Ethnicity**	**Major**	**Prior Programming Experience**	**Course Taken**
Lydia	Other	Biomedical Engineering	AP Computer Science in high school	Introduction to Python

Kai	African American/Hispanic	Industrial Systems Engineering	Community college computer science course (dropped)	Introduction to Python
Jennifer	White	Cybersecurity Management and Analytics	AP Computer Science in high school	Introduction to Python
Isabelle	White	Smart and Sustainable Cities	None	Introduction to Python Intermediate Python (dropped)
Maddie	White	Smart and Sustainable Cities	After school program in 4th grade	Introduction to Python
Charlotte	White	Statistics and Psychology	None	Computational Thinking Introduction to Python
Harper	White	Business Information Technology	None	Introduction to Python

2.5.1.1 Participant Personas

2.5.1.1.1 Lydia

Lydia is a multiracial, first generation, senior, biomedical student. She took Introduction to Python her last semester because it was a graduation requirement to have a coding class. Though she had a choice between a Python and Java course, she chose Python due to the fact that she was a bit more familiar with it. In high school, she took AP computer science, though it was mainly HTML based and was taken almost four years ago. After graduating, her plan is to attend graduate school for designing medical devices. She believes she needs to improve her coding skills to be successful in her career. She expressed an interest in, at some point in the future, taking further computer science courses. In particular, she is looking into a free online course to improve her MATLAB skills.

2.5.1.1.2 Kai

Kai is a multiracial (Black and Hispanic) junior, industrial systems engineering (ISE) student. She took Introduction to Python in her sophomore year, and had previously taken a community college computer science course that she dropped . She could not remember what it covered. In her freshman year, Kai was in a structured and time consuming development program, and joined their cyber security team, but due to the time commitment, she dropped both after her first semester. Going into the introductory computer science class, she was thinking about minoring in computer science, but due to the negative experiences she had, she decided not to pursue computer science further.

2.5.1.1.3 Jennifer

Jennifer is a White, senior, cybersecurity management and analytics student. She took Introduction to Python in her junior year because she was required to take a computing class for graduation. She had a choice between Python and Java but decided to take the Python course because she took AP computer science in high school that was taught in Java and did not enjoy it. Her parents are both electrical engineers and, in high school, Jennifer was planning to be a computer engineering major, but she was waitlisted by the university. So, she went to community college for a year then later transferred in as a political science major to guarantee entry into the university, though she had every intent on eventually switching to engineering. After having a difficult experience in her physics class, she landed on cybersecurity as the next best major to engineering without it being as technical. While she is interested in exploring the more technical side of computing, and expects she will one day have a job where she needs this knowledge, she has no intention of taking another computer science course due to time constraints. She has a government job lined up contracting with the intelligence community, and hopes to have her company pay for a masters in information technology specializing in cybersecurity and networking.

2.5.1.1.4 Isabelle

Isabelle is a White, senior, smart and sustainable cities student with a minor in data decisions and political science. She took both Introduction to Python her sophomore year and Intermediate Python in her junior year. She was required to take an introductory computing course for her data decisions minor and chose Python because she heard it was the easiest of the language options. After enjoying the first class, she decided to continue on to the second class, but she had very negative experiences that led her to dropping the second course. While she has no plan to take another course, she thinks a class that touches on multiple languages would be very interesting, especially since she notes almost all corporate careers are evolving to need some understanding of computer programming. She plans to pursue a masters in public administration before continuing to law school.

2.5.1.1.5 Maddie

Maddie is a White, junior, smart and sustainable cities student with a disabilities minor. She took Introduction to Python because it double counted as a math credit and major elective. While she had prior programming experience via an afterschool program in the fourth grade, all she remembers from that experience was being confused and having code written for her. Because of how much effort she had to put into the introductory course and feeling like programming was not intuitive for her, she cannot imagine taking a more advanced course and thus has no plans to pursue computer science any further. After college, she plans to go into urban planning as an accessibility consultant.

2.5.1.1.6 Charlotte

Charlotte is a White, junior, statistics and psychology student. She took Computational Thinking as a freshman and Introduction to Python as a sophomore. She was required to take the Python course or software design for her statistics major, but was advised that the Python course would likely be more useful to her. She has no plans to take additional computer science courses because she has decided that computer science is just not her thing. She is unsure what she will do after she graduates, deciding between getting a job using her statistics degree or going to graduate school for psychology, but she does not see herself using computer science in her future.

2.5.1.1.7 Harper

Harper is a White, senior business information technology student with a minor in data decisions. She took Introduction to Python in her sophomore year because it was required for her major. She could have taken software design, but heard it was more difficult than the Python option. She also had the option to take Introduction to Java, but having been previously exposed to Java, she was more interested in Python than Java, and felt as though more companies would want her to have experience inPython rather than Java. She has had other computing experiences with her in major courses, learning Visual Basic, R, and SQL, but has no intention of taking more computer science classes. She debated getting a minor in computer science, but decided she was better off getting a certification instead. Her plan is to pursue data analytics, but she does not see herself coding in her future career unless her company specifically asks her to.

2.5.2 Data Collection

In addition to the initial survey data, we conducted semi-structured interviews with our participants. These interviews were held over Zoom and lasted approximately 30 minutes each. The questions focused on students' experiences in their computing courses, their future plans, and their interactions with the larger computer science community. Our interview protocol, designed using Bronfenbrenner's (Bronfenbrenner, 1979) ecological framework as a guide, can be found in the Appendix. After conducting the interviews, we transcribed them using Zoom's automated transcription tool and subsequently reviewed and corrected them manually to ensure clarity and accuracy.

2.5.3 Data Analysis

To analyze the interviews, we employed thematic analysis, a widely used method for identifying and analyzing patterns in qualitative data (Braun & Clarke, 2006; V. Clarke & Braun, 2017). This approach allows for the identification of higher-order themes without being constrained by a priori codes. We followed Braun & Clarke's ((Braun & Clarke, 2006; V. Clarke & Braun, 2017)) step-by-step method for conducting the analysis. First, we familiarized ourselves with the data by either watching the interview video recordings or reading the transcriptions. Next, I coded the interviews, generating their initial codes. These codes highlighted elements in the data that were particularly interesting and served as the basic units for meaningful assessment regarding the phenomenon being studied (Braun & Clarke, 2006; V. Clarke & Braun, 2017)). Example codes and their definitions can be found in Table 2.2, with the full list of codes and their definitions in the Appendix.

Table 2.2. Codebook Excerpts

Code	**Definition**
Background information	Discussion of participant's personal background information (class standing, major, etc.)
Prior programming experience	Discussion of participant's prior experience with programming (or lack thereof)
Reason for taking course	Discussion of participant's reason or motivation for taking introductory CS course
Reason for K-12 engagement	Discussion of why individuals engaged with CS (or not) in K-12
Prior experience influence	Discussion of participant's prior programming experience (or lack thereof) influenced their experiences in introductory course
Impact of course	Discussion of how the course has impacted participant's perceptions, skills, and feelings around CS

Following this, similar codes were grouped together to create themes. During this analysis, themes were repeatedly reviewed, merging similar ones, eliminating themes that lacked sufficient data to support them, and breaking down larger themes into smaller, more concrete categories. Originally, we worked as a group and came up with themes for the first four interviews. Then given the additional three interviews, I created new themes, guided by the original themes that were developed for the subset of the first four interviews, but anchored more to the research questions. The resulting themes and their contained codes can be found in Table 2.3, with the full codebook in the Appendix.

Table 2.3. Code to Theme Mappings from Thematic Analysis

Theme	**Codes**
Negative Course Experiences	Instructor interactions
	Course changes
	Course negatives
	Isolating
	Value-experience misalignment
	Impact of course (course impact)
	Self-efficacy
	Prior experience influence
	Course pace
	Course difficulty
	Male stereotype
	Anti-social stereotype
	Stereotype origin
	CS misperceptions
	Difficult culture

	Stereotype influence
Interest	Non CS interest
	CS interest
	No CS interest
Community Belonging	Insider/outsider
	CS community

2.5.4 Author Positionality

The first author identifies as a woman engineer and currently serves as a faculty member and program director in a computer science department at Virginia Tech. With over 15 years of experience working with underrepresented populations in technology-related fields, she has observed that many stereotypes and lack of support that existed during her own academic journey continue to persist in academia today. Through her research, advocacy on departmental committees, and mentorship of students, she aims to reduce barriers for women, helping them to thrive and feel welcomed in the computing community.

The second author identifies as a woman computer scientist. She holds both a bachelor's and a master's degree in computer science and has significant experience as one of the few women in her computer science classrooms. Although she entered college as a mathematics major, it was her success and interest in her first programming course during her freshman year that inspired her to then pursue a major in computer science. Throughout her academic journey, she has encountered sexism from both peers and professors, grappled with a lack of confidence linked to her gender identity, and successfully navigated the challenges of a gendered microclimate. These experiences enable her to connect with the participants on a personal level and interpret the findings in a meaningful way.

The third author identifies as a woman computer scientist with a degree in Computational Modeling and Data Analytics and as a computer science graduate student, and she feels a personal connection to this study. During her undergraduate studies, despite being actively engaged in the field and developing strong skills, she struggled to feel fully integrated into the computer science community. These experiences have motivated her to explore the challenges faced by women students in similar situations.

Our positionalities have enabled us to authentically connect with participants and engage empathically with their experiences. However, we took care to ensure that our personal experiences did not influence our analysis and reporting of participants' narratives. We remained committed to grounding our work in the lived experiences of the participants, avoiding the temptation to cherry-pick negative stereotypes or create a skewed narrative. Instead, we focused on highlighting their strengths and positive experiences, while also providing counterexamples to themes when appropriate.

2.6 Results

Thematic analysis revealed three themes that help explain why our participants did not pursue a minor in computer science: negative experiences, community belonging, and interest. Each of these themes are further unpacked and explained below.

2.6.1 Negative Experiences: Women have negative experiences in their computer science classrooms

Participants encountered a variety of negative experiences in their introductory computer science courses that influenced their decision to disengage from the field. These experiences were shaped by several key aspects of the course, including instructor and teaching assistant (TA) support and teaching approaches, engagement with assignments and the nature of coursework, the structure and scaffolding of the course, and the social dynamics within the learning environment.

2.6.1.1 Needing More Support from TAs and Instructors

While participants generally praised the supportiveness of professors and TAs during office hours, several participants shared negative experiences related to the logistics and productivity of these sessions. For instance, Lydia recalled waiting over an hour for assistance in office hours but ultimately had to leave for her next class before receiving assistance. Although TAs were diligent in supporting individual students, the long wait times created frustration and hindered accessibility. One participant also noted that office hours did not meet their expectations for effective support. Isabelle described her repeated visits to office hours, only to leave feeling that she had gained little from the experience. After trying both TA and professor office hours without success, she was unable to get the help she needed to be successful and ultimately dropped her course.

> *"[The TA] would meet whenever, but [...] I wasn't getting that much from it. But I was meeting with him all the time [...], and it got to the point where I was like, 'I'm just going to try with the professor'. And I did meet with the professor a few times before I dropped. It was [...] my last ditch effort, but he just [...] wasn't as good about [...] explaining things to me"* -Isabelle

Finally, participants without prior coding experience felt disadvantaged and less supported in their courses. Professors often assumed a baseline level of familiarity with programming concepts that many students without prior knowledge did not possess.

"People that [...] already know everything about CS, who get up in the first 10 min of the lesson and they're like, 'oh, I already know all this', and I'm like, 'oh, this is intro to python class, what do you mean?'" -Kai

2.6.1.2 Perceived Inapplicability of Course Content

While some participants noted how assignments connected to real-world applications, others felt this connection was lacking, which ultimately contributed to their disengagement from computer science. Lydia, for instance, shared that assignments with practical applications would have made the course more engaging. Without these connections, her interest in computer science waned in comparison to other fields, leading her to pursue those fields instead. Kai echoed this sentiment, explaining that assignments grounded in real-world scenarios would have motivated her to engage more deeply with the material.

Due to a lack of practical applications with their coursework, participants also highlighted significant misperceptions about the career opportunities available with a computer science degree, which contributed to their decision to disengage from the field. Many students, based on their limited exposure, believed that computer science was a narrowly defined and restrictive degree, leading primarily to careers in game design, security, web development, artificial intelligence, or software engineering. This constrained view of the field not only failed to align with their interests but also reinforced their decision to move away from computer science.

Lydia reflected on how her perception shifted after seeing her senior friends in computer science pursue “cool” data informatics and visualization projects that deeply resonated with her own field interests. She stated that if she had known about these opportunities earlier, she might have taken more computer science courses or even pursued a minor in the subject. Similarly, Kai shared how she decided to switch from a computer science major to industrial systems engineering (ISE) because of the greater diversity of opportunities she saw in ISE. Kai explained that ISE offered pathways that spanned management, ergonomics, manufacturing, and operations research, which felt broader and more varied compared to the options she perceived in computer science.

"Well, most of the CS majors I talk to are pretty much all doing the same thing, have the same interests and mindset. I feel like [with ISE], you could talk to three people, and there'll be three completely different people doing completely different things. And even in my intro to [ISE] class, I could see all the different avenues and concepts that we cover. [...] It's [...] [used] for things like ergonomics, which is like human factors, manufacturing, operations research, and management. And I'm like, that's already four right there. [...]. But yeah, I think mostly it's just variety. Diversity not just of the degree itself but with the people and opportunities as well." -Kai

The perception of limited career paths in computer science also had deeper psychological effects, negatively impacting students’ confidence and self-efficacy. For instance, Jennifer shared that her limited understanding of the wide range of careers in computer science contributed to feelings of imposter syndrome. Unaware of the diverse roles and career paths in computer science, she felt that her work in cyber networking did not count as 'real' computer science. Her perception of the field was so narrow that she felt her contributions were invalid, as they did not fit into the stereotyped domains of AI, game design, or software engineering. Additionally, Jennifer believed she was not capable of succeeding in computer science because she at times relied on Google to complete her assignments, assuming that 'real' computer scientists did not need such resources.

Other students had misperceptions about how computer science skills applied to actual work environments, further compounding their disengagement. For example, Maddie assumed that liking data analysis over data cleaning meant computer science would not be relevant to her future career, misunderstanding the integral role of programming in data-driven tasks. Similarly, Charlotte, who pursued a degree in statistics, believed that a data analyst role would not require programming. Instead, she thought her work would primarily involve interpersonal tasks, again revealing the underlying stereotype that computer science work is isolating and technical rather than collaborative and people-facing.

2.6.1.3 Needing More Course Structure and Scaffolding

While some aspects of the course structure were beneficial to participants, others posed significant challenges. Assignments and projects emerged as a significant source of frustration for participants, with some feeling that the tasks became increasingly disconnected from the course material. Kai, for instance, described how the third project completely altered her experience of the course. Initially, the first two projects aligned well with the content, but the final project represented a sharp departure in both difficulty and scope. She explained that the project felt disconnected from the rest of the course and was nearly impossible to complete without excessive help. This experience left her feeling like a "guinea pig" and ultimately overshadowed her otherwise positive impression of the course, making her disengage from computer science.

"In the beginning, I was feeling really good about it. [...] When I did those first two projects, I was like, 'okay, [...] I could see how they applied all that'. But towards the end, towards that last project, it just undid everything. I'm not going to lie, I hate to be that person where [...] one bad experience ruined the rest, [...] all the good. But yeah, towards the end, it was just a nightmare. [...] I don't know, I felt like a guinea pig. But [...] for the worse, not the better." -Kai

Another common frustration was the sudden jump in length between weekly assignments and larger projects. Weekly assignments typically required only 5–10 lines of code, while projects demanded much more effort, sometimes involving over 80 lines of code. This lack of scaffolding between tasks left many participants feeling unprepared for the increasing complexity. Additionally, many participants noted that transitioning from simpler assignments to more complex projects was difficult, as the course did not provide enough support to help integrate individual concepts into a cohesive whole.

"I would say honestly, [...] [the] only thing different would be [...] just not throwing a huge project at you when all you've been doing is reading about code and then doing like two lines of code and then five exercises [...] every Sunday." -Charlotte

The shift in course difficulty across weeks was also a significant factor shaping participants' experiences and decisions regarding continued engagement in the field. Many participants noted that the course began at an approachable level and speed but quickly escalated in complexity, leaving them overwhelmed and unprepared. Maddie noted that it was only her prior programming experience that allowed her to keep up with the pace of the course.

Isabelle explained how the building nature of the course exacerbated her struggles: failing to fully understand one concept early in the semester made it increasingly difficult to grasp subsequent material. She explained that the cumulative effect of these challenges combined with a course flow that seemed to jump around in an illogical way led to feelings of inadequacy and a sense of being left behind, contributing to her disengagement from the field.

"And then [...] it was the pace. I think because [...] he did pick up [...] the first 2 or 3 weeks, I was like, 'okay, like this is fine, [...] nice'. And then all of a sudden it kind of [...] went zero to 100. At least I felt like it did. It probably didn't [...]. It was just the pacing was [what] hurt me the most. Because once you don't grasp one topic, [...] I did not get a single thing" -Isabelle

Maddie had a similar experience when the complexity of the material increased. As the course delved deeper into topics like loops and iterations, she began to feel lost, which led her to the realization that computer science was not for her. This shift in her understanding caused her to decisively turn away from the field.

"Honestly, I realized computer science was not for me. [...] At first, it was making a lot of sense and I really liked it. But definitely, once we got more into loops and iterations, I got a little lost." -Maddie

The lack of scaffolding also created additional challenges within the course, leading to negative psychological effects. For example, Charlotte shared how encountering error messages during projects left her uncertain about how to proceed. This frustration decreased her self-efficacy which contributed to her decision to stop pursuing further studies in the field. And Isabelle noted that she needed the course to focus more on explaining how things worked behind the scenes rather than simply teaching the big picture or how to use them.

Finally, participants expressed a desire for more resources, such as a textbook, to provide clarity of flow and allow for independent review of the material. Those without a textbook reported struggling to revisit and synthesize concepts, which hindered their ability to grasp concepts and their connections to other course content.

"I never thought I'd be saying this, but I wish there was [...] a textbook he followed, which usually I'm like, 'oh, I never use the textbook, I wouldn't want to buy it'. But the first course, he had an online textbook [...] [and] assignments within the textbook to do every week. And that was so helpful for keeping me on track. [...] Because it builds on itself, so I can go back and whatever I didn't know, I can go back and look over." -Isabelle

2.6.1.4 Lacking Social Engagement and Representation

A common challenge for our participants was the absence of opportunities for meaningful interactions with peers. Participants noted that they primarily engaged with professors, TAs, or friends they already knew, such as roommates or classmates from their major. Charlotte attributed this lack of interaction to the introverted nature of many students in the class, explaining that she was always the one to start conversations. Others pointed to structural issues, such as the absence of group projects, large class sizes, or professors not fostering collaboration.

Lydia observed that many students skipped class or frequently changed seats, making it even harder to build relationships during class.

"The class environment was basically just like sit down and be quiet and listen" -Kai

This lack of peer interaction left participants feeling isolated. For those without an existing friend in the course, there were limited opportunities to connect with classmates. Even when participants did not find the coursework overly challenging, they still identified the lack of interaction as a negative aspect of the course. For Lydia, working alone on assignments in her room created a sense of disconnection. She described how doing work alone conflicted with her desire for collaboration and teamwork, which she valued in a career. This internal conflict ultimately pushed her away from the field.

"I'm a very social person and I like the collaborative thing. And I found that at least with the computer science class I'd taken in high school and all my other computer science experience is that, [...] for example in this class there was no teamwork or no team project. Everything was completely individual. I was doing the projects and the assignments and the exercises in my home, in my room, just sitting in front of my computer. And I found that I wasn't getting the collaborative or [...] the teamwork aspect that I wanted from the field" -Lydia

Because she did not have opportunities to engage with others, Isabelle perceived herself as the only one struggling in the course, leading her to believe that she was inadequate to learn.

This sense of isolation and self-doubt contributed to her conclusion that computer science was not the right field for her, and ultimately dropped the course.

Due to their experiences in class, where collaboration was limited, participants developed the perception that computer science is an individualistic, non-collaborative, and non-creative field. This view was cited as a significant deterrent from the field. Lydia expressed how the lack of teamwork in computer science courses contributed to her decision to disengage, as it did not align with her desire for collaborative learning environments.

"Computer science and coding is not a social career per se. I think that maybe it was just that stereotype that [...] pushed me away from it originally. And why I didn't choose or why I never was really drawn to computer science." – Lydia

She contrasted this with her biomedical engineering courses, which involved team-based projects and interactions with doctors and patients. While Lydia later recognized that the individualistic stereotype was not universally accurate, this realization came too late, as her decision to leave the field had already been made.

The little peer interaction participants had in class also gave room to notice and develop negative stereotypes of the field. Participants described how the male dominance of the field was immediately apparent. Lydia described how walking into the classroom made her acutely aware of the other women present due to their small numbers. Charlotte highlighted how the stereotype of male dominance shaped her experiences within computer science, leading to feelings of exclusion and lowered self-confidence. She recounted instances where she felt underestimated by her peers, which negatively impacted her self-efficacy and interest in the field. In contrast, Lydia expressed a different perspective. While she acknowledged the male-dominated nature of computer science, she emphasized that it did not influence her decision to take or persist in computer science courses. Lydia explained that she entered the field expecting such gender dynamics and thus was not deterred by them.

"I know this is not a secret that it's a very male-dominated class and field. Unfortunately, [...] it is very clear when you walk into the class. That was something I noticed very quickly, was kind of the other women who are in the class or just the diversity of students who are taking it. But I never let that [...] impact how I felt about taking the course, because I came into it knowing that it was going to be male-dominated. I already knew that from the stereotype and other friends who had CS classes. So that wasn't something that I'd say [...] limited or kind of came into my view or had an impact on my decision to take the class." – Lydia

Another stereotype developed in their courses was that computer science students are socially awkward loners. Kai described her stereotypical image of a computer science major as someone antisocial and isolated, often spending time gaming alone. Charlotte contrasted this image with her own social skills, expressing how she felt fundamentally different from her idea of a typical computer science student, leading her to believe the computer science field was not for her.

"I feel like CS people aren't very emotionally intelligent. That's [...] a really weird answer. I'm just better at talking to people than spitting code out and making code." - Charlotte

Lydia noted that her classroom experiences reinforced this stereotype. She observed that many of her classmates were introverted or socially awkward, which further contributed to her perception of computer science as a field for less extroverted individuals. And it was this alignment between stereotype and experience that ultimately discouraged her from continuing in computer science.

"I see people who just kinda chose this field because they [think] that it's not social. [...] Definitely a stereotype with computer science and coding that it is for introverted, awkward people. [...] Unfortunately, I feel like a lot [of my] classmates I have talked to [are] very awkward. [...] I feel like [there are] not as many extroverted personalities. At least [...][that] I was exposed to in my classes. So I think the stereotype started kinda early on in my brain and unfortunately kinda stuck with me in those classes." – Lydia

2.6.2 Community Belonging: Women lacked a sense of belonging to the field, and had little motivation to belong

When asked who constitutes the computer science community, participants provided diverse and nuanced definitions. The most common definitions centered around individuals' skills, intelligence, and academic majors. Many participants suggested that being 'smart' or proficient in multiple coding languages, or being a computer science major or an adjacent STEM major, were key criteria for inclusion in the community. In describing who would be considered a member of the community, Isabelle answered:

"Computer science majors. And [...] computer related engineering majors, and I think that's it." -Isabelle

Some participants framed their definitions through the lens of existing stereotypes. For instance, Kai associated the computer science community with stereotypical gamers rather than individuals driven by a broader curiosity about the field, while Maddie perceived the community as predominantly male. Lydia, in contrast, described the community in terms of personality traits, emphasizing the importance of patience and passion over technical skills or identity markers. These varying definitions reflect participants' interpretations of the field's culture and the implicit barriers they perceive to entry.

When asked whether or not they thought they belonged within this community, participants revealed complex relationships with the computer science community and belonging in relation to their decision not to pursue a minor in computer science. None of the participants identified themselves as insiders within the community. Approximately half explicitly referred to themselves as outsiders, but most framed this status neutrally or even positively. For example, Charlotte viewed her outsider status as an asset, suggesting that her superior interpersonal skills distinguished her from those within the community, showing little desire or motivation to be included within the community.

However, some participants associated their outsider status with negative feelings. Jennifer, for instance, expressed a sense of inferiority and imposter syndrome when comparing herself to those she perceived as part of the computer science community.

"Definitely an outsider. I think that people in the CS community have an advantage over people in my community for sure, because they have this knowledge that allows them to just [...] do anything. And so they're really in demand and can just be taught anything." -Jennifer

She described how individuals in the community seemed to possess a breadth of knowledge and versatility that made them indispensable, whereas her role in cyber networking was limited to using systems programmed by others. Similarly, Isabelle described the computer science community as tight-knit, noting that those outside of it are alienated. Both participants exhibited a low sense of belonging within the field, with Jennifer also experiencing additional barriers related to reduced self-efficacy, that influenced their decision to disengage.

Other participants had a self-awareness about their outsider status but still felt confident in their own skills and rather prioritized their belonging in other communities. While they did not consider themselves insiders, they also did not view their exclusion as stemming from a lack of ability. Instead, their identification as outsiders reflected their personal choices, priorities, or interests. For example, Lydia noted that she did not engage in independent coding projects, which she associated with passion rather than technical capability. Similarly, Harper explained that having taken only one computer science course precluded her from feeling like a member of the computer science community, but she emphasized that this had no bearing on her ability to code. Even Isabelle, who expressed a low sense of belonging, acknowledged that this did not imply she lacked the ability to acquire computer science knowledge.

" It's just [...] we're different majors, I think more of [...] CS majors rather than [...] a community. If someone's [...] a CS minor, I'm also like, 'that's so cool'. But I'm just [...] not a part of that community because I only took [...] one CS class here. But that doesn't mean [...] I haven't coded" -Harper

These participants displayed confidence in their technical skills, suggesting that their decision not to engage further with computer science stemmed from a deliberate prioritization of other interests or commitments rather than a lack of self-efficacy or perceived ability. Their engagement, or lack thereof, reflected a conscious choice to pursue other passions rather than a perception of being unqualified for the field, once again showing little motivation for wanting to belong.

2.6.3 Interest: Women lacked interest in computer science and had greater interest in other fields

Interest played a large role in shaping our participants' decisions to not pursue a minor in computer science. Two participants explicitly noted a decline in their interest after taking their introductory course, citing this as a pivotal factor in their decision to disengage. They explained that while they had initially been curious about computer science, their negative experiences in the course made them realize the field was ultimately not for them, with Maddie describing the work as unintuitive and requiring more effort than she felt it was worth.

> *"But it's not the type of work I like to do. I definitely was able to, again, as I had mentioned, use the knowledge from that course in a major, specific course. But it wasn't necessarily the work I hoped to be doing in my classes or in my professional career [...]."* - Maddie

For those who expressed a genuine interest in computer science, particularly in coding and problem-solving, their interest in computer science was not enough to drive them towards a minor, as they ultimately found greater passion in other fields. For three participants, interest in other fields served as the main decisive factor in choosing not to continue with computer science. For instance, Lydia, described herself as really enjoying coding and likened computer science problems to solving mathematical equations, a subject she loves. But despite this interest, her long-term goal of pursuing graduate studies in biomedical engineering and designing medical devices took precedence. She described her passion for biomedical engineering as simply outweighing her interest in computer science, even though she acknowledged computer science as intellectually engaging.

"But once I started doing my senior design and taking more of the biomedical classes, I found that I loved doing medical device design. Having problem identification, walking through the steps of having a patient or treating at the personal level, and designing a product to help someone." -Lydia

Similarly, Harper displayed a notable interest in computer science but cited external constraints and competing commitments as barriers to deeper engagement. In high school, she found the work her boyfriend did in computer science intriguing but prioritized her leadership role as editor-in-chief of her school newspaper and her commitments to dance. These time constraints for other passions, coupled with a lack of encouragement from others, diminished her ability to pursue her interest in computer science. When Harper contemplated minoring in computer science during college, her interest in the field was not strong enough to withstand other influences. Her decision was influenced by the discouraging attitudes of her peers, who questioned the practicality of such a choice. Concerns about potential impacts on her GPA, financial costs, and limited perceived benefits ultimately led Harper to graduate early instead of pursuing the minor, despite her genuine curiosity about computer science.

"I [have] always been interested, but I was editor in chief of my school newspaper for two years and also on my dance team and was super involved with that. And then also dance outside [...] [of school]. So there was just [...] no time. More of a time constraint rather than like lack of interest. And I had a boyfriend at the time that was [...] into [...] [CS]. And I always thought like, 'cool'. And then would move on. I'd always be like, 'oh, that would be cool to do'. And then [...] store that in my brain interest but not like direct interest just because things taking up my time."

-Harper

Kai identified both a lack of interest in computer science and a stronger passion for other fields as driving forces behind her disengagement. She described how her interests diverged significantly from those of her computer science classmates, which heightened her sense of misalignment with the field. She repeatedly commented on feeling as though she did not belong due to these differing interests, which ultimately reinforced her decision to leave computer science and pursue an area she found more fulfilling.

Finally, while many participants appreciated the transferable skills inherent in learning to code, their understanding of transferability was limited to the computer science field. They noted that understanding fundamental programming concepts enabled them to learn new languages with relative ease and learn other technical skills, but there was a lack of understanding how their skills and interest in computer science could be applied to some of their bigger passions.

2.7 Discussion

Our findings reveal that all levels conceptualized using Bronfenbrenner's ecological systems theory played a role in shaping participants' decisions not to minor in computer science. Notably, the experiences women had at system levels closer to their immediate experiences reinforced and influenced their perceptions of the larger macrosystem. This emphasizes the importance of addressing the micro- and mesosystem levels, ensuring their inclusivity and ability to provide support. When students feel disconnected, unsupported, or alienated in their immediate academic environments, their perception of the entire field can be negatively shaped, reducing the likelihood that they persist or further engage. If the experiences conceptualized within these layers do not receive careful attention, changing women's perceptions of the broader field, represented by the macrosystem in this study, becomes increasingly difficult, as perceptions of this layer seem to harden over time. Below, we discuss the influences and interactions of each system layer and how they tie into our three resulting themes from analysis.

2.7.1 Microsystem

The microsystem includes students' direct interactions with peers, TAs, and instructors, and these interactions either reinforced stereotypes or challenged them. In our study, many participants described their classmates as predominantly male and introverted, reinforcing the stereotype of the lone, geeky coder (Cheryan et al., 2013). These interpersonal dynamics further shaped their perceptions of the macrosystem and contributed to their belief that they did not fit into the larger computer science field. But the microsystem was also shaped by the mesosystem, as course structures did not foster collaboration or peer engagement, which meant students had fewer opportunities to form supportive relationships. Without intentional community-building efforts, participants interpreted the lack of social interaction as a defining feature of computer science itself.

Instructors and TAs were other influences at the microsystem. While some were described as approachable, many were seen as insufficiently available for help or unhelpful, particularly during office hours. Additionally, the assumption of prior knowledge by instructors made the material feel inaccessible to students new to the field, leaving them feeling unsupported. These challenges negatively impacted participants' self-efficacy and sense of inclusion. Previous research shows that faculty support and interactions significantly predict women's persistence in computer science (Barker et al., 2014), and our findings align with this, showing that encounters with gatekeeping behaviors and assumed prior knowledge diminished participants' confidence and sense of belonging.

Notably, some participants were also influenced by peers outside the classroom. For instance, Harper was dissuaded by friends who questioned her interest in computer science. While not a formal academic influence, these interpersonal dynamics demonstrate how students' broader microsystem contexts can shape their educational decisions. Prior work has shown how these individuals at the microsystem layer, such as family member support, can influence decision making (Sax, Lehman, Jacobs, et al., 2017), and how peer support can influence sense of belonging (Sax et al., 2018). While interventions targeting these individuals can be challenging, being aware of outside influences is essential to understanding the entire context of women's decision making.

2.7.2 Mesosystem

The mesosystem, which includes structures and policies at the course level, emerged as the most influential system layer in our study. Participants' experiences with course structure and teaching practices strongly impacted their academic confidence and perceptions of computer science as a field, and the influence of the mesosystem can be seen across each of the three result themes.

2.7.2.1 Negative Course Experiences

Most participants entered their computer science courses with limited or no programming experience. Course structures, however, often assumed baseline knowledge, creating a misalignment between students' preparedness and the instructional approach. The rapid pace of coursework, lack of scaffolding, and minimal acknowledgment of diverse entry points contributed to participants' decreased self-efficacy. Prior research shows that early exposure and prior experience are strong predictors of success and persistence in computer science (Bui et al., 2023; S. Katz et al., 2006), and that women are less likely than men to enter college with such experience (Wilcox & Lionelle, 2018). These differences can cause comparisons between peers and may lead a self-reinforcing cycle of doubt and disengagement (Bandura & Wessels, 1997), where women students question their competence even when they are objectively succeeding (Wilcox & Lionelle, 2018). While earlier work suggests that feeling challenged and being successful can buffer challenges of persistence for computer science major students (Milesi et al., 2017), our findings counter those, as all participants earned high grades, yet still opted not to continue in computer science. This contrast may be due to differences in our participants, as they were not initially intending to major in computer science. But despite their success, the field and their experiences within the field did not draw them to pursue a computer science minor.

2.7.2.2 Belonging

Belonging was a nuanced theme. Some participants felt academically competent at the micro and meso levels, as they were confident in their ability to succeed in class, but still expressed a lack of connection to computer science as a field more generally. This is further supported by prior research that found women in engineering are more likely to have a sense of belonging to their universities rather than their engineering disciplines (Glisson, 2023). Interestingly, not all reported that the absence of belonging was distressing; rather, they simply did not want to belong. This finding aligns with our asset-based study design, which intentionally centers participants' agency and reframes the absence of belonging not as a deficit, but as a deliberate and self-determined choice.. This also suggests a distinction between lacking a sense of belonging and lacking the desire for it, which can be closely related to belonging versus domain identification. Domain identification can be defined as the degree to which an individual sees the domain as an important part of their 'self' (Osborne & Jones, 2011). Prior research on STEM persistence (Banchefsky et al., 2019; Hansen et al., 2024) links belonging to academic engagement, particularly for underrepresented students. However, our findings highlight that even when the capacity to belong exists, the desire to belong, or domain identification, must also be cultivated, an insight that expands our understanding of belonging in computer science contexts.

2.7.2.3 Interest

Although participants described greater intrinsic interest in other fields, their declining interest in computer science was not purely personal preference. Rather, it was shaped by features of the mesosystem, especially course design. Assignments lacked connections to real-world applications, which made computer science seem abstract and detached from participants' values and goals. Research has shown that students are more likely to remain engaged in STEM when they see personal relevance and application of course material (N. Davis & Burkholder, 2024; Van Wart et al., 2014). Participants also noted a lack of opportunities for collaboration or discussion, contributing to the perception that computer science lacked social engagement, which was then projected onto the macrosystem. Prior work has shown that technical dimensions are often valued in computer science and engineering spaces over social dimensions (Carrigan, 2017), and as a result, our participants pursued fields in which they observed stronger social engagement and real-world alignment. Women are more represented in some STEM areas than others, and the fields they are more represented in are fields in which there is a greater association of social interaction and social good (Sax & Newhouse, 2018). Even within engineering that has a very low representation of women, the exact gender breakdown varies by subdiscipline. For example, in biomedical engineering, women are largely represented, which has also been linked to its social and application focused nature (Gutierrez et al., 2017).

2.7.3 Exosystem

The exosystem encompasses institutional policies and structures that affect students indirectly. For example, many participants took computer science courses because they were required for their majors, not only out of personal interest. Several participants noted that they might have explored computer science further if they had encountered it earlier or had more room in their schedules. Institutional policies that enable computer science courses later in students' academic journeys, when major and minor paths are more firmly set, limit the flexibility to consider further engagement. Structural constraints like course prerequisites, rigid major requirements, and scheduling challenges may all act as silent barriers (Ganesan et al., 2025; Smith, 2024), even when there is interest present.

Exosystem-level decisions can also shape the mesosystem. For instance, hiring and training policies affect who teaches introductory courses and how they are prepared. Are institutions prioritizing instructors with training in inclusive pedagogy, real-world contextualization, and beginner-oriented instruction? If not, the resulting mesosystem may inadvertently replicate exclusionary norms and reinforce the cycle of disinterest and attrition.

2.7.4 Macrosystem

Participants' perceptions of the broader field, represented by the macrosystem in this study, were shaped almost entirely by experiences in the more immediate layers. The field was viewed as isolating, challenging, and lacking in human interaction. While participants had little direct experience with industry, the cultural messages they received, from media, classmates, and course structures, converged to form a clear picture of a field where they did not belong and had little interest in being.

The stereotypes participants held of individuals in the field played a major role in shaping their perceptions of the macrosystem. Many described a mismatch between their self-concept and the perceived identity of a ‘typical’ computer science professional, a perception they developed through interactions at the micro and mesosystem layers. This dissonance is consistent with research showing that misalignment between personal identity and STEM stereotypes reduces women’s interest and persistence (Cheryan et al., 2013; Diekman et al., 2010; Kendall, 2011; Master et al., 2016). Importantly, the macrosystem’s influence was not fixed; it was shaped and reinforced by patterns within the micro and mesosystem levels. Changing perceptions of computer science culture, then, requires shifting norms and practices in these more proximal spaces.

Interestingly, participants extended their negative experiences and lack of interest at the micro and mesosystem layers to shape their perceptions of the broader macrosystem, but did not extrapolate belonging at these inner layers to the macrosystem. This suggests that women are more likely to make assumptions based on negative experiences, but hesitate to make assumptions about things they do not have experiences with when positive experiences are involved. In sum, positive experiences at the micro and mesosystem levels are critical in fostering better perceptions of the macrosystem, and policies at the exosystem level can support this process by improving the teaching and learning environments in computer science programs.

2.8 Recommendations

Based on our findings, we offer several recommendations for policies and practices that can help support the sustained participation of women in computer science. Our findings suggest that it is crucial for introductory computer science courses to be thoughtfully developed, as outlined in the recommendations below, and that they are introduced early in students' academic careers. This timing would allow ample opportunity for further exploration or for students to plan to pursue a minor if desired.

TAs and professors were identified as major influencers on participants' experiences. In introductory computer science courses, TAs should be carefully chosen for their ability to explain concepts clearly, provide effective and sufficient tutoring, and be adaptive to all prior programming backgrounds. Professors should be selected for their ability to encourage students, be approachable for questions, and simplify complex information. In general, both course instructors and TAs should be caring, knowledgeable, and skilled communicators to effectively support student success, especially for those new to the field.

Projects in introductory computer science courses should encourage creativity, both in design and development, as well as in the purpose or application of the project. These projects should be closely aligned with real-world computer science applications and clearly demonstrate their relevance. Additionally, incorporating at least one open-ended project, where students can personalize the project's purpose or application to areas of personal interest, may help foster future engagement of women in computer science.

Introductory computer science courses should be thoughtfully structured, with ample scaffolding to support students' learning. In instances where classrooms have limited human resources, instructors can incorporate generative AI into the classroom to help provide 1-1 support for students (R. Liu et al., 2024). Students should have multiple opportunities to practice and apply their knowledge, starting with small, manageable problems and gradually progressing to larger, more complex projects. The course flow should be clear, with explicit connections made between concepts throughout the course and should maintain a reasonable and consistent pace throughout the semester. The pacing should be steady from the start, avoiding an overly slow beginning that leads to a sudden, overwhelming increase in difficulty later on in the course. Instead, the course should provide time for students to grasp material based on its complexity, rather than the quantity of topics covered. Additionally, instructors should design courses assuming that students have no prior knowledge of programming, avoiding any assumptions about students' background. Professors should also provide access to resources outside of lectures, such as textbooks, to reinforce their understanding, provide alternative explanations, and offer further opportunities for self-guided practice.

Introductory computer science courses should be designed to reflect the collaborative work environments commonly found in the industry. Students should be exposed to and gain experience with teamwork early on in their studies. Many programs reserve group work for electives or upper-level courses, such as senior design or capstone projects. However, our data suggests that without early exposure to collaboration, students may develop the misconception that careers in computer science do not involve this type of work, ultimately deterring them from the field. Incorporating even a small amount of group work in introductory courses can help challenge this belief, while also providing opportunities for peer support to enhance learning and understanding.

Finally, instructors should provide students with a broad understanding of what a career in computer science can look like. This should go beyond the stereotypical roles such as software engineers, game designers, or cybersecurity professionals. Instead, students should be introduced to a variety of career paths within computer science, with a focus on some of the less conventional options. Instructors should also take the time to learn about their students' individual interests and demonstrate how computer science can connect to those passions, helping to highlight the relevance of the field in diverse career contexts. This exposure should occur early in introductory courses, giving students the opportunity to explore how computer science might align with their future career goals. This early introduction will help students make informed decisions about whether and how to pursue computer science as part of their academic and professional paths.

2.9 Limitations and Future Work

This study has several limitations. First, our sample comes from a single university context. Although this context is relatively representative of other large, public, R1 universities, the results should be interpreted with caution and not generalized to a broader population. Second, our participant pool was predominantly White, meaning our findings do not address how race may influence individuals' decisions to pursue a computer science minor. Future research should explore the role of race as a potential factor in these decisions.

Third, most of our participants took the same introductory computer science course, although they did so at different times and with different instructors. It's possible that other courses, which might have approached the subject differently or included content that our participants felt was missing, could have influenced their decisions differently. Future work could explore how varying teaching approaches or course content affect women's decisions.

Additionally, our discussion frequently references participants' self-efficacy, which we inferred from their responses rather than measuring it directly. Unlike quantitative studies that assess self-efficacy through established metrics, we did not employ such measurements. Self-efficacy is highly task specific (Bandura & Wessels, 1997) and this study could contribute to developing appropriate quantitative measures for deeper exploration. Lastly, while all of our participants reported high performance in their courses, this was self-reported data, as we did not have access to their actual grades. As such, there is a possibility that some participants may have overstated their performance. Additionally, because our study focused on high-performing individuals, our findings may not fully represent the experiences of all women students. A broader sample that includes a wider range of performance levels could reveal different dynamics.

Looking ahead, there are several avenues for future research. First, studies could examine high-performing men non-CS majors to better understand gender-specific experiences and influences, and how they compare to those of women. Second, a longitudinal study could provide more insights by tracking shifts in students' experiences and feelings throughout the course, rather than relying on retrospective reflections. Third, future research should explore the prevalence and impact of a lack of belonging versus a lack of desire to belong among non-CS majors, and how these factors influence their decision to pursue computer science. Finally, future studies could investigate strategies to help women bridge their interests in other fields with those in computer science.

2.10 Conclusion

This study examined the experiences of seven predominantly white high-performing women non-CS majors who completed an introductory computer science course for non-majors, aiming to understand why they chose not to pursue a computer science minor. Thematic analysis revealed several challenges that negatively shaped their experience: limited support from TAs and instructors, difficulty with course content, a lack of structure and scaffolding, and minimal opportunities for social interaction, all of which impacted their interest and self-efficacy. While participants expressed a lack of belonging in the computer science field, they also reported little desire to belong, which further reduced their motivation to continue. Many were also more deeply invested in other academic fields, which ultimately took priority.

Using Bronfenbrenner's ecological systems theory, we found that experiences within the micro- and mesosystem layers, such as classroom interactions and course design, played a critical role not only in shaping individual experiences, but also in informing perceptions of the broader macrosystem, or their cultural narrative of computer science. These findings suggest that introductory computer science courses must be designed with care, as the more negative the experience at the micro and mesosystem levels, the more difficult it becomes to shift students' perceptions of computing at the macrosystem level.

An important outcome of this study was due to the use of Bronfenbrenner's Ecological Systems Theory to frame and interpret the findings. While this study identified motivators commonly documented in prior research, such as negative classroom experiences, interest in other fields, and a low sense of belonging, situating these themes within the broader computer science system provided a more holistic understanding of students' experiences. By applying this framework, the study captures how factors across multiple levels of students' environments interact to shape their experiences and decisions within computer science pathways. This approach moves beyond documenting isolated barriers, revealing patterns and relationships between individual, institutional, and societal influences. In doing so, it supports recommendations and interventions that address both individual outcomes and the broader structures and contexts contributing to them. This perspective offers a unique contribution to the literature on computing education and student attrition and provides a foundation for future work to design multi-level strategies aimed at fostering inclusion and persistence in the field.

Chapter 3: Manuscript 2

3.1 Introduction

There is a growing demand for individuals with knowledge in computer science, driven by the increasing reliance on technology in fields even outside of computer science (Schibelius et al., 2022). For example, by 2026, 1.2 million jobs in the computer science industry are projected to go unfilled (Bureau of Labor Statistics, 2021), and this gap is expected to widen over the next 5 years (Krutsch, 2022). These unfilled positions represent a significant barrier to economic growth and technological advancement (Stephenson et al., 2018). While much research has focused on attracting and retaining students in computer science degree programs (Amelink et al., 2018; Biggers et al., 2008; Cheryan & Plaut, 2010; Giannakos et al., 2017; Peckham et al., 2007), one crucial pool of untapped talent is overlooked: students majoring in non-CS fields who are already taking introductory computer science courses and may be well-suited to pursue a computer science minor.

Students in non-CS fields who excel in introductory computer science courses are particularly well-positioned for interdisciplinary roles, which are increasingly in demand in today's tech-driven world (Brodley & Barr, 2022). These individuals bring expertise from their primary disciplines, whether in the humanities, social sciences, engineering, or natural sciences, coupled with the foundational skills of computer science. As industries across sectors seek professionals who can bridge gaps between technical knowledge and domain-specific applications, these interdisciplinary professionals become critical in driving innovation and solving complex problems (Han et al., 2023).

Another untapped talent pool that many prior studies have focused on is women (Engineering and Engineering Technology by the Numbers, 2022). A significant body of research has explored why women are less likely to enter or remain in computer science. Key factors include lower initial interest in introductory courses and a diminished sense of belonging due to gendered stereotypes that depict computing as a male-dominated field (Beyer, 2014; Corbett & Hill, 2015; Sax, Lehman, Jacobs, et al., 2017; Yücel & Rızvanoğlu, 2019). In such environments, women often experience reduced self-efficacy in computing, even when they perform well academically (Beyer, 2014; Lehman et al., 2016). Additional barriers, such as needing to prove competence, male-dominated discussions, and discriminatory remarks, further deter women's persistence, underscoring the need for more inclusive educational practices (Blackburn, 2017; Cheryan et al., 2017; Falkner et al., 2015; Lapan & Smith, 2023).

Despite growing insights into the factors behind the gender gap in computer science, most research has overlooked men's perspectives on disengagement, even though men's choices significantly influence gender ratios Cheryan et al. (Cheryan et al., 2017). By focusing on men's perspectives, this study provides a foundation for comparing findings across research that focuses on women's decisions to identify gender specific patterns. Although this comparison is not the primary focus of this manuscript, it is explored further in Chapter 5 of the larger dissertation.

The purpose of this paper is to address these gaps in the literature by investigating why high-performing men in introductory computer science courses, who are not majoring in computer science, choose not to pursue a computer science minor. By focusing on this group, the study achieves two key goals. First, it offers new insights into how the computer science field can better engage students from non-CS disciplines, thereby increasing both the number and diversity of individuals entering computing-related careers. Second, by examining men's experiences in relation to prior research on women's disengagement, the study provides a clearer understanding of whether the barriers to engagement are gender-specific or represent broader issues that affect all students. This perspective will help distinguish between gendered challenges and those that might be experienced universally across various student populations.

3.2 Background

3.2.1 Attrition and Retention in computer science

Several factors contribute to the attrition of students in computer science, with key influences ranging from academic challenges to personal circumstances. Research has shown that students who are further along in their education, who believe they will perform well, and who find the subject matter less demanding are more likely to persist in the field (Pappas et al., 2016). However, factors such as financial difficulties, health issues, family responsibilities, and low attendance also play a significant role in student retention (Setosta et al., 2017). Additionally, negative perceptions of the field and a lack of understanding of what a computer science career entails contribute to attrition (Carter, 2006; Rosson et al., 2011). Xenos et al. (Xenos et al., 2002) categorized reasons for dropout into five main areas, each with varying levels of impact: professional factors (62.1%), academic challenges (46%), family-related issues (17.8%), health concerns (9.5%), and personal factors (8.9%).

Beyond personal and academic challenges, external perceptions of the computer science field, often shaped by media portrayals, also influence students' decisions to persist or abandon the field. Media stereotypes about computer scientists can discourage potential students from pursuing or continuing their studies. Common stereotypes paint computer scientists as technology-obsessed individuals with limited interest in people or social activities (Beyer et al., 2003; Margolis & Fisher, 2002). These portrayals suggest that computer scientists are primarily focused on programming and electronics (Cheryan et al., 2011; Margolis & Fisher, 2002), with little outside interest or engagement in collaborative work (V. A. Clarke & Joy Teague, 1996;

Diekman et al., 2010). And those who do have interests outside of programming, have hobbies that are generally associated with men (Cheryan et al., 2009, 2011).

Additionally, computer scientists are often stereotyped as socially awkward, highly intelligent "nerds" or "geeks" who lack interpersonal skills (Beyer et al., 2003; Kendall, 2011; Margolis & Fisher, 2002; Mercier et al., 2006). These images can be especially alienating for students who do not identify with these stereotypes but may feel pressured to conform to them. Cheryan et al. (Cheryan et al., 2013) summarize, “the image of a computer scientist that emerges in the U.S. is one of a genius male computer hacker who spends a great deal of time alone on the computer, has an inadequate social life, and enjoys hobbies involving science fiction” (p.60).

Such stereotypes can have a significant impact on students’ perceptions of their fit in the field. Undergraduate students often compare themselves to existing professionals to assess their own potential for success and to determine if they belong in the field (Creamer et al., 2007). When students cannot relate to the dominant media portrayal of computer scientists, they may question their ability to thrive in the field, contributing to higher rates of attrition.

3.2.2 Gendered Barriers in Computer Science

Given the significant gender gap in computer science, many studies have focused on understanding the reasons why women leave the field. These studies have identified several key barriers to women's persistence in computer science, including negative stereotypes, gender biases, and masculine classroom cultures (Eagly et al., 2000; Riegle-Crumb et al., 2019). Women often face sexism in the form of having to prove themselves before receiving help, being excluded from conversations or experiencing "mansplaining," and encountering discriminatory comments from professors (Falkner et al., 2015; Lapan & Smith, 2023). Other challenges include a lack of computer self-efficacy and a fluctuating sense of belonging (Beyer, 2008, 2014; Good et al., 2012; Lehman et al., 2016), all of which can hinder women from persisting in computer science and pursuing a career in the field (Blackburn, 2017; Cheryan et al., 2017). Additionally, the stereotype that computer scientists are predominantly male can contribute to women's attrition (Beyer et al., 2003; Diekman et al., 2010). Studies have shown that these perceptions can lead to a loss of interest in the field, particularly for women, as they may feel alienated or excluded if their identity does not align with the dominant stereotype.

These problems create a vicious cycle: when women leave the field due to sexism, the gender disparity in computer science increases, leading to additional challenges. First, the absence of women in the field means fewer women role models for students, and research shows that role models play a significant role in influencing persistence (Yates & Plagnol, 2022). Second, this gender imbalance reinforces the stereotype that computer science is a field for men, which can deter women from pursuing or remaining in the field. This stereotype has been shown to reduce interest in computing and negatively impact students' sense of identity within the field (Eagly et al., 2000). Third, when women do not see others who resemble them in the field, their sense of belonging and expectations of success diminish, further discouraging their persistence (Cheryan et al., 2011).

3.2.3 Men's Experiences in STEM

Men's experiences in STEM share similarities and differences with those of women. Like women, men find a sense of belonging in STEM through being heard, having the opportunity to contribute, seeing representation, feeling safe to take risks, forming interpersonal relationships, perceiving competence, nurturing personal interest, and developing a strong science identity (Corson & González-Morales, 2024; Rainey et al., 2018). However, unlike women, men often conceptualize belonging in terms of success and merit, and they tend to be more optimistic that everyone can feel a sense of belonging in STEM.

Regarding interest, more men than women report an early interest in STEM, which they often attribute to activities like tinkering, building, and from the media (Maltese & Cooper, 2017). This interest often grows through solitary activities. Men also "over-persist" in STEM fields, meaning they are more likely to retake failed courses even when it results in lower earnings later in life compared to not retaking them (Penner & Willer, 2019). For men, interest is the primary factor in persisting in STEM, with only 10% leaving STEM majors for non-STEM fields (Maltese & Cooper, 2017). Despite overestimating their math abilities (Penner & Willer, 2019), poor performance and negative teaching experiences are the top reasons men leave STEM fields (Maltese & Cooper, 2017).

However, not all men are overrepresented in every STEM field. While men dominate fields like computing, engineering, and physical sciences, they are underrepresented in life sciences and health-related STEM fields (Fry et al., 2021). Furthermore, men with intersecting identities are underrepresented even in the fields where men dominate. Men with disabilities, for instance, are less likely to pursue STEM due to barriers related to their disabilities (Cech, 2022). Additionally, men in same-sex relationships are less likely to earn a bachelor's degree in STEM compared to their heterosexual peers (Sansone & Carpenter, 2020). And men of color, particularly Black, Hispanic, and Native American men, remain underrepresented in STEM fields (Fry et al., 2021). These intersecting identities can significantly affect their experiences in STEM classrooms and their decision-making processes.

White, able-bodied, heterosexual men tend to dominate STEM spaces, but they are often unaware of the role race and gender play in shaping the experiences of others within these fields

(Dancy et al., 2020). And these individuals benefit most from STEM culture, experiencing greater social inclusion, professional respect, career opportunities, higher salaries, and higher persistence than any other intersectional groups (Cech, 2022).

3.2.4 Choosing an Academic Field

When examining decisions to pursue a minor, it is important to consider the factors that influence individuals' academic field choices. A variety of theoretical frameworks have been proposed to understand the factors influencing students' decisions in selecting their fields of study. One such framework is the Five-Factor Model, introduced by McCrae and Costa Jr. (Costa & McCrae, 1999), which posits that these decisions are influenced by an individual's inherent tendencies, personal adaptations, self-confidence, life history, and external contexts. This model identifies five key personality traits, extraversion, agreeableness, conscientiousness, neuroticism, and openness, that collectively capture personality diversity. Research indicates that students pursuing different academic majors tend to display distinct personality profiles, highlighting the significant role personality traits play in major selection (Balsamo et al., 2012).

Another influential theory for academic decision making is Holland's Theory of Personality and Vocational Choice (Holland, 1959), which categorizes individuals into six personality types, realistic, investigative, artistic, social, enterprising, and conventional, that correspond to specific vocational paths. This model has been particularly relevant in explaining STEM field selection, with students exhibiting stronger investigative traits being more likely to choose STEM majors compared to those with artistic preferences (Chen & Simpson, 2015).

Lastly, Bandura's Social Cognitive Theory (Bandura, 1986), later refined as the Social Cognitive Career Theory by Lent et al. (R. W. Lent et al., 1994), underscores the role of personal, behavioral, and environmental factors in shaping individuals' career interests, goals, and actions. For students in STEM fields, both interest in and ability to prepare for a chosen career are among the leading motivators for major selection (Maltese & Cooper, 2017). And research on SCCT reveals that factors such as social support, career opportunities, and the potential for societal impact play a critical role in students' decisions to pursue computer science (Alshahrani et al., 2018).

Few studies have focused on developing a framework to explore minor decision making. However, in a case study looking at a computing minor for social science majors, students noted that they enrolled in order to improve their data analysis skills, better prepare themselves for the job market, and because they believed basic computing knowledge was necessary for the future (Carr et al., 2021). After taking the courses, roughly 87% stated that they wanted to pursue a career or further studies that would utilize their minor.

3.2.5 Literature Gap

While considerable research has examined attrition and persistence in computer science, particularly focusing on women's experiences, far less attention has been given to the experiences of men who choose not to continue in the field. Moreover, most existing studies concentrate on major selection or attrition from computer science majors, leaving a gap in understanding why students in adjacent pathways, such as those with the option to pursue a computer science minor, decide not to engage further. This is especially important in light of the rapidly evolving AI landscape, as the automation of routine programming skills may reshape how students, particularly those from non-CS disciplines, perceive the value and relevance of a computer science minor. Investigating why high-performing men opt not to pursue this pathway provides an opportunity to assess whether existing academic options remain meaningful and to compare how members of the field's dominant group make educational and career decisions relative to women. This perspective can help clarify whether barriers to engagement in computer science are gender-specific or reflective of broader, systemic issues affecting a wider range of students.

3.3 Theoretical Framework

The theoretical framework for this study is the same that is utilized in manuscript 1, Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979). As is discussed in manuscript 1, this theory emphasizes an individual's decision-making within the context of multiple, interconnected layers of influence. By focusing on the individual within their environment, it highlights not only personal factors but also the role of relationships and external influences, which can affect the individual even when they are not directly involved in the environment. Bronfenbrenner's framework consists of four environmental layers:

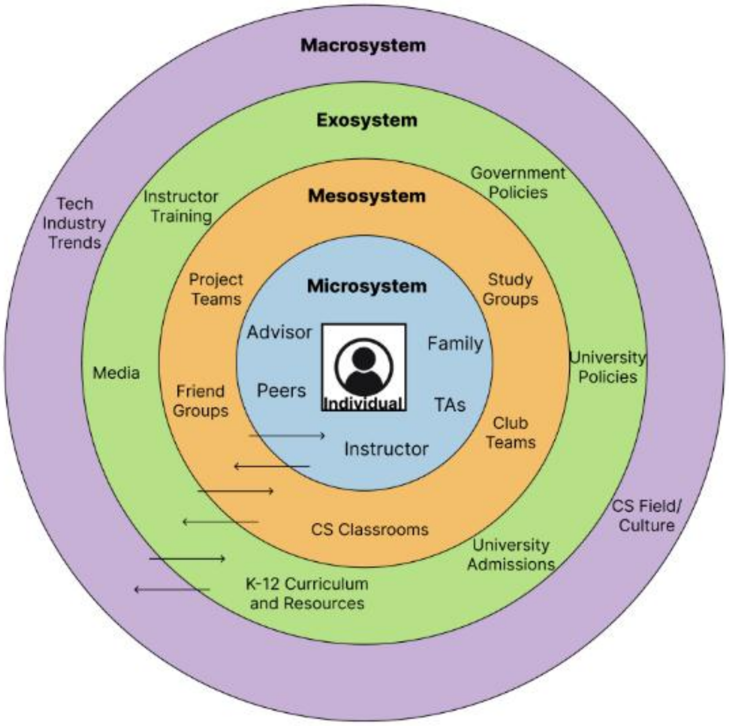
1. **Microsystems**: These are settings and relationships directly experienced by the individual, such as interactions with family, peers, academic advisors, and instructors.
2. **Mesosystems**: This level encompasses the connections between microsystems, such as classroom settings, study groups, or project teams where different parts of the individual's environment interact.
3. **Exosystems**: These are settings in which the individual is not directly involved but is still influenced by, like college policies, admissions processes, or the priorities of instructors.

4. **Macrosystems**: This level includes larger societal influences, such as industry trends or the cultural climate of the university or department and computer science as a field.

Figure 3.1 illustrates these layers, with each successive level containing the one below it, placing the individual at the center. By organizing the environment in this way, Bronfenbrenner's framework underscores the environmental influences on an individual, which is crucial for understanding academic decisions, such as choosing or changing a major or pursuing a minor. This ecological approach, in contrast to more individual-focused frameworks, allows for a deeper exploration of how external factors shape academic choices, especially in the context of academic transitions.

Previous research has applied Ecological Systems Theory to a variety of related topics. Onal and Temko (Onal & Temko, 2024) emphasized the significant impact of the microsystem, mesosystem, and macrosystem on major selection among students of color in engineering, while Ngambeki (2012) used the theory to explore factors influencing all students' decisions to pursue engineering. The theory has also proven to be one of the most effective frameworks for understanding the underrepresentation of certain groups in gifted courses (Crawford et al., 2020). Additionally, several studies have employed it to investigate student belonging (El Zaatari & Maalouf, 2022; Glisson, 2023), and to examine students' experiences in computer science within higher education (Arishi et al., 2024).

Figure 3.1 Adapted Bronfenbrenner's Ecological Systems Theory



This study takes an asset based approach to the attrition problem. Because our participants are high-achieving, the problem we are studying is not one of deficit, but rather one of choice based on the interactions the students have with their environment in computer science classes and the broader computer science culture. This asset-based, anti-deficit approach aligns with Bronfenbrenner's theory, which allows us to focus on how the environment influences students' decisions, rather than any perceived deficiency on the part of the students themselves.

We used Bronfenbrenner's framework to shape the interview protocol, as was also used in manuscript 1. Questions were designed to address each level of the ecological system. For the microsystem, participants were asked about their interactions with classmates, instructors, and family. For the mesosystem, we inquired about their classroom experiences. To explore the macrosystem, questions focused on their future plans and their perceptions of the larger computer science community. The full interview protocol, included in the Appendix, mirrors that of manuscript 1. We did not ask specific questions about the exosystem, as students are typically unaware of how this layer impacts them. However, when students mentioned policies or processes that affected their experiences, interviewers were sensitive to these influences and asked follow-up questions as needed.

3.4 Methods

This study follows the exact methods that were used in manuscript 1. Because this study looks to answer the same research question as manuscript 1 on a different population, the same protocol, and analysis methods, but different sample population were used. Each of the methodology pieces discussed in manuscript 1 are described again below, with only minor changes made for this study.

The sample for this study consisted of men undergraduate students from non-CS disciplines who had enrolled in an introductory computer science course designed for non-CS majors at Virginia Tech. In both the spring and fall semesters of 2023, all students registered in one of the five introductory computing courses available to non-CS majors received an invitation to participate in a survey. The survey collected demographic information and asked students if they were interested in joining a 30-minute interview for a $20 Amazon gift card. Based on their survey responses, six men students, who performed well in the course (earning an A or a B), were selected for interviews. The six participants were selected incrementally until it became clear that additional participants were no longer yielding new themes or meaningful insights. This suggests that the sample size was adequate to capture diverse and relevant experiences consistent with the goals of the study. Efforts were made to primarily ensure diversity in the participants' academic majors, and secondly on race/ethnicity and prior experience when available. A summary of the participants' demographic details is provided in Table 3.1.

Table 3.1. Participant Demographics

Pseudonym	**Race/ Ethnicity**	**Major**	**Prior Programming Experience**	**Course Taken**
Trevor	White	Chemistry	● AP Computer Science in high school ● Engineering course in high school	● Introduction to Python
Ishan	Other	Financial Technology (minor in Math)	● None	● Introduction to Python ● Introduction to Software Design ● Software Design and Data Structures
Min	Asian	Computational Modeling and Data Analytics (minor in Math)	● AP Computer Science in high school ● Community College dual enrollment in cybersecurity academy	● Introduction to Python ● Intermediate Python
Amir	Multiracial	Civil Engineering	● Two high school programming courses	● Introduction to Python
Omar	Multiracial	Cybersecurity Management Analytics	● Self-taught Kahn Academy in high school	● Introduction to Python
Brady	White	Economics	● AP Computer Science in high school	● Introduction to Python

Along with the survey data, semi-structured interviews were conducted with participants via Zoom, each lasting approximately 30 minutes. The interviews explored students' experiences in their computing courses, their future career plans, and their interactions with the broader computer science community. The interview protocol was designed using Bronfenbrenner's ((Bronfenbrenner, 1979) Ecological Framework as a guiding structure, and the full protocol can be found in the Appendix. After the interviews were completed, they were transcribed using

Zoom's automated transcription tool, with the research team manually reviewing and correcting them to ensure clarity and accuracy.

We analyzed the interview data using thematic analysis, a well-established method for detecting and interpreting patterns within qualitative datasets (Braun & Clarke, 2006; V. Clarke & Braun, 2017). This technique facilitates the emergence of overarching themes without being limited to predefined coding frameworks. Our process followed the step-by-step approach outlined by Braun and Clarke ((Braun & Clarke, 2006; V. Clarke & Braun, 2017)). To begin, I immersed ourselves in the data by either viewing the video recordings or reading through the transcripts of the interviews. I then conducted the initial coding, identifying segments of the data that stood out as particularly relevant or meaningful in the context of our research focus (Braun & Clarke, 2006). A sample of these codes, along with their definitions, is provided in Table 3.2, and a comprehensive list can be found in the Appendix.

Table 3.2. Codebook Excerpts

Code	Code Definition
Impact of prior experience	Discussion of how prior computing experience influenced their experience in their course
Social nature of course	Discussion of course environment in terms how it supports or does not support social interactions
Course positives	Discussion of course aspects that participant liked
Instructor interaction	Discussion of how instructor or TA interacted with participant (does not include what instructor did in class unless it specifically was targeted as a 1-1 interaction)

Once the initial codes were developed, related codes were clustered together to form preliminary themes. Throughout this phase, I iteratively refined the themes, merging those with overlapping content and discarding themes that lacked sufficient evidentiary support or did not directly answer the research question. Table 3.3 illustrates each theme and their associated codes, with the complete codebook included in the Appendix.

Table 3.3 Code to Theme Mappings from Thematic Analysis

Theme	Codes
Course Experiences	Course challenges
	Impact of prior experience
	Course difficulty
	Questioning course design
	Social nature of course
	Course negatives
	Self-efficacy
Community Belonging	CS community
	Insider/outsider
	Friendly community
Interest	CS interest
	Outside CS adjacent classes
	Future CS engagement
	Non CS-interest
	Course impact

3.4.1 Participant Personas

3.4.1.1 Trevor

Trevor is a White senior majoring in chemistry. He took Introduction to Python in his junior year, not to fulfill a general education requirement since he had already satisfied those, but because he wanted an easy course and college credit for something he had already learned in high school. In high school, he took AP Computer Science, which focused on Java, and an engineering course where he programmed Raspberry Pi devices using Python. After graduating, Trevor plans to attend graduate school for chemistry and anticipates using computing for data analysis in his future career. Despite this, he does not intend to take any more computer science courses, as they are not required for his major.

3.4.1.2 Ishan

Ishan is a senior majoring in financial technology. In his first year, he took Introduction to Software Design and Software Design and Data Structures, followed by Introduction to Python in his junior year. During his sophomore year, he enrolled in Introduction to Computer Organization but dropped the course when he realized it was not relevant to his major. Ishan's career goal is to work in trading or quantitative finance, fields that require coding knowledge for data analysis and manipulation. To prepare for this, he took a Python for Finance course within his major but felt it would not provide the necessary skills. To bridge this gap, he pursued additional computer science courses. Initially, Ishan planned to minor in computer science but changed his mind after taking computer organization, realizing that the minor would not be useful for his career and could negatively impact his GPA. He entered college without any prior programming experience. Although he is interested in taking more computer science courses, such as Issues in Scientific Computing, Quantum Computing, and Parallel Computing, he does not think his schedule will allow it. After graduation, Ishan will work at Citi Group, where he interned, in sales and trading. Ultimately, he hopes to pursue a career at a hedge fund.

3.4.1.3 Min

Min is an Asian, first-generation sophomore majoring in Computer Modeling and Data Analytics with a minor in Mathematics. In his first year, he took Introduction to Python and

Intermediate Python as required courses for his major. In high school, he completed an advanced Python course and participated in a cybersecurity academy through dual enrollment at a community college, giving him three to four years of programming experience before college. Currently, he knows Python, HTML, Java, and Bash. For his major, Min is also required to take a data structures course, which he plans to complete in Java. Although not mandatory, he is interested in taking a programming with math course to support his goal of becoming a data scientist.

3.4.1.4 Amir

Amir is a multiracial junior majoring in Civil Engineering. He took Introduction to Python to fulfill a science and engineering elective, thinking it would be an easy course due to his prior experience with Python in high school. Although he took two programming courses in high school, he describes his exposure to computer science as limited. Amir does not plan to take any additional computer science courses but expects to enroll in civil engineering classes that require programming. After graduation, he plans to enter the workforce but is open to pursuing an accelerated master's program if accepted.

3.4.1.5 Omar

Omar is a multiracial junior majoring in Cybersecurity Management Analytics. In his sophomore year, he chose to take Introduction to Python instead of Web Page Design using JavaScript because he already had some knowledge of JavaScript. Although he did not take any formal computer science classes in high school, he learned on his own using Khan Academy. Omar does not plan to take any additional computer science courses and is uncertain about his plans after graduation.

3.4.1.6 Brady

Brady is a White sophomore majoring in Economics. He took Introduction to Python in college and AP Computer Science in high school. Although he currently has no plans to take more computer science courses, he is open to learning another programming language in the future. Brady is considering a data science specialization within economics, which might require him to take additional computer science classes. He is also contracted to join the Marines after graduation and plans to become a pilot.

3.4.2 Author Positionality

The first author identifies as a woman in computer science, though her path to the field began outside of it. Initially a math major, she took a single computer science course to meet a degree requirement and found it to be an enjoyable experience. Motivated by this newfound interest, she decided to pursue a computer science double major, ultimately earning both a bachelor's and a master's degree in computer science. These personal experiences enable her to connect with participants, who, like her, initially engaged with the field as non-majors in introductory computer science courses. However, unlike the participants, she ultimately chose to pursue computer science further, allowing her to draw meaningful comparisons in interpreting their decisions to disengage from the field.

The second author identifies as a woman engineer and currently serves in both administrative and faculty roles within a large computer science department at an R1 university. Over the past 15 years, she has worked extensively with individuals in technology-related fields and has consistently observed persistent stereotypes and a lack of support for students. Through her research, service on departmental committees, and student mentorship, she is dedicated to reducing barriers in the field of computer science and fostering a more inclusive and welcoming environment where all students can succeed.

3.5 Results

Through thematic analysis, I identified three key factors that shed light on why participants chose not to pursue a computer science minor: course experiences, community belonging, and interest. Each of these factors is explored in greater detail in the sections that follow.

3.5.1 Course Experiences: Men were frustrated with their computer science courses

Participants encountered a variety of experiences in their introductory computer science courses that influenced their decision to disengage from the field. These experiences were shaped by several key aspects of the course, including the structure of the course, course assignments, and the social dynamics within the course.

3.5.1.1 Frustration with Course Difficulty and Connection

Participants cited both the difficulty and ease of the course as reasons for disengagement. For example, Omar found the pacing problematic, noting that equal instructional time was allocated to both basic concepts like print statements and more complex topics like loops, which became overwhelming towards the course's end, leading him to turn away from further computer science courses. Compared to someone like Min, who reported that much of the course material covered content he already knew, leading to feelings of redundancy that fueled his disengagement. He expressed frustration that he was not allowed to skip the course despite his prior knowledge, believing he should have received credit without participation. Min was also irritated by peers asking him basic questions in class, feeling that such queries could be resolved through simple online searches.

> *"I think I should have skipped intro to Python. I think they should have given me credit for it. I think I should have just took an exam to get out of that class. That class, that class was at least the professor was engaging or else the class would've been boring for me because it was a long walk to that class. And I sometimes I just wish I just didn't go to the class"* -Min

Additionally, participants expressed a sense of disconnection from the course content, perceiving it as lacking practical application or personal relevance. Ishan, for example, criticized the course for its limited focus on real-world applications, arguing that without opportunities to apply the material in meaningful contexts, the knowledge felt superficial and difficult to retain. He contended that the course content could easily be self-taught and questioned the value of the formal class structure, suggesting that it did not offer added benefits beyond independent learning.

3.5.1.2 Criticism of Course Assignments

A recurring source of dissatisfaction among participants was the format and implementation of course assessments, particularly quizzes. Several participants expressed frustration with the emphasis on memorization required for quizzes, contrasting this with the more applied, open-ended nature of programming projects.

> *"The quizzes were fairly challenging because you had to you didn't have any reference material when you were doing them, so you had to do it all from memory, which on the*

one hand is understandable, but I feel like it's also not really indicative of a development environment" -Trevor

Trevor criticized this assessment format, arguing that it did not reflect authentic programming practices where referencing documentation and external resources is common. This disconnect between assessment methods and real-world programming environments led to feelings that the quizzes were not meaningful indicators of their coding abilities. In addition to concerns about relevance, participants were dissatisfied with the grading practices associated with quizzes. Amir expressed frustration with what he perceived as arbitrary grading, noting that TAs were often unable to provide clear justifications for the grades assigned. This lack of transparency in evaluation contributed to a sense of unfairness and further diminished perceptions of the value of these assessments. In addition to quizzes, Amir also noted that project descriptions were often unclear and required extra support to identify what was being asked. He admitted that, despite his prior experience, some projects were difficult and required attending office hours for additional support.

"In the course, I went to office hours a lot, particularly for the project because we had three big projects. If I didn't go to office hours, they would have been impossible" -Amir

3.5.1.3 Lack of Social Engagement and Field Misalignment

A prominent negative experience and source of frustration discussed by participants was the perceived lack of social interaction and community within the classroom environment.

Multiple participants described their classes as isolating, with limited opportunities for collaboration or meaningful peer engagement.

"Most of the people that I interacted with were some of my friends from outside the class already. I already knew them for the most part and I guess that's really kind of the only community that I had in that class." -Brady

Trevor noted that the course did not foster a close environment, while Amir described classmates as pretty closed off, making it difficult to form connections. Brady echoed this sentiment, stating that his interactions were limited to friends he already knew prior to the course, rather than forming new relationships within the class. This lack of social connection was particularly concerning given the collaborative nature of professional computer science work. Ishan explicitly criticized the course's emphasis on independent work, arguing that discouraging collaboration runs counter to real-world programming practices, where teamwork and code reviews are integral.

"I will say the lack of allowing for collaboration, bad. It's cool, it's fine. You say, okay, you have to do everything yourself. I get it right. But if you're preventing people from collaborating, then that literally goes against how CS is in real life." -Ishan

Many participants found the course setup counterintuitive to the field of computer science and would have preferred group work over individual assignments. The independent and isolating nature of the course led them to avoid pursuing similar types of computer science courses, ultimately disabling them from obtaining a computer science minor.

3.5.2 Community Belonging: Men place little value on belonging within the computer science community

Many participants associated the computer science community with those formally pursuing a computer science major, a definition that emphasized a shared passion and depth of knowledge in the field. For example, Brady described computer science majors as individuals deeply knowledgeable about the subject, eager to expand their expertise, and often serving as go-to resources for peers seeking guidance. Similarly, Trevor broadened this definition to include math majors, recognizing the significant overlap in coding and computational thinking within their coursework.

"My initial impression, not that I have anything to base it off of, it seems as though the computer science community is comprised mostly of people directly in computer science. Maybe in mathematics too, actually, now that I think about it. So a professor who said he collaborated with people in the CS department" -Trevor

Alternatively, several participants conceptualized the computer science community as open to anyone with an interest in being part of the field. Amir viewed community membership as a matter of self-identification, suggesting that it holds subjective significance rather than objective criteria.

"If they want to be, you know, it's just an identification thing, it's not really, it doesn't have any real substrate to it." -Amir

In contrast, Min acknowledged a minimal knowledge threshold for community inclusion but argued that this requirement was easily attainable, reinforcing the idea that the computer science community is accessible to those willing to engage.

Participants expressed mixed feelings about their sense of belonging within the computer science community, reflecting both insider and outsider identities. Min identified as an insider based on his proficiency and active engagement with computer science concepts. Conversely, Ishan described himself as partially an outsider despite his strong technical skills, which highlights his self-efficacy within the field. He articulated that while he could comprehend complex programming discussions, he lacked experience in building sophisticated systems. Ishan framed insider-outsider status as roles that represent different life experiences rather than hierarchical positions or knowledge.

"So knowing more than you and being in a different field are two different things. So okay, someone can know more than me and they're in their field completely, understandably because they've spent the same amount of time that I spent in my field and their field. So I think like when someone knows more than me in my own field, that's what I'm like, oh, I got to step my game on it. It's feeling it like an outsider is not. I don't, I don't think it's inherently feeling like you know less or you're like inadequate or anything like that. Feeling like outsider means that they have literally just spent more of

their time. Part of their life is different because of what they do compared to what you do." -Ishan

For those who identified fully as outsiders, this designation was not associated with negative emotions. Trevor, for example, acknowledged his outsider status but did not feel excluded, attributing this to his STEM background, which he believed garnered respect from computer science peers. Amir similarly perceived himself as an outsider, not due to exclusion but because he felt no intrinsic need to affiliate with the computer science community, aligning with his belief that community membership is a personal choice. Brady echoed this sentiment, noting that while he found computer science enjoyable and regarded the community positively, his lack of deep passion for the subject reduced his desire to immerse himself within it.

"I mean, I'm assuming it's a fine community but I mean, computer science is just kind of like it's another area, it's another field. It's not like a burning passion that I have. So it's cool to learn a fun to be around, don't need to be around it, you know." -Brady

Despite these varied self-perceptions, participants consistently described the computer science community as friendly and welcoming.

"I don't really feel like unwelcomed at all" -Omar

Ishan highlighted the abundance of shared resources and collaborative opportunities in the broader field, such as YouTube and Stack Overflow, as indicators of an inclusive environment.

Min emphasized the community's openness to dialogue, and Brady remarked on the overall welcoming nature of computer science spaces. This framing highlights a welcoming community where, even when individuals identify as outsiders, their decision not to pursue a computer science minor is not rooted in a lack of belonging. However, even those who identified as insiders acknowledged that their sense of belonging was subjective and lacked a deeper meaning. And many participants did not feel the need to identify as outsiders, further suggesting that belonging to the community was not a primary factor in their decision to pursue a minor. Ultimately, it appears that community and belonging have little influence on men’s choice to pursue a computer science minor.

3.5.3 Interest: Men have greater interest in other fields and can learn and connect these fields to computer science on their own

The majority of participants expressed a clear interest in computer science, often explicitly stating their fascination with the subject or their enjoyment of the introductory course. This interest manifested in several ways, including intentions to enroll in future computer science courses, engagement with personal projects, and aspirations to integrate computer science knowledge into their careers and other academic fields. Several participants demonstrated their interest by planning to take additional computer science courses. For instance, Min was already enrolled in a Java Data Structures course for the following semester, indicating a strong commitment to further study computer science despite not declaring a formal degree. Similarly, Omar expressed interest in taking an Introduction to JavaScript course in the future, though without immediate plans. However, not all participants intended to continue formal computer science education. Some, like Ishan, cited scheduling constraints rather than a lack of interest as barriers to further engagement. Ishan expressed a desire to take advanced courses such as

Quantum Computing or Parallel Computing but was unable to do so due to being in his final semester with a full course load.

"So I think like if I had the time, I would definitely be taking something like quantum computing or like maybe parallel computing or something." -Ishan

Amir also chose not to enroll in additional computer science courses but noted that his CS-related learning would continue through computing courses offered within his major, Civil Engineering, such as "Computer Applications in Civil Engineering."

Interest in computer science extended beyond the classroom, as evidenced by participants' involvement in personal projects. Min, for example, developed advanced projects beyond the course curriculum, including scripts that could start or stop with a clap command.

"I usually did do extra work out assignments like my own personal projects. That was because those projects were useful for my day to day cases. Okay. All right. But it was more advanced than what's taught in class because I would write scripts that would like play pause when like I clapped my hand or something" -Min

Ishan applied his computer science skills to a financial technology capstone project, building a Principal Component Analysis (PCA) model. These examples illustrate how participants leveraged their computer science knowledge in creative, self-directed ways. Moreover, participants frequently discussed the interdisciplinary application of computer science, highlighting their enthusiasm for combining computer science with their primary academic interests. Min expressed a strong interest in integrating computer science with mathematics, while Amir focused on applying coding skills within the context of civil engineering.

"Yeah, absolutely. When I used Mat Lab I found it to be so helpful and interesting. It made me like computer science a little more. I know it's not fully computer science, but it is really just coding. The application of coding to something like civil engineering, where you could see graphs come out and really just make it do whatever you want. That was really cool. I genuinely enjoy that course, even though it's probably the hardest one I took last semester." -Amir

For some participants, the introductory course served as a catalyst for recognizing the broader potential of computer science. Omar, for example, expressed that the course helped him envision a future where he could engage more deeply with computer science, suggesting an increased openness to incorporating computer science into his academic or professional trajectory. Similarly, Brady highlighted his newfound awareness of the diverse and expansive applications of computer science, noting that the course broadened his understanding of how computer science can intersect with various fields and industries.

"my understanding changed mostly just like in the amount of things that I figured out that I could do with it, even in some of the smallest, like outside tasks, use it like you wouldn't really think of like oil field workers as needing computer science to do their jobs." -Brady

As a result of this new understanding, participants also envisioned using computer science in their future careers, even if they did not plan to minor in the field. Those with defined career goals consistently indicated that programming would play a role in their professional lives.

“There's a good chance I'll have to use computing in my future career with respect to say, data analysis, like I think most chemistry instruments use R, or something proprietary otherwise. Okay, Yeah, my future career looks like it's going to be a lot of data handling. Of course, I'm going to need to do computing.” -Trevor

Trevor anticipated a career involving substantial data handling, necessitating computing proficiency. Brady, with aspirations to become a military pilot, recognized the relevance of computer science in aviation technology. Even participants like Omar, who were uncertain about their specific career paths, acknowledged that programming would likely be part of their future work.

Despite this widespread interest, it was not sufficient to motivate participants to pursue a computer science minor. For some, their passion for other fields, such as economics or civil engineering, outweighed their interest in computer science. However, these individuals did not view this as a binary choice, as they actively sought to integrate computer science knowledge into their primary areas of study. Others recognized that, while they found computer science intriguing, it did not captivate them enough to warrant a commitment. Amir, for example, considered majoring in computer science but was deterred by concerns about the evolving job market, particularly the impact of artificial intelligence on entry-level programming roles. He preferred the application of computer science within civil engineering rather than computer science as a standalone discipline. Similarly, Brady acknowledged his interest in computer science and his intention to continue learning about it informally but concluded that it did not sufficiently inspire him to pursue it as a minor. Ultimately, men are not pursuing a computer science minor not due to a lack of interest, but because they lack interest in a formal qualification. Our participants have the ability and desire to learn independently or take specific computer science courses that align with their interests, even without earning a minor. They are able to apply computer science to their other passions on their own terms, which leads them to feel no need to obtain a computer science minor.

3.6 Discussion

Our findings reveal that we saw evidence that multiple levels of systems as conceptualized using Bronfenbrenner's ecological systems theory influenced participants' decisions not to minor in computer science. Men were more likely to interpret and critique the micro-, meso-, and exosystem layers in relation to their broader perceptions of the macrosystem, which we define as the computer science field as a whole. Their career decision-making appeared to be less shaped by experiences within the course and more by whether those experiences aligned with their preexisting or broader beliefs about the field. This suggests that interventions focused solely on classroom-level improvements may be less impactful for this group unless they clearly connect to shifting or reinforcing positive perceptions of the broader computer science field. Below, we examine the interactions across system layers and how they relate to the themes identified in the data.

3.6.1 Individual

At the individual level, interest and belonging played nuanced roles in shaping participants' decisions. Many men expressed interest in computer science but felt greater passion or alignment with other fields. Notably, several were able to integrate or connect computer science with these other interests. However, this integrative potential was often derived from their own understanding of computer science at the macrosystem level, not from connections fostered by the course (mesosystem) or their interactions with individuals (microsystem). While our participants connected these interests in various ways, prior work has identified personal projects as the most common form of informal learning (McCartney et al., 2010).

Similarly, participants’ sense of belonging was largely filtered through their perception of the computer science field as being open and accessible. While some noted that they did not feel a strong sense of belonging, this was often framed not as exclusion but as a personal choice, suggesting that belonging was less a barrier and more a non-factor. This reflects prior work that shows men in STEM more easily and frequently feel a sense of belonging (Banchefsky et al., 2019; Daniels et al., 2019). For our participants, belonging was less about being welcomed into the field and more about whether the field, as they understood it, aligned with their goals and identity, which more closely aligns with domain identification (Osborne & Jones, 2011).

3.6.2 Microsystem

Notably, there was very little influence at the microsystem level that discouraged participants from pursuing a minor in computer science. Min expressed irritation of his peers when he was frequently asked for help, as his extensive prior experience made him significantly more knowledgeable than many of them. And Amir was frustrated by interactions with teaching assistants, particularly when they were unable to clearly explain their grading practices.

However, there were no common influences of the microsystem across all participants. In fact, the most influential factor at the microsystem level was the general lack of interaction within this layer. This absence of meaningful engagement was shaped by policies and structures at the mesosystem level, which is further discussed in the section below.

3.6.3 Mesosystem

Though the macrosystem shaped participants' overall attitudes, many of their critiques centered on the mesosystem, focusing on the course structure, pace, and assignments. A recurring theme was that the content lacked real-world application and did not reflect the dynamic, applied nature they associated with computing in practice, which has previously been found to be linked with STEM persistence (N. Davis & Burkholder, 2024; Van Wart et al., 2014). Participants' prior experience with computer science (individual layer) appeared to inform their macrosystem perceptions, which then shaped their expectations for the course. When the mesosystem failed to reflect these expectations, it contributed to disinterest or disinvestment with experiences at the mesosystem layer.

This disconnect also extended to social engagement. Participants noted limited peer interaction or collaboration, a course component found to improve student achievement and satisfaction (Gharbaoui et al., 2024). However, rather than shaping their perception of the computer science field, this lack of social engagement seemed to reinforce their existing views that the course did not align with their understanding of the field's collaborative and interdisciplinary nature. In short, micro- and meso-level experiences were used not to construct new understandings of the field but to evaluate the course's authenticity against existing beliefs.

3.6.4 Exosystem

The exosystem, or the institutional policies and broader university structures, also played a significant role in men's decision-making. In addition to frustration about being required to take a course they perceived as redundant, several participants cited logistical barriers to pursuing a minor. These included a lack of room in their schedules, unclear pathways to completion, or a mismatch between required courses and their academic or professional goals. Some preferred to take computing-related courses offered through other departments that more directly aligned with their interests.

This highlights a potential broader concern: participants may not have viewed the computer science minor as flexible or adaptive to interdisciplinary interests. When structural elements such as prerequisites, sequencing, or departmental silos fail to accommodate student goals, they may opt out, not due to lack of interest or negative experiences, but due to structural inefficiencies. This is consistent with prior work that found structural barriers to pursuing further computing courses and degrees (Ganesan et al., 2025; Smith, 2024). It also reinforces the idea that increasing participation of men in computer science minors may require not just reframing the field, but reforming curricular pathways to make them more relevant, adaptable, and accessible.

3.6.5 Macrosystem

For our men participants, the macrosystem (i.e., their perception of the overall computer science field), appeared to function as the most influential system layer. Rather than being shaped by classroom experiences, their perceptions of the field often preceded their coursework and served as a lens through which they evaluated their academic experiences. These perceptions were shaped by prior experiences, as nearly all of our participants had some programming experience before taking the course, a background that research shows is more common among men than women. (Du & Wimmer, 2019). For men, existing views of the field were often used to confirm or critique their classroom experiences (mesosystem) rather than reshape their field views.

This phenomenon was particularly evident in critiques of course content. Participants described the introductory computer science course as too easy and lacking in application which they did feel reflected the true nature of computer science work, especially for those with prior experience, who generally perform better in these kinds of classes (Li & Chen, 2020). These findings are in contrast to prior work that has found non-CS students are more satisfied with their introductory computer science course when it is specifically designed for non-CS majors (Dawson et al., 2018). This critique extended beyond the course itself to a condemnation of university or departmental policies (exosystem) requiring it. Participants believed that students with prior knowledge should have the option to test out or bypass the class entirely, suggesting frustration with rigid curricular structures that failed to accommodate different entry points into computing. These frustrations reflected a broader misalignment between institutional structures (exosystem and mesosystem) and their beliefs about what computer science looks like at the macrosystem level.

3.7 Recommendations

From our findings, there are many recommendations that can be made for policy and practice that will help support continual engagement in computer science by non-CS major men. These policy and practice changes have the potential to diversify not only who enters the computer science field, including a broader range of personalities across men, but also the types of knowledge and perspectives they contribute to interdisciplinary roles. Our findings highlight that introductory computer science courses should be thoughtfully designed to reflect real-world practices both in terms of application and social engagement. Assignments should encourage students to adopt working practices consistent with industry standards. Courses should be structured to mirror the collaborative work environments prevalent in the tech industry. Introducing teamwork early in students' education helps them develop essential communication and problem-solving skills needed for real-world computer science careers. However, many programs delay group projects until advanced electives or senior-level capstone courses. Incorporating group work in introductory courses can provide a more accurate representation of industry practices while also fostering peer support and enhancing learning experiences. Additionally, it helps students build connections and a sense of community within the classroom, which can contribute to greater engagement and retention.

Courses should be designed to accommodate students with varying levels of experience and abilities. While the material should be accessible for those without prior programming knowledge, it should also offer enough flexibility to prevent more experienced students from losing interest. This could involve offering project options that allow advanced students to delve into more complex concepts or providing extra practice and optional assignments to challenge them further. Additionally, universities could establish more comprehensive systems for assessing students' existing knowledge, enabling those with prior experience, such as self-taught individuals, to test out of introductory courses. Our data suggests that, even without formal AP credit, some students already possess the foundational knowledge typically taught in these courses.

Finally, universities should reexamine course requirements within the computer science department to identify opportunities for greater flexibility and interdisciplinary integration. Our data suggest that students are primarily interested in acquiring the specific skills and knowledge they need to succeed and apply computer science in their areas of interest, rather than pursuing a formal degree. Creating pathways that allow students to engage with computer science content without requiring completion of all foundational courses typically mandated for a computer science minor could help increase accessibility and improve engagement.

3.8 Limitations and Future Work

This study has several limitations that should be acknowledged. First, the data were collected from students at a single institution. While this university shares many characteristics with other large, public, R1 universities, findings should be interpreted within this specific context and not assumed to represent the experiences of all students in similar settings.

Second, the majority of participants entered the course with some prior programming experience. As such, the findings may not reflect the perspectives of students encountering computing for the first time. Future research should examine how prior exposure shapes men's decision-making, particularly given that participants appeared to hold established views of the broader computing culture (macrosystem) before stepping into the classroom.

Third, although participants took the same introductory computer science course, they did so across different terms and with various instructors. It remains possible that alternate versions of the course, with different content, teaching styles, or framing, could yield different outcomes. Future work might explore how instructional variation and curricular design influence men's engagement and continuation in computer science. Finally, all participants indicated strong academic performance in their courses, though this was based on self-reported data. Therefore, it is possible that some participants may have exaggerated their performance. Moreover, because our study specifically focused on high-performing individuals, the results may not fully capture the experiences of all men students. A more diverse sample that includes students from varying performance levels could uncover different dynamics.

There are several promising directions for future research. Longitudinal studies could shed light on how students' perspectives evolve during their time in introductory computer science. Further work should also investigate which prior experiences most strongly shape students' initial views of computing culture. Finally, researchers could explore how experiences at the micro- and mesosystem levels, such as classroom interactions or peer dynamics, help reshape or reinforce macrosystem-level beliefs for future targeted interventions.

3.9 Conclusion

This study explored the perspectives of six high-achieving non-CS major men who completed an introductory computer science course designed for non-majors, with the goal of understanding why they opted not to pursue a computer science minor. Thematic analysis identified several areas of dissatisfaction in their introductory computer science course that caused them not to pursue a minor in computer science, including the course's perceived lack of rigor, limited relevance to real-world contexts, unengaging assignments, and minimal opportunities for social connection. Additionally, although participants acknowledged not feeling a strong sense of belonging in computer science, they also expressed little interest in cultivating such belonging, further decreasing their motivation to obtain a minor. Finally, most were more committed to other academic disciplines, and while they recognized connections between those fields and computer science, they felt confident in acquiring any necessary computer science skills independently and saw limited value in fulfilling the minor requirements.

Framing these findings through Bronfenbrenner's ecological systems theory, we observed that participants' views of computing were not primarily shaped by their immediate academic environment (micro- and mesosystems) or institutional structures (exosystem). Instead, they evaluated these micro- and mesosystems through the lens of pre-existing macrosystem beliefs, which had been shaped by prior personal exposure to computing. As a result, interventions aimed at reshaping men's perceptions of computer science may be less effective at the introductory course level, suggesting the need to engage earlier or in different contexts that influence those broader cultural narratives.

A significant outcome of this study stemmed from the application of Bronfenbrenner's Ecological Systems Theory as a lens for analyzing the findings. While this study uncovered themes previously reported in prior research, interpreting these themes within the context of the larger computer science system offered a deeper understanding of men's experiences. This framework made it possible to examine how influences across individual, institutional, and societal levels interact to shape students' pathways and decisions in computer science. It also highlights interconnected patterns that influence these themes within the broader environment. Importantly, this study lays the groundwork for future gender-based comparisons, offering insights into how different groups may engage with and be impacted by the same system in distinct ways. Such comparisons can reveal unique differences in experiences, challenges, and supports, ultimately informing more tailored, multi-level interventions to improve inclusion, persistence, and diversity in computing education.

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4.1 Introduction

As the demand for computing knowledge continues to grow in the workplace, with an expected increase of 682,800 new jobs by 2031 (Krutsch, 2022), the need for individuals with a computer science background becomes increasingly critical. However, the field faces significant challenges with retention, with students being more likely to leave computer science than be recruited into it (George et al., 2022), a long-standing issue in computer science education (Obaido et al., 2023). Recent data indicates that computer science has the highest dropout rate among university majors, with an attrition rate of 10.7% (Winograd, 2024). Additionally, the technology industry experiences a high turnover rate of 12.9%, with employees frequently leaving for better pay, fewer work hours, or more engaging work (Bao et al., 2017; J. Davis & Kuhn, 2003; Lewis, 2022).

This combination of growing demand and high attrition presents a serious concern for both the field and the economy. According to the Bureau of Labor Statistics (2021), the U.S. is projected to have over 1.2 million unfilled computing jobs by 2026. Understanding why individuals leave computer science is therefore critical to addressing this workforce gap. While some prior literature has pointed to a lack of interest as reasons why individuals leave the field (Cheryan et al., 2015; Margolis et al., 2000), others point towards difficulty with attainment (Albarakati, 2020; Barr & Kallia, 2022) and unsupportive work environments (Giannakos et al., 2017). If individuals disengage due to a lack of interest, it may reflect a natural career shift. However, if structural or environmental factors are discouraging participation, especially among underrepresented groups, this points to systemic issues that require targeted intervention.

Addressing these challenges could help reduce attrition and improve the computing workforce pathway.

There are several limitations to our understanding of computer science retention. First, few studies have investigated the problem beyond the academic degree setting, such as students who successfully complete their degrees but do not enter the computer science workforce afterwards, or those who enter the workforce in computer science but eventually leave the field. Second, many of the studies are qualitative in nature and rely on small sample sizes or focus on a specific context, making their findings difficult to generalize to the larger problem (Queirós et al., 2017). Additionally, those that are larger studies are quantitative, which limits their ability to capture the nuanced, in-depth understanding necessary to fully explore the issue (Queirós et al., 2017). But with the advent of artificial intelligence (AI), it has become possible to expand qualitative research to analyze larger datasets, providing insights on a scale previously unfeasible. Building on these advancements, this study leverages generative AI to explore departure from computer science at a scale never before achieved, offering a comprehensive and broader perspective on this phenomenon within the field.

This study addresses these two gaps in literature by investigating the decision making process of individuals leaving the computer science field across various departure stages by leveraging Reddit data in a large-scale qualitative analysis. This study aims to provide nuanced insights across diverse contexts, contributing to a more generalizable understanding of the retention problem in computer science. This approach also allows us to evaluate the problem at various points, revealing how the issue may evolve throughout an individual's career, enabling targeted interventions at the right time. To do this, we answered the following research questions:

RQ1: What are the reasons individuals choose to leave the field of computer science at various departure stages?

RQ2: What external or contextual factors influence the decision-making process for individuals considering leaving the field of computer science at various departure stages?

To efficiently and effectively conduct this large-scale qualitative study, we leveraged generative AI for data processing and analysis. Specifically, we used generative AI to streamline both data filtering and thematic analysis. The AI played a critical role in generating a codebook and identifying initial themes, as well as in applying the codebook across the data set. To enhance the accuracy and depth of AI-generated themes, we employed a human-in-the-loop approach, in which a human reviewer actively evaluated and interpreted the AI's outputs. This process allowed us to refine the AI-generated themes, ensuring that the final insights were both nuanced and contextually meaningful. Guided by Social Cognitive Career Theory (R. Lent et al., 2002) as our theoretical framework, the researchers contextualized AI-generated themes within established career development principles, deepening our understanding of why individuals choose to leave the computer science field. This combination of generative AI assistance and human expertise allowed us to manage a large volume of data while maintaining the depth and reliability necessary for qualitative research.

4.2 Background

4.2.1 Computer Science Attrition

Research shows that 15% of students who begin a computer science degree ultimately drop their computer science major (*Persistence & Retention | National Student Clearinghouse Research Center*, n.d.). Most students make this decision within their first two years, often while taking introductory courses (Huang & Brainard, 2001; Pappas et al., 2016). And faculty face challenges in retaining these students due to the diverse backgrounds and preparedness levels among those who enroll (Sax, Lehman, & Zavala, 2017).

Studies have identified several reasons for leaving computer science. Common factors include financial struggles, health issues, family obligations, and disengagement from coursework (Setosta et al., 2017). Other key influences include low expected GPA (Pappas et al., 2016), negative perceptions of the field (Rosson et al., 2011), and a lack of understanding of computer science career paths (Blaney, 2021; Carter, 2006). Xenos et al. (Xenos et al., 2002) categorized dropout reasons into professional (62.1%), academic (46%), family (17.8%), health-related (9.5%), and personal (8.9%) factors. Similarly, Hein et al. (Hein et al., 2012) grouped influences into three categories: (1) academic environment and resources (e.g., coursework, faculty interactions, support systems), (2) perceptions of the field and career prospects (e.g., self-confidence, societal impact), and (3) personal experiences, including exposure to stereotypes and computing culture.

While computer science attrition is a broad issue, it disproportionately affects underrepresented groups, including women and persons of color. Research highlights that women often leave computer science due to discrimination, microaggressions, and a lack of belonging (Barker et al., 2009; Benbow & Vivyan, 2016; Bunderson & Christensen, 1995; Cheryan et al., 2009; Gokhale & Stier, 2004; Lapan & Smith, 2023; Singh et al., 2007; Yates & Plagnol, 2022). Additionally, women and persons of color are told that they are not what a computer scientist looks like (Diekman et al., 2010). Stereotypes portraying computer science as a male-dominated field requiring innate intelligence further contribute to feelings of alienation (Cheryan et al., 2013). Similarly, students of color face systemic barriers in computer science. Building community in computer science spaces can be challenging for these individuals due to the field's individualistic culture (Ong et al., 2018) and unwelcoming department environments that lead to increased feelings of isolation (Charleston et al., 2014; Hernandez, 2023; Rankin & Thomas, 2020).

Despite these challenges, certain factors contribute to persistence in computer science. Students are more likely to stay when they recognize the value of the degree (Giannakos et al., 2017), experience positive social integration (Cohoon & Aspray, 2006; Lehman et al., 2023; Rosson et al., 2011; Weng et al., 2010; Xenos et al., 2002), and have supportive academic environments (Tan, 2015) or family support (Blaney, 2021). High self-efficacy and prior programming experience also play a significant role in retention (LeBlanc et al., 2020).

4.2.2 Career Transitions

Research on unfilled industry positions often focuses on increasing the number of graduates in those fields. However, this perspective overlooks individuals who complete degrees but ultimately choose not to pursue careers in their respective fields. For example, nearly half of STEM graduates enter non-STEM careers (Jelks & Crain, 2020). One explanation is that STEM degree holders develop highly transferable skills that allow them to seek employment in a variety of industries (Delaney & Devereux, 2022). This flexibility enables individuals to prioritize factors such as better pay, job security, or alignment with personal interests and needs. Additionally, many STEM fields present barriers that contribute to attrition, including negative stereotypes, unsupportive and discriminatory work environments, and social isolation (Jelks & Crain, 2020).

More broadly, research on career satisfaction and job departure reveals patterns that extend beyond STEM. Job satisfaction tends to decline the longer individuals remain with a single company but improves when they change companies frequently (Dobrow et al., 2018).

However, satisfaction can be moderated by job rewards such as salary and benefits. Job stress, a key factor in workplace dissatisfaction, is positively correlated with burnout (Wu et al., 2021). A meta-analysis on job retention identified several key factors influencing career decisions (Kiazad et al., 2024). First, individuals weigh both professional and personal needs, making career decisions at the intersection of work and home life. Second, systemic barriers disproportionately impact individuals from underrepresented groups, shaping their career trajectories. Third, job satisfaction is influenced by workplace relationships, organizational culture, and personal attitudes toward the job. Finally, the longer individuals stay in their careers, the less likely they are to leave. These findings help explain why individuals across various fields, including STEM, may ultimately choose to exit their professions.

4.2.3 Generative AI for Qualitative Analysis

There are many different types of qualitative data analysis techniques, one of which is Clarke and Braun's (V. Clarke & Braun, 2017) thematic. Thematic analysis allows researchers to identify themes or patterns within qualitative data through a process of generating a code book and organizing these codes into themes (V. Clarke & Braun, 2017). This process utilizes six steps: (1) getting familiar with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing the themes, (5) defining and naming the themes, and (6) producing results. This is a very labor-intensive process and can take significant time and cognitive-effort, as there are important considerations involved in defining a code, differentiating between codes and themes, and identifying the relevant information needed to answer the research questions. As a result, it takes time for researchers to produce meaningful insights. Thus manual thematic analysis does not scale well to large qualitative data sets.

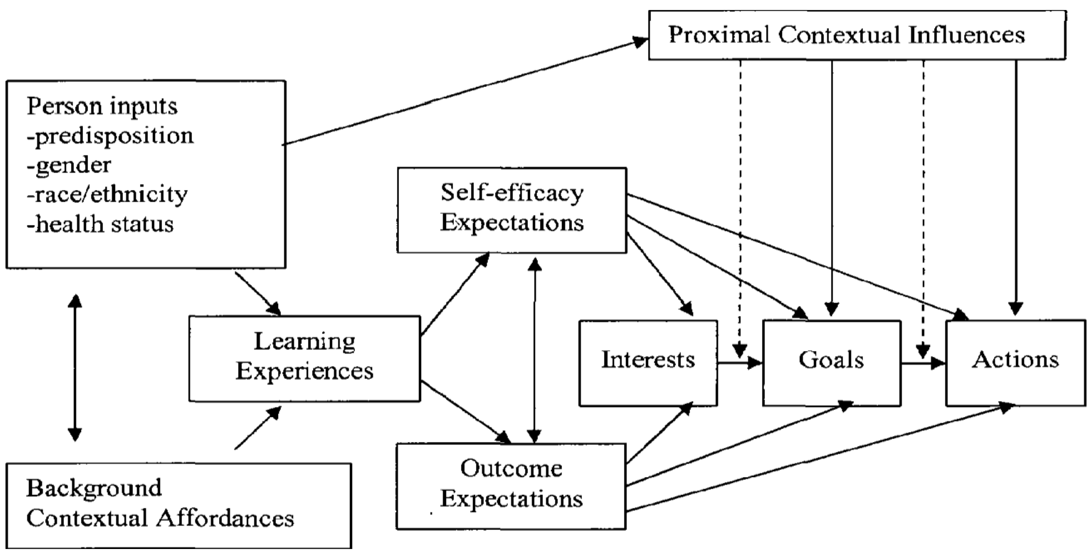
Because of the labor-intensive nature of thematic analysis, work has been done to reduce the time and effort it takes to conduct thematic analysis by utilizing machine learning and natural language processing techniques. Blei et al. (Blei et al., 2003) utilized latent Dirichlet allocation (LDA) to identify topics within a qualitative data set. Building on traditional topics modeling, BERTopic is a transformer-based language model that utilizes more modern LDA approaches to identify topics within text (Grootendorst, 2022). Other studies have utilized large language models (LLMs), particularly ChatGPT and open-source language models, to develop workflows for thematic analysis. De Paoli (De Paoli, 2024), and Katz et al. (A. Katz et al., 2023) developed methods for human in the loop LLM assisted thematic analysis. Perkins and Roe (Perkins & Roe, 2024), Gamieldien (Gamieldien, 2023), and Lixandru (Lixandru, 2024) performed comparative studies between manual analysis and AI-assisted analysis that showed promise for using AI for thematic analysis.

4.3 Theoretical Framework

This study utilizes Social Cognitive Career Theory (SCCT) (R. Lent et al., 2002) to make sense of the AI generated themes. SCCT, shown in Figure 4.1, combines three overlapping and interacting models, including Bandura's Social Cognitive Theory (Bandura, 1986), to explain the processes through which people develop career interests; make, forge, enact, and revise occupational choices; and achieve career success (R. W. Lent et al., 1994). SCCT explains the formation of academic and career interests as well as the continual decision-making process, making it useful for understanding why individuals leave the field across all departure stages.

The goals of SCCT are to connect individuals and their career related choices, taking into account their environment in which they made these decisions; connect cognitive processes, such as self-efficacy, with interpersonal and background factors; and identify connections between self-imposed and externally-imposed influences or limitations to career attainment.

Figure 4.1. Social Cognitive Career Theory (Lent et al., 1994)



SCCT has been widely used to study attrition and decision-making in computer science, as it contextualizes individuals and highlights motivating factors. Most studies have used it to examine initial career interests. For example, Alshahrani et al. ((Alshahrani et al., 2018) identified key influences (social support, job potential, societal impact, and prior coding experience) that shape students' decisions to major in computer science. Additionally, Sax et al. (Sax, Lehman, Jacobs, et al., 2017) tracked trends in computer science majors, emphasizing the evolving contributors to the gender gap in the field. However, SCCT can also be used to understand career transitions. George et al. (George et al., 2022) used SCCT in a longitudinal study, finding that two years after introductory courses, only 53% of students remained interested in computing careers, with more leaving than joining the field. Factors like initial interest, family support, group involvement, a sense of belonging, and computing self-efficacy positively influenced students' decisions to pursue computing majors.

SCCT is based on three core components: self-efficacy, outcome expectations, and goals. Self-efficacy refers to individuals' beliefs in their ability to perform a task and is influenced by both the environment and personal factors. Outcome expectations are the anticipated effects of an action and are linked to self-efficacy, as higher self-efficacy often leads to more positive outcome expectations. Goals reflect how much and how well an individual aims to accomplish something, and are shaped by self-efficacy and outcome expectations. For instance, quick progress toward a goal can enhance both self-efficacy and outcome expectations. These components form the foundation for four models explaining career interest development: the interest, choice, performance, and satisfaction models.

4.3.1 SCCT Interest Model

The interest model posits that self-efficacy and outcome expectations influence interest which in turn influences our goals, actions, and thus our performance attainments. For example, individuals may choose to major in computer science because they believe they can succeed in the field, and as they take courses, they develop skills that enhance their chances of success.

4.3.2 SCCT Choice Model

The choice model builds on the interest model to include the environment. Individuals' performance experiences act as a feedback loop in which successes and failures influence future choices, self-efficacy, and outcome expectations. As a result, making a choice can make future choices more or less likely. However, the success or failure can be determined by the environment, meaning that environments play a part in choosing individuals. For example, success in a job interview is influenced not only by the individual interviewing, but also the company values and needs. This means that the choice process is influenced by the environment and people do not make value-free or influence-free decisions. This model also expands sources that influence self-efficacy and outcome expectations to include personal inputs, such as gender, race/ethnicity, health, etc.., and background or contextual factors such as social class. In effect, it posits that choices are shaped by interest, environmental, and personal factors.

4.3.3 SCCT Performance Model

The performance model focuses on the level of success an individual has in reaching their goals, and it overlaps with the choice model through the perseverance individuals show in the face of failure. Because past performance influences self-efficacy and outcome expectations, what people perceive as possible for future performance is influenced by past and present performance. And past, present, and outcome expectations of future performance all influence individuals' future goals. For example, if an individual fails their first introductory computer science course, their self-efficacy and outcome expectations will be negatively affected, altering their future goals, and potentially leading to the decision to change majors.

4.3.4 SCCT Satisfaction Model

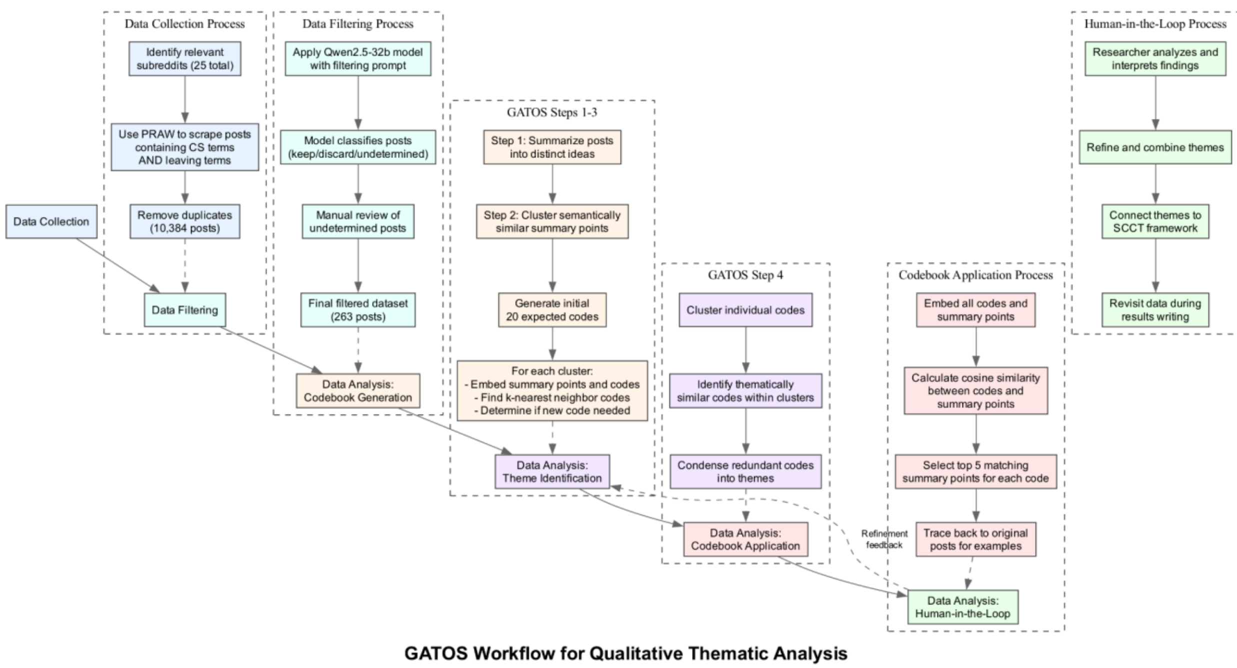
The satisfaction model focuses on an individual's satisfaction in an academic field or career. The factors that provide satisfaction are present in the other models and include: value alignment, perception of making progress towards their goals, high self-efficacy, access to an environment that supports their self-efficacy and goal attainment, personality, and working conditions. In this model, there are many pathways to influence work satisfaction, both through individual characteristics and the environment. As a result, it evaluates satisfaction at a personal level and as something that is changeable. For example, an individual might feel satisfied in a job with limited social interaction early in their career. However, as they grow older, they may develop a stronger need for social engagement, which could lead to increased dissatisfaction in their role.

4.3.5 Use of SCCT in the Current Study

In this study, SCCT was used to interpret and contextualize themes generated by AI. SCCT was not involved in the initial codebook creation, as the focus of the study is on investigating AI for codebook generation and application. Once the AI generated the themes, researchers analyzed them through the lens of SCCT, mapping AI generated factors to the relevant models to better understand how they influenced individuals' decisions to leave the field.

4.4 Methods

Figure 4.2. Overview of Methodology: Data Collection and GATOS Analysis



4.4.1 Terminology

For this study, there were two terms that we needed to define. First is the computer science field and what jobs or industry sectors count as being in this space. Our definition is grounded in the U.S. Bureau of Labor Statistics computer occupational profile (*List of SOC Occupations*, n.d.) and includes computer and information analysts, computer and information research scientists, computer support specialists, database and network administrators and architects, software and web developers, programmers, and testers, and miscellaneous computer occupations. We then expanded the miscellaneous group to include IT professionals and data scientists or analysts.

The second term we needed to define was attrition in computer science. Using the above definition of the computer science field, attrition in the computer science field for our study referred to the transition of individuals out of the computer science field into unrelated domains at both the academic and industry levels. At the degree level, this encompasses students who change majors from computer science to a non-related field, excluding adjacent disciplines such as software engineering or cyber security. At the industry level, attrition signifies individuals who leave computer science altogether to pursue careers outside the field, rather than shifting to a different role or type of field within it. For instance, a transition from being a software developer to teaching English would qualify as attrition, while moving from database administration to web development, or from a software developer role to a computer science faculty position, would not. This definition, using the previously outlined definition of the computer science field, emphasizes movement from within the computer science field to an entirely separate domain.

4.4.2 Data Collection

To collect data, we utilized public and anonymous information from the social media platform Reddit.com. As one of the top ten social media platforms in the U.S. (*Social Media*, n.d.), Reddit allows users to post content and questions while engaging with others who respond to these posts. The platform hosts a diverse user base, with 54% identifying as male and an equal 33% representation across low, middle, and upper-class demographics. While we cannot assume demographic information about Reddit users, and only those who participate in data collection surveys get recorded in user descriptive surveys, Berdanier et al. (Berdanier et al., 2020) contend that users are likely to disclose information they perceive as relevant to their circumstances. Users also span various educational levels, from high school graduates to those with doctoral degrees, and include individuals from Generation Z to Baby Boomers (*Social Media*, n.d.), with the largest group (44%) of Reddit users being between the ages of 18 and 29 (*Reddit User Age, Gender, & Demographics (2025)*, 2025), an age where many individuals are making key career decisions. Reddit is organized into "subreddits," which focus on specific topics, including several that discuss the computer science field.

Previous studies in STEM education have leveraged Reddit posts as a data source to investigate reasons why students leave engineering graduate programs (Berdanier et al., 2020) and the challenges women face in STEM (Jacobs et al., 2020). There are three primary advantages to using Reddit posts instead of conducting interviews. First, Reddit users voluntarily share information they consider important to their personal situations, often seeking advice from others. This contrasts with interviews, where the information collected may be influenced by the researcher's beliefs and perspectives. Second, the anonymity of Reddit encourages users to share more candidly. In interviews, participants may experience feelings of shame, embarrassment, or social desirability (Bergen & Labonté, 2020) which can hinder their willingness to disclose certain types of information. Third, utilizing Reddit allows for the rapid collection of a large volume of data without the extensive time and effort required to recruit numerous participants for interviews.

To collect Reddit posts, we used data collection methods guided by those employed in prior studies (Berdanier et al., 2020) (Berdanier et al., 2020; Jacobs et al., 2020). Twenty-five subreddits, listed in the appendix, were identified based on their relevance to the research questions and suitability as data sources. The first 15 subreddits were previously identified and utilized in a study examining why students leave engineering graduate programs (Berdanier et al., 2020). The remaining 10 subreddits were selected as the most popular for discussing CS-related topics, as determined by Reddit's "popular" tab. Posts were then scraped from these subreddits using the Python Reddit API Wrapper (*PRAW 7.7.1 Documentation*, n.d.). A post was scraped and collected if it contained at least one term from the following list identifying computer science as a topic: "computer science," "CS," "compsci," or "comp sci." Additionally, the post needed to include at least one term from the list indicating leaving as a topic: "leave," "leaving," "dropping out," "drop out," "quit," "quitting," "mastering out," "left," "done," "withdraw," or "withdrew." The initial scraping yielded a total of 10,384 posts after removing duplicates.

4.4.3 Data Filtering

Once the original posts were collected, a subset of them were read and analyzed for their relevance in answering the research question. That is, we inspected the posts to see if they were actually about an individual in computer science talking about completely leaving the field. It was found that many of the posts were not relevant to answering the research questions, and thus further filtering of the 10,384 posts was needed. Due to the large data set, this filtering was done with the help of generative AI, which provided clear utility in identifying which posts to focus on in a manageable way.

The open-source generative text model Qwen2.5-32b was used for this filtering task. We used this model because it was the most accurate among the four open source models we tested (phi-3-14b, llama 3.1-8b, and mistral-nemo-12b were the others). Note that the ‘b’ in the model names refers to the number of billions of parameters in the model. We tested those models because they each had some form of open-source license (e.g., Apache-2.0, MIT). To perform the filtering, we prompted the model using prompts 1 and 2, listed in the appendix. The prompts first summarized the posts and then used those summaries as part of instructing the model to consider the inclusion/exclusion criteria and eventually suggest whether or not to keep or discard the post after applying a series of reasoning steps. The model returned a response to either keep the post, discard the post, or was unable to determine. We then manually went through the posts that were labeled as unable to be determined by the model and decided whether they should be kept or discarded. After filtering, there were 263 posts remaining that were used for analysis.

Although filtering significantly reduced our sample size, the remaining 263 posts still constituted a dataset substantial enough to justify the use of generative AI for analysis. Prior studies analyzing Reddit posts with traditional qualitative methods typically worked with around 30 posts (Berdanier et al., 2020), and our dataset is more than nine times that size. Furthermore, while some Reddit posts are brief, others extended up to 9,823 characters (approximately 4 pages), with an average length of 1,882 characters (approximately 0.75 pages). In total, our dataset spanned over 197 pages. While this volume is not insurmountable for manual qualitative analysis, it would be highly time-consuming. Additionally, manually contextualizing findings across 263 distinct posts adds another layer of complexity. Given these factors, generative AI provides clear utility, enabling a more efficient analysis while also serving as a pilot study to inform future research on larger datasets where manual analysis would be impractical.

4.4.4 Data Analysis: Categorization

To address our research questions across various departure stages, we first defined these stages and categorized the Reddit posts accordingly. After an initial review of the data, we identified four distinct departure stages, which are outlined in Table 4.1. These categories were determined based on the key decision points individuals face: leaving a degree program, deciding what to do after completing a degree, and leaving the industry. Within the post-degree decision stage, we further distinguished between individuals considering additional schooling and those seeking employment, as the factors influencing each group's choices were contextually distinct.

Table 4.1. Computer Science Departure Stages

Departure Stage	**Definition**
Degree Abandonment	Individuals who entered but did not complete and left a computer science degree program (including associates, bachelors, masters, Ph.D., etc.)
Post Degree Academic Shift	Individuals who completed a computer science degree program but decided to pursue another degree program outside of computer science (including bachelors, masters, Ph.D., etc.)
Post Degree Industry Shift	Individuals who completed a computer science degree program but then pursued a job outside of the computer science field unrelated to their computer science degree
Industry Exit	Individuals who held a job in the computer science field and then left the field (does not include individuals who simply changed jobs within the computer science field)

To categorize our data, we once again used the same generative text model to apply one of these four labels. In particular, we used prompt 2.1 in the appendix. The prompt was designed to provide task instructions, formatting instructions, background context, and the full reddit post. The output from the model was a suggested best match for labeling the stage of that post.

4.4.5 Data Analysis: Codebook Generation

To analyze the data and develop a codebook, a previously identified method of thematic analysis using generative AI, known as the Generative AI-enabled Theme Organization and Structuring (GATOS) workflow (A. Katz et al., 2024), was followed. The goal of this method is to identify recurring patterns in the data by utilizing multiple natural language processing techniques along with generative text models in a multi-step workflow to perform inductive qualitative analysis. This workflow mimics the steps taken by a human coder when conducting thematic analysis: reading the raw data, summarizing the data, generating codes that capture recurring patterns, and identifying themes present among the codes.

The first step of GATOS was to summarize the data into distinct ideas. This step was important because oftentimes, our raw data contains multiple ideas in a single post. When models are given the raw data to analyze, not having clear ideas can make it difficult to accurately analyze. Extracting these key ideas makes it easier for models to then analyze them in future steps. Again, we used the Qwen-2.5-32b generative text model for these steps and prompt 3 in the appendix. The prompt was formatted to assign a persona to the language model, provide background definitions for constructs relevant to the task, and formatting instructions for the output. Moreover, because we had already summarized the posts as part of the filtering process, we were able to recycle those summaries here for the codebook generation.

The second step of GATOS was identifying semantically similar summary point ideas. Here the goal was to group together similar ideas despite them being expressed in different ways throughout the data. This step allowed us to more easily assign codes to each group because ideally, there should be only one distinct idea in each cluster rather than the multiple ideas found in the original dataset.

The third step of GATOS was to create the codebook. This was done by iteratively reading through each cluster of summary points and deciding whether or not to create a code for the cluster. We used prompt 4 in the appendix for this step. Here, the prompt was much more intricate than the prior prompts because the model needed to perform several tasks, including identifying a potential code that could describe the data in that cluster of summary points and then deciding whether it was redundant with the existing codes. In particular, to start this step, we asked the model to generate 20 codes it would expect to find in our data about people leaving the computer science field. These 20 codes acted as the start of the codebook, however it would grow as we stepped through each of the summary clusters. Stepping through each cluster, we then embed each summary point within the cluster along with all current codes in the codebook. Then, we find the k-nearest neighbor codes for the extracted summary points in the cluster using cosine similarity matching. In this study, we used k=4 to ensure sufficient coverage without distracting the model with too much extraneous information. These k-nearest neighbor codes were then used in the prompt given to the generative model to decide whether the existing codes were sufficient to provide thematic coverage to the cluster, or whether a new code needed to be generated. This step was repeated for each cluster of summary points.

The fourth and final step of the GATOS workflow was to simplify the codebook by identifying themes. We used prompt 5 for this step, which again used persona assignment, step-by-step instructions, and structured output to improve the model's performance on this task. The purpose of this step is to reduce the redundancy of codes throughout the codebook by condensing codes that belong together at an abstract level into one theme. This was done by clustering individual codes and prompting the model now to look at each cluster of codes and identify thematically similar codes.

4.4.6 Data Analysis: Codebook Application

The codebook was applied by first embedding all codes and all summary points. We then calculated cosine similarity scores between the embeddings for each code and the embeddings for all the summary points. This operation produced a list of possible semantically similar summary points for each code. We then selected the top five matches of summary points, tracked where those summary points came from in the original posts, and used this method for identifying example posts that corresponded to each code.

4.4.7 Data Analysis: Human-in-the-Loop

After the themes were generated and the codebook was applied, a human researcher analyzed and interpreted the findings. The researcher's familiarity with the data, gained through prior reading to assess the generative AI's performance in data filtering, enabled this analysis. This process involved combining and refining themes and connecting them back to SCCT to better understand their influence on career decision-making. The finalized codebook is provided in the appendix. Researchers also revisited the data during the results-writing phase to ensure that the findings were contextualized, meaningful, and accurate. Incorporating a human-in-the-loop ensured research quality and precision, allowing generative AI to assist without sacrificing the contextual nuances and depth inherent in traditional qualitative analysis.

4.4.8 Research Quality

To ensure research quality, several measures were implemented. First, all steps involving generative AI analysis were closely monitored by human researchers. In cases where generative AI results were inaccurate, multiple iterations of prompt development and model selection were conducted until an acceptable level of accuracy was achieved. Additionally, manual verification played a key role in developing the final codebook, which was then applied to the data. Quotes from the data were also used to support the generated themes, further ensuring accuracy. All generative AI prompts are provided in the appendix to maintain transparency in our methods. Limitations related to our methods and data sources are discussed in the limitations section.

4.4.9 Positionality

The first author identifies as a woman in computer science, and her perspective on this study is shaped by both her academic background and personal experiences navigating the field. Having encountered aspects of the computer science industry that felt isolating and unaligned with her values, she chose a career in teaching, a space that allows for more social connection and the opportunity to foster a supportive and inclusive learning environment. These experiences give her a dual perspective: understanding the technical demands of computer science while recognizing the social and structural factors that can make the field unappealing. This positionality informed her approach to studying why others might choose to leave computing and the need for environments that better meet diverse needs and aspirations.

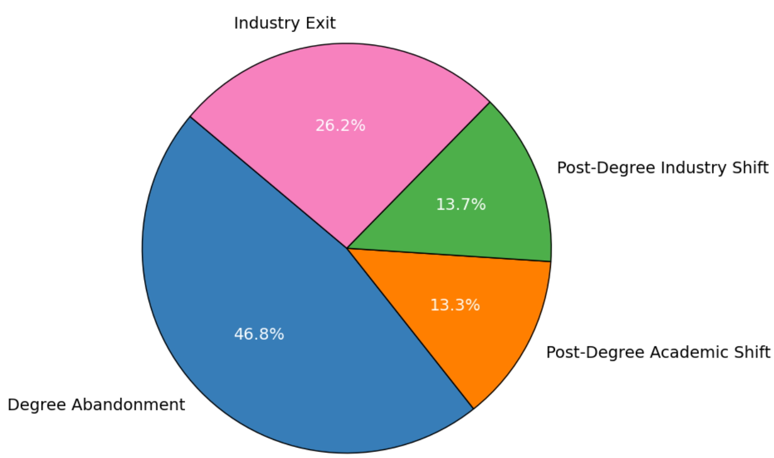
The second author is a faculty member in a Department of Engineering Education who researches applications of NLP in teaching and research in engineering education. Author two's background is not in computer science and thus has a different set of experiences across multiple domains compared with author one. Author two's connection to this project is two-fold:

understanding the extent to which generative text models can help scale up qualitative data analysis and characterizing decision-making processes that students and professionals navigate. Thus, while author two acknowledges the importance of characterizing departure decisions that people make when leaving the computer science field, their initial motivation for engaging in this work was to develop general mechanisms to study STEM students' and professionals' decision-making processes.

4.5 Results

Figure 4.3 shows the results of data categorization. The majority of our data falls within the degree abandonment departure stage, with industry exit being the second largest. The results of thematic analysis for each question are detailed below.

Figure 4.3. Distribution of Reddit Posts Across Departure Stages



Percentage of Reddit Posts Within Each Departure Stage

4.5.1 RQ1: What are the primary reasons individuals choose to leave the field of computer science?

There were six major themes that explained why individuals wanted to leave the computer science field: job dissatisfaction, aspirations and motivation for another field, psychological and emotional factors, academic struggles, health and well-being, and industry concerns. Each of these themes is further discussed in detail below. Figure 4.4 shows the percentage of posts within each stage of leaving that mention each theme, along with the total count of posts in each stage that contained the theme. The figure illustrates that all themes appear across every stage, with psychological and emotional factors, job dissatisfaction, and aspirations and motivations for other fields being the most prevalent across all stages.

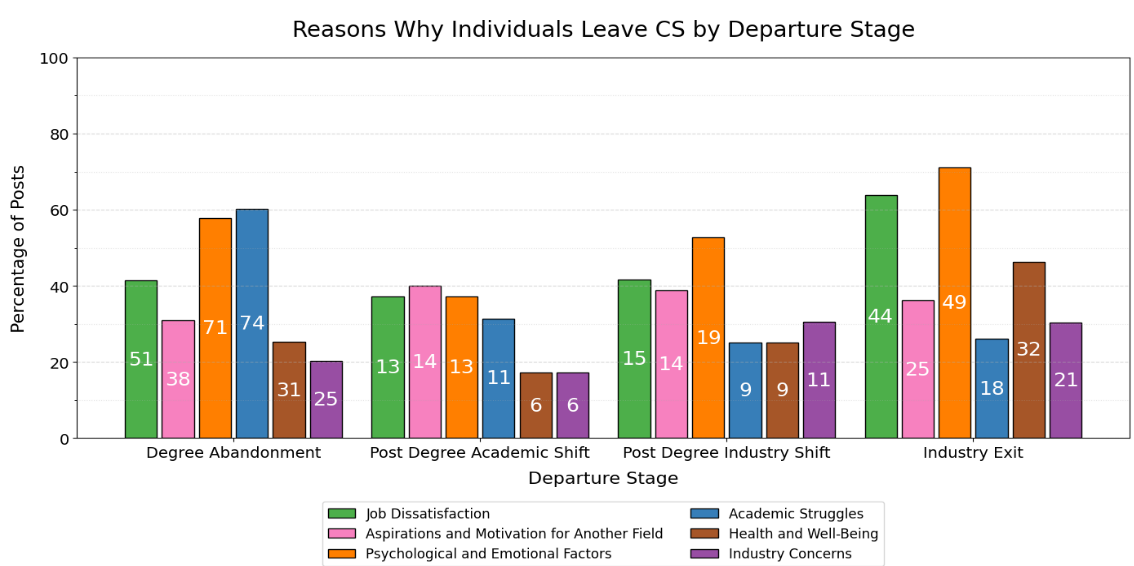
While academic struggles appear most frequently at the degree abandonment stage, they also surface when individuals reflect on their decisions to leave the field at later stages, even in industry settings. This happens because individuals may frame their decisions to leave the field by providing background on their earlier experiences with computer science. For example, one individual who left the field after working in industry reflected on his academic challenges to help explain their disengagement.

> *"I graduated from college in Spring 2018, with a degree in computer science and minor in mathematics. I've been a software developer/engineer for two years, with internship experience prior. [...] [I] have been rethinking my history with CS/programming and if it's the right fit for me anymore, or ever was to begin with. [...] I've never been the perfect student and had difficulties in buckling down to study. [...] I refuse to spend my life doing something that I ultimately don't care much about and am not even good at."*

This quote highlights how previous academic struggles, such as difficulty with more complex topics, can persist and undermine an individual's confidence in their abilities. Even after successfully transitioning from academia to industry, unresolved academic challenges can resurface and cause individuals to doubt their ability, making them question whether computer science is truly the right field for them, and ultimately contributing to the decision to leave the field beyond the degree abandonment stage.

Finally, health and well-being and industry concerns are mentioned less frequently than other themes. However, health and well-being emerges as the third most common theme at the industry exit stage. Similarly, industry concerns become slightly more prominent at the industry exit and post-degree industry shift stages, where individuals are more directly engaged with industry compared to the degree abandonment or post-degree academic shift stages.

Figure 4.4. Theme Prevalence for Reasons for Leaving Computer Science by Departure Stage[1]



[1] Y-axis shows percentage of posts within each stage containing theme, while labels on bars are the total count of posts containing theme within stage

4.5.1.1 Job Dissatisfaction

Job dissatisfaction emerged as a key reason individuals left computer science, aligning with the satisfaction model of SCCT which states career satisfaction depends on factors such as value alignment, perceived progress toward goals, self-efficacy, supportive environments, personality traits, and working conditions. These factors were evident in our data, as many individuals reported that their work lacked personal meaning and engagement, which undermined their sense of progress and fulfillment. The repetitive nature of the work left them feeling unmotivated and disengaged, as their daily tasks failed to provide a sense of growth or purpose. This disconnect between personal values and workplace norms was particularly evident in the lack of social interaction. Spending long hours on a computer with minimal social engagement left users feeling isolated and out of place, especially when they saw colleagues who seemed content with limited social interaction.

Challenges related to self-efficacy and supportive environments further drove dissatisfaction. Users described frustration with work environments, citing outdated codebases, poor documentation, and ineffective onboarding processes as barriers to success, particularly for those new to company-specific technologies. A lack of effective mentorship and support from management and colleagues compounded these issues, leaving individuals without the necessary guidance to succeed and diminishing their sense of self-efficacy.

Finally, overwhelming work demands and poor work-life balance further eroded satisfaction, with individuals stating their contributions held little value. Constant availability and the expectation of immediate responses to emails and requests created ongoing pressure, while frequent task-switching undermined productivity.

Table 4.2. Job Dissatisfaction Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Job dissatisfaction	This theme is about persons talking about their decision to leave computing based on things they are dissatisfied with at their current or the outlook of a future job in computing	" I have 3 developer jobs during the past year and I hated all of it. [...] I found out is that I hated everything about it from sitting down at an office cubicle for 8 hours day in front of a screen, it felt unfulfilling, not much human interaction, and I found no interest of doing development or any computer science related jobs."
		"Nothing is properly documented or commented and my senior is rarely available for questioning or pair programming [...]. My workdays have extended from a classic 9-5 to 8 a.m to midnight shifts where I can barely get 30 minutes of break in. [...] I even had to start working through weekends and holidays to deliver things in a timely manner. Sometimes I had tickets that were very unclear, imprecise or simply lacking in

		information. [...] My working speed consistently gets compared to the senior devs [...].”
		“There seems to be an expectation to act like chattel and be ready to fix and respond to requests at nearly any time of the day or night, and immediately respond to all emails, which is a big problem”

4.5.1.2 Aspirations and Motivation for Another Field

Aspirations and motivations to pursue careers outside of computer science emerged as a key reason why individuals wanted to leave the computer science field. Individuals described a genuine interest in other fields, often describing "dream jobs" or careers they found particularly intriguing that contrasted sharply with their computing experiences.

Individuals who expressed interest in other areas were drawn to pursue a wide range of interests outside of computer science, often shifting into fields like art and design, business and entrepreneurship, life sciences, and psychology. Others explored careers in health or veterinary care, legal work, fitness, and even landscape architecture. Others expressed interest in the type of job rather than the specific field, with some seeking more physical jobs, temporary or contract-based work, part-time positions, military roles, or opportunities in teaching.

At times, this theme was related to the previous theme of dissatisfaction, as their dissatisfaction motivated them to consider alternative fields. However, some individuals expressed aspirations for other fields without indicating dissatisfaction in computing, suggesting an intrinsic interest rather than a reaction to negative experiences as the primary reason for leaving. This dual perspective aligns with SCCT's emphasis on interest-driven career decisions, which can arise independently or as part of a broader assessment of career satisfaction. These findings underscore how interests contribute to decision-making by interacting with self-efficacy, environmental influences, and personal values, ultimately guiding individuals' trajectories both within and beyond computing.

Table 4.3. Aspirations and Motivation for Another Field Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Aspirations and motivation for another field	This theme is about persons talking about their decision to leave computing based on an interest or motivation to pursue another field outside computing	"Kind of realized [...] that CS is not where my interest lies; I'd rather go into a more tangible, design-related industry, and I love to be creative and work with outdoor spaces."
		"I'm ready to move on, there's nothing really getting me excited to go into work. The work is just very boring and stressful, and the atmosphere is derisive and bitter. [...]. I think it would be nice to try something more blue collar, or something outdoors."

		"I don't like compsci at all. [...] Every time I look at potential CS career paths or look for an internship I get filled with incredible dread. I want to do something meaningful and adventurous, and I don't want to stare at a screen for 8 hours[...]. I want to do something more social. I'm thinking about doing biology. Medical research would be my dream. Frankly, any science seems more interesting to me than CS."
		"I'm currently a sophomore/junior chimera on leave from a degree in computer science [...]. I left for a medical reason, and I just don't know if I want to go back. In highschool, I took this really awesome primateology, and I was recently reading through the research papers I had saved from it; I realized how much fun I was having and how it didn't feel like work at all. I watched a PBS thing on the evolution of man and it further served to remind me of how fascinating I think anthropology is.

		[...] The work they showed seemed more appealing to me.”

4.5.1.3 Psychological and Emotional Factors

Psychological and emotional factors played a significant role in why individuals left the field, often interacting with the earlier theme of dissatisfaction. Low interest and engagement in computing led to feelings of depression, which worsened motivation and self-efficacy. As individuals perceived themselves falling behind in skills or failing to keep up with new technologies, anxiety increased, further hindering performance and reinforcing negative emotions. Overwork and poor work-life balance also contributed to stress and burnout, with limited time off, unsupportive management, and high workloads amplifying isolation and emotional exhaustion. For some, these stressors left them overwhelmed, sometimes to the point of tears, and led to a sense of not belonging in the field.

Imposter syndrome emerged as a powerful force influencing self-efficacy. Many individuals reported feeling inadequate or incapable of meeting job demands, doubting their abilities and struggling to keep up with industry expectations. They felt out of place and unable to contribute to discussions, while peers advanced more quickly in their careers. These experiences reinforced a belief that they lacked the ability to achieve their goals, leading to diminished self-confidence and, ultimately, a decision to leave the field.

Table 4.4. Psychological and Emotional Factors Theme and Supporting Evidence from Example Quotes

Theme	**Theme Definition**	**Example Quotes**
Psychological and	This theme is about persons	“My GPA is awful at a 2.7 due to my high

emotional factors	talking about their decision to leave computing based on negative psychological or emotional factors	failure rate [...]. I try to do well and usually come up short; [...] All of this has driven me into a depression and it's hard to feel much of anything but stress and disappointment in myself and my inability to succeed. I want to quit, [...] I want to have purpose [...]. [...] I picked CS because [..] I've been told that the industry is doing well and is ripe with opportunity. But I don't think I can go on like this."
		"Getting to this point was really stressful [...]. After getting in I completely crashed [...] and I nearly committed suicide out of depression. I got out of my depression [...], but noticed that I have a hard time keeping up with all of the course work [...]. This has gotten so bad that I sometimes start crying after a little bit of work [...]. Making me only feel even more stressed. [...] Here I am in tears full of self doubt and stress. Wondering if I should take leave early from this path and leaving me be forever

		be disappointing in myself, or continuing killing myself with stress until I get expelled [...].”
		"I'm a frontend dev with about 4-5 [...] I'm beginning to think this career just ain't cut out for me and I should start considering another career path. [...] The amount of skills that is demanded for frontend dev just feels astronomical and seems to grow and change faster than I can reasonably keep up with [...]. The crazy thing is [LIST OF SKILLS AND APPLICATIONS EXPECTED TO KNOW] probably seems incredibly basic and probably even boring to all the giga brain comp sci chads. [...] Should drop the thousands of hours I've already invested in this industry to pursue an easier/less challenging career?”

4.5.1.4 Academic Struggles

Several academic factors contributed to decisions to leave the computer science field, often tied to self-efficacy, performance expectations, and learning experiences. Individuals left the field due to failing courses, struggling to fully grasp the material and difficulty in applying concepts to larger projects, and superficial understanding of core courses that led to challenges in advanced courses. These academic struggles were further compounded by external factors like the COVID-19 pandemic, family issues, non academic commitments, and mental health challenges, which hindered their ability to perform well and sustain their self-efficacy.

Negative classroom and teaching experiences also weakened students' self-efficacy and reshaped their career goals. Many cited ineffective instruction, where professors assumed advanced prior knowledge or employed "weed-out" techniques that undermined their confidence. Oftentimes these students were left to teach themselves, which proved unsuccessful. Students also struggled with limited support for neurodiverse learning needs in the classroom environment, which affected their engagement and sense of belonging in the field.

Other academic and financial factors led to disengagement from computing as a field. For some, a lack of funding or financial support necessitated leaving school entirely, with no perceived pathway into computing without a degree. Additionally, as students researched job and internship opportunities, some found that their coursework alone seemed insufficient to prepare them for industry roles. The vast array of skills required in computer science led them to conclude that extracurricular projects were essential to be job-ready, yet many lacked the motivation to pursue such projects outside of their academic commitments.

Table 4.5. Academic Struggles Theme and Supporting Evidence from Example Quotes

Theme	**Theme Definition**	**Example Quotes**
Academic Struggles	This theme is about persons talking about their decision to leave computing based on	"I've been in an introduction CS class this summer and only 4 weeks in with an F in the class. I'm incredibly lost even after

	struggles they face getting a degree in computer science that either make them question if they want to continue pursuing a degree in computer science or make it so they are unable to do so	hours of studying and I can't figure out how to make any of the homework programs work. I'm at rock bottom and disappointed that I will have to change degrees.”
		“This semester however, I am taking Introduction to Object Oriented Design with a professor who, while nice, isn't a great teacher at all[...]. [...] Its not the greatest environment. In class lectures are slow and would drag on, content itself was difficult to understand, and the assignments feel excessive.”
		“When I look on linkedin/indeed software engineering positions vary wildly in terms of the technologies they want you to know of [...], several coding languages, and a whole host of things that made me say ‘this degree doesn't particularly feel like it is preparing me to be competitive in the job market and this seems like a train leading to broken tracks.’”

4.5.1.5 Health and Well-Being

Health challenges were another key reason for leaving computer science. Physical concerns played a role, with some individuals feeling that the sedentary, computer-centered nature of computing work led to back problems, weight gain, and even vision issues. Specific workplace conditions further exacerbated health issues for some, such as black mold worsening asthma and causing respiratory infections. These health-related struggles often lowered self-efficacy, as individuals questioned their ability to sustain a successful career in computing while managing ongoing health concerns. In some cases, health issues also led to probation due to attendance problems, further diminishing confidence and causing shifting career goals. Additionally, many found that computing work conflicted with their preferred lifestyle. The demanding hours and lack of work-life balance limited time for hobbies, travel, and family, factors stated as essential to individuals' well-being.

Table 4.6. Health and Well-Being Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Health and well-being	This theme is about persons talking about their decision to leave computing based on how a career in the field would or is affecting their wealth and well-being	"I am interested in making an exit from the IT world, for various reasons: [...] Back issues causing me to have concern for sitting in a chair 8 hours a day for several decades."
		"At the end of the day I just want a position that makes me happy, and I value

		that 10 fold over money."

4.5.1.6 Industry Concerns

The choice model of SCCT emphasizes that the environment plays a significant role in shaping career decisions, effectively "choosing" individuals based on the conditions it sets. This perspective is evident when individuals cite industry trends as reasons for leaving the computer science field. Individuals expressed concerns about future job prospects, claiming high numbers of computer science graduates, insufficient job openings, and waves of layoffs as signs that job prospects in the field are low. Some attributed these trends to generative AI potentially automating entry-level roles, while others thought a drop in salaries for positions they once expected to be high-paying signaled too many people being qualified. Such industry shifts decreased individuals' self-efficacy, leading them to doubt their ability to reach their career goals and ultimately consider leaving the field.

For some, these industry concerns simply generated anxiety; for others, they felt the effects firsthand. Individuals described difficulties finding computing jobs post-graduation despite strong academic performance, citing the challenging nature of technical interviews and applications to hundreds of positions with no responses. This highlights SCCT's idea that individuals' career choices are not made in a vacuum; in many cases, the environment itself limits their ability to succeed, leaving them with few options but to leave the field.

Table 4.7. Industry Concerns Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Industry concerns	This theme is about persons	"The trajectory of this industry is really

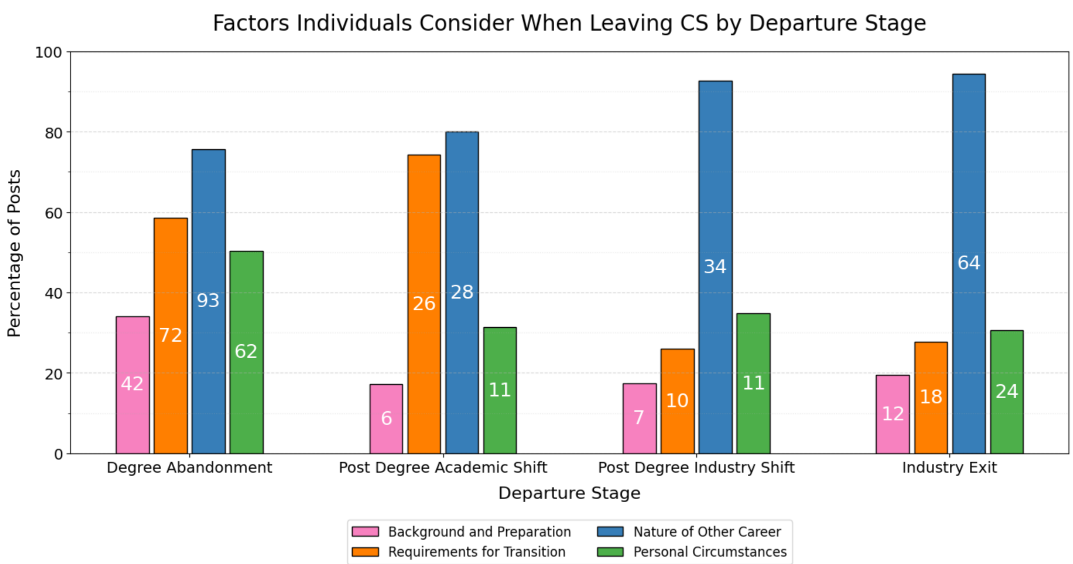
	talking about their decision to leave computing based on their perception of the computing industry, including concerns about the competitive market and the fear of not being able to find a job.	concerning. The tax code worries me, the amount of cs majors worries me, outsourcing and ai are both big concerns too. [...] I read posts here and it seems like landing a job is all about who you know more than that you know. I guess I'm just kinda worried about the job market and not sure if I should focus elsewhere."
		"Last year before corona and everything I managed to finish my master degree in computer science [...]. One year later I'm unable to find a job."

4.5.2 RQ2: What external or contextual factors influence the decision-making process for individuals considering leaving the field of computer science?

Before individuals decide to leave the computer science field, they often weigh the costs and benefits, questioning whether leaving is truly worthwhile despite their current dissatisfaction. To answer this research question, we investigated the factors that contribute to individuals' decisions to exit the field. Analysis revealed four main types of factors that frequently influenced these decisions: background and preparation, requirements for transition, the nature of alternative fields, and personal circumstances. Each of these themes is discussed in detail below.

While these themes appear at different rates across each stage, all are present in every stage. Figure 4.5 shows the percentage of posts within each stage that mention each theme, along with the total count of posts in each stage that contained them. Notably, the nature of other careers is the most commonly discussed factor across all stages. After that, requirements for transition is the next most frequently discussed theme at the degree abandonment and post-degree academic shift stages but becomes less prominent at the industry exit and post-degree industry shift stages, where individuals are more directly engaged with industry. Finally, individuals' background and preparation are the least commonly discussed factors across all stages.

Figure 4.5. Theme Prevalence for Factors Individuals Consider When Leaving Computer Science by Departure Stage[2]



4.5.2.1 Background and Preparation

Past learning experiences significantly influenced individuals' self-efficacy in assessing their readiness to leave computer science for a new field. Many evaluated their prior experiences, such as coursework, degrees, internships, and job roles, against the skills they believed were

[2] Y-axis shows percentage of posts within each stage containing theme, while labels on bars are the total count of posts containing theme within stage

essential for success in their target field. Additionally, individuals reflected on the transferability of their current skill sets from computer science to their new field of interest. For some, extensive knowledge of the desired field, whether through education, past work, or hobbies, provided confidence; others had limited knowledge but expressed strong interest.

Table 4.8. Background and Preparation Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Background and Preparation	This theme is about persons considering the decision to leave computing while thinking about their personal background and individual factors that influence this decision	"I am a senior majoring in CS [...]. [...] I've taken up to calc 3(plus linear alg), and I've never done any undergrad research. Are there any mathematical grad school options for someone who's interested in math [...]? [...] Since I majored in CS, my math courses weren't my core focus and so I mostly only have B/B+'s in them (one A)."
		"I'm applying for a job as a part-time library technician with a local council. [...] [REQUIRED EXPERIENCES] I don't have these qualifications or experience, but

		am confident that my abilities and transferable skills are not only relevant, but make me a strong candidate (as long as I can convince them of that)."

4.5.2.2 Requirements for Transition

Past learning experiences also shape individuals' self-efficacy by informing their assessment of necessary actions for a successful transition to a new field. Here, self-efficacy and prior learning experiences interact with future goals and actions required to achieve them. Many individuals identified considering the specific requirements for entering a different field when deciding whether to leave computer science. These requirements ranged from obtaining additional degrees or certifications, interview processes, or alternative entry pathways. This theme often intersected with the theme of background and preparation, as individuals frequently reflected on their existing degrees, coursework, and skills to gauge their readiness to pursue the transition requirements. This reflection further influenced their self-efficacy by helping them determine whether they could meet these new requirements successfully.

Additionally, individuals evaluated the type and nature of the transition requirements. They considered whether the requirements were flexible, such as the option to study part-time, or difficult, like needing a PhD rather than a certificate. Generally, the fewer or more flexible the requirements, the more motivated individuals were to pursue a field outside computer science. Furthermore, if multiple pathways existed into a field, or if requirements were minimal, individuals felt more encouraged to leave computer science, as it aligned more favorably with their self-efficacy and outcome expectations.

Table 4.9. Requirements for Transition Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Requirements for transition	This theme is about persons considering the decision to leave computing while thinking about what would be required to transition to a new field	“I've been considering civil engineering [...]. [...] Since my undergrad in comp sci shares little with other engineering majors course work wise, I believe most programs would want me to take the undergrad courses first.”
		“Can I somehow get into a MSc in Mech Eng/Biomed Eng and get a job? Or do I have to start over with a BEng? Because if so, I want to weigh it up against starting over with medical school.”

4.5.2.3 Nature of Other Career

When considering leaving the computer science field, individuals often assess whether a future career path would offer greater satisfaction. While individuals identified factors that contributed to their dissatisfaction in computer science, they also sought to find these factors better met in potential alternative careers. Additionally, they prioritized a work environment that aligned with their values, with a focus on work-life balance, advancement opportunities, an environment conducive to their physical and mental health, and positive social interactions.

This theme closely aligns with the job dissatisfaction theme from research question one, revealing that individuals often seek improvements in these factors when contemplating a career change rather than switching fields solely out of interest. In short, individuals look for career moves that address past dissatisfactions, aiming for improved alignment with their values and career needs.

Table 4.10. Nature of Other Career Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Nature of other career	This theme is about persons considering the decision to leave computing while thinking about what a career in a non computing field would be like	"Overall just hoping for something with more stability and a decent pay floor."
		"Something that I would be kind of interested in doing is becoming an elementary school teacher. [...] Not to mention summers off, and just enjoying a bright elementary school setting"

4.5.2.4 Personal Circumstances

The final set of factors influencing individuals' decisions to leave the computer science field are personal inputs. In addition to weighing the new field's alignment with their values and their perceived potential for success, individuals also evaluate how well the new career would suit their personal circumstances. Key considerations include physical and mental health, such as whether their condition would allow them to perform the work adequately, or if the new field offers the flexibility needed for regular medical appointments, and family responsibilities and financial pressures. Other personal factors include relocation requirements and the feasibility of moving due to family circumstances, as well as age, which may impact the practicality of transitioning to a new field or meeting certain requirements. Additionally, individuals assess the support available from friends, family, or programs within the field they're considering. This theme underscores SCCT's choice model, which emphasizes that decisions are influenced by contextual factors beyond an individual's direct control. In this way, personal circumstances are pivotal in determining both the ability to leave the computer science field.

Table 4.11. Personal Circumstances Theme and Supporting Evidence from Example Quotes

Theme	Theme Definition	Example Quotes
Personal circumstances	This theme is about persons considering the decision to leave computing while thinking about their personal situation and circumstances	"I feel like quitting and never going back, but my financial situation won't let me. I know I need to find a new career, but I just can't seem to think of anything financially viable that I can switch to without going back to school (I already have 35k debt in student loans)."

4.6 Discussion and Implications

4.6.1 Use of Generative AI

Generative AI proved valuable in this study for several reasons. First, it greatly improved the data filtering process, helping to ensure we had accurate and relevant data. Our initial dataset of over 10,000 Reddit posts was reduced to just under 300, highlighting that keyword-based collection alone is insufficient for filtering relevant content (Firoozeh et al., 2020). For instance, our keywords could capture posts about individuals leaving another field and entering computer science rather than leaving computer science. At this scale, manually verifying each post's relevance would be highly inefficient. Generative AI allowed us to identify more relevant data efficiently, enhancing both the quality and accuracy of our findings.

Generative AI also enabled efficient data analysis. Traditional qualitative methods would be time-consuming and challenging to apply at this data scale, as a human coder would have difficulty forming representative conclusions or detecting accurate patterns across so many different posts. AI-generated results captured our dataset effectively, allowing us to explore the issue of computer science attrition at a larger scale. However, incorporating a human-in-the-loop was crucial for meaningful contextualization and validation. This step allowed us to assess the accuracy of AI-generated themes, refining or discarding codes that lacked relevance to our research question or were developed inaccurately. The human-in-the-loop approach ensured rigorous analysis by continuously reflecting on the themes, validating them against the original data, and enhancing the overall accuracy and depth of our results.

Using generative AI for analysis raises several ethical concerns. First, there is the issue of data privacy (Gupta et al., 2023). Many generative AI models are open source and may require participant data to be shared beyond the research team. In our case, since we are using publicly available data, users have already consented to their information being shared online. However, if we were to use other types of data, it would be essential to obtain explicit consent from participants for their data to be utilized in this manner. Second, bias is a significant concern (Ferrara, 2024). AI models are trained on existing datasets, which may contain inherent biases, and this can lead to the perpetuation of those biases during analysis. Third, accuracy is critical; we must ensure that generative AI provides an accurate representation of the data and does not oversimplify it. To address both bias and accuracy concerns, incorporating a human-in-the-loop is essential. This human oversight allows for the assessment of results, a review of the original data, and careful checks for inaccuracies or biases. Finally, transparency is an important consideration, as the processes behind generative AI are not always clear or well documented. To address these ethical issues, we have committed to transparency in our methods. We explicitly state where generative AI has been used in our analysis and provide the prompts utilized to interact with the AI models, ensuring that our processes are clear and accessible.

4.6.2 Contextualizing Decision Making Within SCCT

4.6.2.1 Interest Model

According to SCCT, interest plays a critical role in shaping individuals' career decisions (R. Lent et al., 2002). Our findings indicate that both a strong interest in other fields and a lack of interest in computer science were pivotal factors in individuals' decisions to leave the field. SCCT also posits that self-efficacy is a key determinant of interest, a relationship that prior studies have confirmed within computer science. To enhance self-efficacy and increase interest in computer science, various interventions have been implemented, including the use of visual programming languages for teaching programming basics (Tsai, 2019), computational creativity exercises (Peteranetz, Wang, et al., 2018), and project-based learning (Rezvanifar & Amini, 2019).

However, our findings reveal that while low self-efficacy is a common challenge in academic settings, industry professionals and individuals who successfully complete computer science degrees still leave the field due to persistent self-efficacy issues and related concerns. While numerous studies have examined interventions aimed at students (Nhien, 2025; Wei et al., 2021; Yilmaz & Karaoglan Yilmaz, 2023), there is limited research on strategies to support individuals beyond the academic stage. One study identified workplace practices that influence self-efficacy (Ribeiro et al., 2023), but further research is needed to develop targeted interventions that improve self-efficacy among industry professionals.

Beyond the issue of low self-efficacy, our findings highlight that many individuals left computer science because they were drawn to other fields. Prior research suggests that even the stereotype that women have less interest in computer science contributes to their departure from the field (Master et al., 2021, 2025). Rather than attempting to replace these non-CS interests with an interest in computer science, interventions should aim to integrate computing with other disciplines. For example, Carnegie Mellon University offers numerous interdisciplinary programs that merge computing with other fields, such as the Bachelor of Computer Science and Arts, Music and Technology, Human-Computer Interaction, Computational Biology, and Computational Finance (Carnegie Mellon University, n.d.). Expanding opportunities like these could help retain individuals who might otherwise leave due to strong interests in other domains.

4.6.2.2 Choice Model

The choice model of SCCT highlights the significant role of the environment in shaping individuals' career decisions (R. Lent et al., 2002). Our findings reinforce this model in two key ways. First, in many cases, the environment itself limits individuals' ability to succeed, leaving them with few viable options other than leaving the field. SCCT's choice model suggests that the environment actively "selects" individuals based on the conditions it imposes. This is evident in cases where individuals leave computer science due to industry concerns or academic struggles, situations where the decision to leave is less of a personal choice and more a consequence of perceived or actual barriers to success. This may explain why industry concerns are more prominent at the post-degree industry shift and industry exit stages, as individuals transition from academic to industry environments, which then become the primary selecting force. Similarly, academic struggles are a more significant factor at the degree abandonment and post-degree academic shift stages, where students must navigate the highly competitive academic landscape. The demanding and high-stakes nature of the computer science field is well-documented. Prior studies have shown that computer science courses, especially introductory courses, are often structured with a weed-out culture (Weston et al., 2019), which disproportionately drives women out of the field at higher rates than men (Sanabria & Penner, 2017). Additionally, while there is a growing demand for computer science professionals, entry-level positions are increasingly being replaced by AI (Sandybayev, 2018), further shaping individuals' career trajectories.

Second, our findings highlight that career decisions are not made in isolation but are deeply influenced by personal circumstances and environmental factors. Many individuals leave computer science due to stress, burnout, and concerns about their mental health and well-being. While previous research has examined the challenging work environments of academic computer science programs (Barker et al., 2002; Barker & and Garvin-Doxas, 2004), less attention has been given to computing work environments in industry. In engineering fields, workplace conditions are a major factor in women's decisions to leave, with issues such as inadequate compensation, poor working conditions, and inflexible policies that fail to support work-life balance (Fouad et al., 2017). Our findings align with this literature, showing that across all career departure stages, the primary factor individuals consider when leaving the field is whether their comfort and working conditions will improve.

Ultimately, fostering more supportive and adaptable environments in both academia and industry could help reduce attrition. A literature review examining job satisfaction across various fields identified four key strategies for improving worker retention: (1) cultivating a friendly, positive, and supportive workplace culture; (2) offering competitive compensation and benefits; (3) providing opportunities for career growth and advancement; and (4) adopting inclusive leadership practices that value diversity, demonstrate empathy, and maintain clear, effective communication (Y. Wang, 2024). Implementing these strategies within computer science education and industry settings could create more sustainable career pathways and reduce the number of individuals leaving the field.

4.6.2.3 Performance Model

Within SCCT's performance model, self-efficacy and past performance shape future goals and actions (R. Lent et al., 2002), making this framework particularly relevant for understanding the psychological, emotional, and academic challenges that drive individuals to leave the field of computer science. SCCT posits that self-efficacy, formed through learning experiences and academic struggles, directly influences decisions to persist in or exit computing. Experiences of failure, perceived gaps in preparation, and inadequate support systems erode individuals' confidence in their ability to succeed. Our findings highlight how these negative experiences can impact decisions both at the moment they occur and later in one's career, as academic struggles appear across all four departure stages. This suggests that interventions targeting academic environments could not only reduce student attrition but may also help prevent industry professionals from leaving the field later in their careers. Prior research has found that game-based learning approaches (Zhu et al., 2020), increased exposure to computing experiences (Doyle et al., 2005), and peer instruction in the classroom (Zingaro, 2014) can enhance students' self-efficacy in computer science.

SCCT suggests that people tend to pursue careers in areas where they feel competent (R. Lent et al., 2002). If this were the primary factor, more individuals might have cited their background and preparation as factors they considered when leaving computer science. However, our findings suggest that many instead focused on improving their work environment and quality of life in their new field. This points to a broader issue: the work culture in computer science is often perceived as so negative that individuals are willing to enter new fields where they may be less successful just to escape it. Studies on underrepresented groups in computing have similarly identified the unwelcoming culture of the field as a key factor driving their departure (Charleston et al., 2014; Hernandez, 2023; Master et al., 2016; Ong et al., 2018; Rankin & Thomas, 2020). However, our data do not indicate instances of individuals transitioning back into computer science after leaving. Future research could explore whether those who struggle in new fields ultimately return to computer science, aligning more closely with SCCT's framework.

4.6.2.4 Satisfaction Model

Our findings highlight job dissatisfaction as a primary factor driving individuals to leave the field at every stage of departure, making the satisfaction model of SCCT particularly relevant. According to SCCT, individuals experience greater career satisfaction in environments that actively support and align with their personal values (R. Lent et al., 2002). Our data suggest that dissatisfaction was not just a passive factor in career changes, as individuals were not leaving simply for something different but were actively seeking something better. This underscores the importance of addressing sources of dissatisfaction in computer science environments to improve retention. As previously discussed, fostering a supportive and inclusive workplace, offering competitive salaries and benefits, providing clear pathways for career advancement, and implementing leadership practices that prioritize diversity, empathy, and transparent communication are among the most effective ways to enhance job satisfaction (Y. Wang, 2024).

Additionally, SCCT defines satisfaction as dynamic rather than fixed (R. Lent et al., 2002), which would explain the increasing dissatisfaction observed as individuals transition from academia to industry. As people grow and their priorities evolve, their satisfaction requirements shift as well. This suggests that interventions should not be one-time efforts but rather ongoing assessments and adjustments to ensure continued support and engagement throughout individuals' careers.

4.7 Limitations and Future Work

There are a few limitations to this study that can be placed in different categories. First, there are limitations in using generative AI for data filtering and analysis. Although model performance was high, it was not perfect, resulting in some relevant data being excluded and some irrelevant data being retained. This imperfect filtering means that the data analysis results may not be entirely accurate. However, we mitigated this limitation by incorporating a human-in-the-loop process to review and refine AI-generated themes and verify the accuracy of the reported results by returning to the original data.

Second, our dataset has a few limitations. The dataset is not time-constrained; while Reddit is less than 20 years old, it is challenging to determine whether some issues highlighted in our results have been addressed in the last 10 to 15 years. Additionally, while posts indicate an intent to leave the field, our data does not confirm whether these individuals actually did. Nevertheless, regardless of whether they ultimately left, their posts still provide valuable insights into the factors driving their desire to exit the field. As previously noted, demographic and background information cannot be collected for our data, limiting our understanding of who is represented in our study, and the demographic data that is available for the representation of Reddit users does not mirror the broader field of computer science, as the platform has a higher proportion of women compared to the gender distribution typically seen within the field of computer science. Using Reddit data introduces potential bias, as social media platforms often amplify the voices of the most vocal individuals, who may be expressing only negative experiences. However, this bias does not invalidate their experiences and is comparable to the selection bias inherent in interviews or surveys, where participants are self-selected. Finally, utilizing Reddit posts means we cannot engage in further follow-up questions or accuracy measures such as member checking in the same way that can be done with traditional interviews.

Future research should aim to better understand how to mitigate the factors identified in this study that lead individuals to leave the field. One approach could be to examine the fields individuals are transitioning to and explore how these fields address the issues highlighted in our findings. Additionally, studies could focus on measuring the impact of various factors that individuals consider when deciding to leave, gaining insight into which factors are most influential. Finally, future work should continue to explore the use of generative AI for qualitative analysis, with an emphasis on developing and evaluating additional human-in-the-loop approaches to enhance the accuracy and performance of AI-assisted thematic analysis.

4.8 Conclusions

The purpose of this study was to investigate the primary reasons why individuals leave the computer science field and the factors that influence their decision to leave across various departure stages. To address these questions, we collected and thematically analyzed Reddit data with the assistance of generative AI, employing a previously tested method, GATOS, to develop a codebook. We then extended this method by incorporating a human-in-the-loop step to contextualize and assess the AI-generated results against Social Cognitive Career Theory, verifying accuracy by cross-referencing the original data.

Our findings reveal that people leave the field for various reasons, including job dissatisfaction, interest in other fields, psychological and emotional challenges, health and well-being concerns, and concerns specific to the industry. When deciding to leave, individuals aim to mitigate these factors in a new career while also considering their preparedness for entering a new field, the requirements for doing so, and how the transition will affect and support their personal circumstances. Notably, all these reasons and factors appeared at every departure stage.

Using generative AI for this large-scale qualitative study enabled us to identify more generalizable insights into why people leave computer science, offering a broad perspective across contexts and departure stages for a more holistic view that can inform industry and academic policies and practices. By demonstrating the effectiveness of these methods in addressing this complex problem, we contribute to the development of more efficient, scalable workflows for future qualitative research.

Chapter 5: Results, Discussion, and Implications

5.1 Summary of Findings

The demand for computing expertise is rapidly growing, across more fields than strictly computer science (Bureau of Labor Statistics, n.d.; Schibelius et al., 2022). Yet, despite the high demand, computer science programs struggle with high attrition rates (Winograd, 2024). Additionally, the computer science field faces a severe gender gap (Engineering and Engineering Technology by the Numbers, 2022). The combination of high dropout rates and gender disparities threatens the ability of the tech industry to meet labor demands and create inclusive and equitable technology solutions (Loiacono et al., 2016; Teodorescu et al., 2021). Addressing these issues is vital for economic growth, workforce sustainability, and technological fairness (Stephenson et al., 2018).

This dissertation consisted of three manuscripts, each looking at the problem of attrition in computer science across an understudied population. An overview of each manuscript, along with their key findings can be found in Table 5.1. Manuscript 1 looked at an understudied population of individuals who are outside of the traditional computer science pathway, that is, who are not pursuing a major in computer science. It looked at high performing women in introductory computer science courses and investigated why they did not pursue a minor in computer science. Results showed that women in the study had a wide variety of negative experiences in their computer science courses, which turned them away from the field. Many women also expressed greater interest in other fields that took priority, and they were unable to see meaningful connections between those fields and computer science. As a result, they perceived a computer science minor as less valuable. Additionally, participants reported lacking a sense of belonging in the computer science community. However, they also lacked motivation to develop that sense of belonging, which discouraged them from pursuing a minor in the field.

Table 5.1. Overview of Dissertation Manuscripts

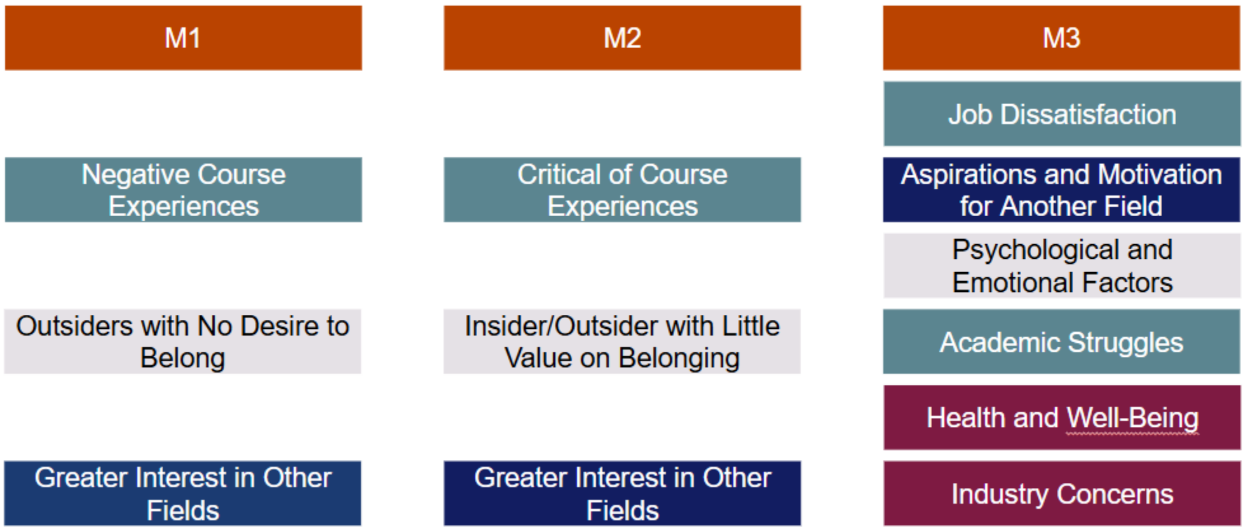
Manuscript	1	2	3
Research Question	Why do women who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor?	Why do men who perform well in introductory computer science courses for non-CS majors not pursue a computer science minor?	RQ1: What are the primary reasons individuals choose to leave the field of computer science? RQ2: What external or contextual factors influence the decision-making process for individuals considering leaving the field of computer science?
Theory	Bronfenbrenner's Ecological Systems Theory	Bronfenbrenner's Ecological Systems Theory	Social Cognitive Career Theory
Methods	Semi-structured interviews with seven women high performers in introductory computer science course for non-CS majors, analyzed with thematic analysis	Semi-structured interviews with six men high performers in introductory computer science course for non-CS majors, analyzed with thematic analysis	Reddit posts from individuals who are in the computer science field but who have decided or are considering leaving the field, analyzed using generative AI for thematic analysis
Key Findings	1. Women have negative experiences in their computer science classrooms 2. Women lacked a sense of belonging to the field, and had little motivation to belong 3. Women lacked interest in computer science and had greater interest in other fields 4. Women's perceptions of the macrosystem were not fixed, it was shaped and reinforced by patterns within the micro and mesosystem levels	1. Men were frustrated with their computer science courses 2. Men place little value on belonging within the computer science community 3. Men have greater interest in other fields and can learn and connect these fields to computer science on their own 4. Men's perception of the macrosystem were more fixed and used to critique the micro-, meso-, and exosystem layers	1. Most prevalent reasons for why people leave across all departure stages were psychological and emotional factors, job dissatisfaction, and aspirations and motivations for other fields 2. Nature of other field is most common factor individuals consider when leaving 3. There is a clear distinction between academic settings and industry settings for factors considered with respect to requirements for transition 4. Generative AI is helpful for thematic analysis, but a human-in-the-loop element is required for accuracy

Manuscript 2 was designed similarly to manuscript 1 and looked at another understudied population, again investigating those outside the traditional pathway of the field. It looked at high performing men in introductory computer science courses and investigated why they did not pursue a minor in computer science. Results showed that men were dissatisfied with their introductory courses for a variety of reasons that decreased their interest in pursuing a minor in computer science; men had greater interest in other fields and were able to learn the computer science material needed to connect computer science to those other interests on their own, therefore decreasing the value of pursuing a minor in computer science; and while men had mixed feelings of belonging within the computer science community, they viewed belonging as trivial and it was therefore not a strong motivating factor to pursue a minor in computer science.

Manuscript 3 looked at the problem of attrition at various departure stages and identified reasons why people wanted to leave the field and factors they considered when deciding whether or not they leave the field. These reasons and factors were then analyzed across departure stages, including leaving a degree granting program in computer science, completing a computer science degree but pursuing further studies not in computer science, completing a computer science degree but entering industry not in the computer science field, and leaving the computer science industry. Results showed that the main reasons for leaving the field were job dissatisfaction, aspirations and motivation for another field, psychological and emotional factors, academic struggles, physical health and well-being, and industry concerns. Factors that were considered included background and preparation, requirements for transition, the nature of alternative fields, and personal circumstances. These reasons and factors were present at every departure stage, with job dissatisfaction, aspirations and motivation for another field, psychological and emotional factors, and nature of the alternative fields as the most prevalent themes.

In each manuscript, I explored the reasons individuals disengage from the field of computer science. Although I examined different populations, forms of disengagement, and points of departure, similar themes emerged across the studies. Figure 5.1 illustrates how these themes connect across manuscripts, with related reasons for leaving highlighted in the same color.

Figure 5.1. Theme Overlap Across All Three Manuscripts



5.2 Discussion

5.2.1 Comparison Between Genders

Due to the nature of study design in manuscripts 1 and 2, results can be easily compared to reveal key differences and associations of gender when analyzing participants' decision not to pursue a minor in computer science. These differences include reasons for disliking the social nature of the course, course difficulty due to prior experience, interest in computer science and pursuing formal qualifications, community definitions and belonging, and overall agency within the field. Each of these are further discussed below.

5.2.1.1 Dislike of Social Nature of Course

Both men and women cited the lack of social interaction as a negative aspect of their courses, influencing their decision not to pursue a minor in computer science. However, while the complaint was similar for both genders, the reasons behind it varied. Women described feeling isolated and lonely due to the course format, attributing this to large class sizes, the structure of assignments, and the introverted nature of their peers. These experiences, they noted, contrasted with their personal values and needs for a future career. For women, there was a disconnect between their individual and the micro- and mesosystem, which they then projected onto the macrosystem. While some men also reported feeling isolated, they did not express the same personal disconnect. Instead, they viewed the lack of collaboration as problematic because it did not reflect the teamwork-oriented nature of real-world programming. This led to frustration and criticism of the course, rather than an internal conflict. For men, there was a disconnect between the mesosystem and their perceptions of the macrosystem, but their perceptions of the macrosystem influenced how they interpreted and experienced their mesosystem, rather than the mesosystem influencing their perceptions of the macrosystem.

The gendered differences in how students experienced isolation is further supported by prior research. Studies have shown that social interaction and peer support are crucial factors in retaining students in the computer science field, particularly for women (Pantic & and Clarke-Midura, 2023). Moreover, while men emphasized that the lack of social interaction in their courses did not reflect industry norms, it is equally important to recognize that women's retention in computer science is strongly influenced by their understanding of real-world work dynamics. Courses that foster collaborative environments and simulate industry practices tend to better support women's retention as well (Pantic & and Clarke-Midura, 2023). In addition, social interaction in the classroom not only improves retention but can also enhance learning outcomes, as students who have higher perception of collaboration perform better than those with lower perceptions of collaboration (Z. Liu et al., 2024). Without opportunities to engage with peers, students are less likely to form these positive perceptions of collaboration and see its benefits.

Furthermore, the communication climate in computer science classrooms can exacerbate these issues when social engagement does occur. Previous studies indicate that communication in these environments often aligns more with defensive behaviors than with supportive interactions (Garvin-Doxas & Barker, 2004). The lack of peer support and positive communication climates is particularly problematic in light of existing gender disparities in computer science exposure before college. Research has shown that men generally have more prior exposure to computer science concepts than women (Barrett et al., 2024; Hur et al., 2017), which may contribute to the difference in how they process the lack of social interaction. This gap in exposure aligns with our study's findings and helps explain why men may be more focused on the course's reflection of real-world teamwork, while women are more likely to feel personally disconnected from the material and their peers.

5.2.1.2 Prior Experience and Course Difficulty

A key difference between men and women in this study was their perception of course difficulty. Despite all participants being successful in their courses, women, on average, found the course more challenging, while men often described it as easy. However, a few women with prior coding experience found the course more manageable and aligned more closely with the men's experiences. These women acknowledged that, without their prior experience, they would have struggled more. Similarly, a few men with less coding experience found the course difficult, aligning more with the women's experiences. This suggests that perceived difficulty is influenced more by prior exposure to coding than by gender alone, a finding supported by prior literature (Gjelsten et al., 2021). However, prior exposure is gendered, as most men in the study had prior experience, while only a few women had significant coding backgrounds. While course difficulty itself may not be inherently gendered, gendered disparities in early programming exposure (Wilcox & Lionelle, 2018) contribute to differences in how men and women experience introductory computer science courses. In fact, differences in prior programming experience result in grade disparities even in higher-level computer science courses (Alvarado et al., 2018). This gap in experience may stem from gender biases in K-12 education, where boys are more often encouraged to explore coding through extracurricular activities than girls.

The same pattern observed with disliking the social nature of the course also appeared in reactions to course difficulty. Women often internalized the struggle, associating the difficulty with the idea that computer science might not be the right field for them, or losing interest as a result. In contrast, men tended to externalize the challenge, criticizing the course structure or the nature of the assignments. This difference in perspective illustrates that women were more likely to blame themselves for the difficulty, while men blamed the course, a phenomenon often seen in STEM fields (LaCosse et al., 2016). While gender may have played less of a role in how difficult the course was compared to prior programming experience, though the qualitative design of the study prevents me from confirming this, prior research shows that women often have lower expectations of success (Jones et al., 2023) and feel less prepared for their computer science courses (Alvarado et al., 2017). Despite the course difficulty being less directly influenced by gender, the way participants reacted to it was gendered. Women, who tended to internalize the problem, may be more likely to avoid future computer science environments, while men, who externalized the problem, may be more open to trying new computer science environments to see if their challenges improve. This is consistent with prior research that has found men to be more likely to persist when faced with challenges in computer science compared to women, especially those who already doubt their abilities (Milesi et al., 2017).

5.2.1.3 Interest and Connections

There was a notable difference in how men and women acted on their interest in computer science. While both groups showed some level of engagement, men generally expressed stronger interest (Beyer, 2014; Scott et al., 2023), with some women explicitly stating that they realized computer science was not for them. Men not only demonstrated greater enthusiasm but also frequently envisioned how computer science would integrate into their careers, citing its relevance to fields like civil engineering, chemistry, and finance. In contrast, although women found aspects of computer science engaging, they were less likely to see it as directly applicable to their professional paths. This finding is in contrast to earlier work that has found women are more likely to connect computer science to other fields, whereas men are more likely to see it only within the discipline (Margolis et al., 1999). However, more recent work aligns with our findings and shows that women who are less familiar with the broad applications of computer science are less likely to pursue computer science degrees (J. Wang et al., 2015). Participants' disconnect was partly due to their misconceptions about the field, such as believing that coding is rarely used for data analysis, that computer science professionals do not rely on external resources, or underestimating the diversity of coding applications. This aligns with prior work that has found women to have limited knowledge and understanding of computer science careers (Hur et al., 2017). While both men and women chose not to pursue a computer science degree, men still saw value in applying computer science knowledge within their primary fields. For them, it was not a choice between computer science and another discipline, but rather an integration of both. Women, however, were more likely to perceive their decision as binary, needing to choose computer science or their other fields of interest.

Men's enthusiasm for applying computer science concepts to other areas of interest might suggest that they would be motivated to pursue a computer science minor. However, as our results showed, this was not the case. Instead, men seemed to value the knowledge itself more than formal qualifications. Rather than pursuing the courses necessary for a minor, they chose to continue taking computer science courses that were either within their major, aligned with their interests, or learned independently. They valued the integration of computer science into other fields, but did not see the need for the formal qualification of a minor. This may be because the courses required for a minor were not directly relevant to their interests, still contained the same aspects they disliked in the introductory course, or simply because they lacked the time to take them. Regardless of the reason, men valued knowledge without feeling the need to pursue a formal qualification, a pattern reflected in broader STEM fields, where men are often not held to the same standards of proof or formal credentials as women. In fact, women with STEM degrees tend to hold positions more comparable to those held by men without formal STEM degrees than to those held by similarly qualified men. (VanHeuvelen & Quadlin, 2021).

This phenomenon also relates to another gendered difference: women's lower confidence in saying "I can" compared to men. Women were just as confident as men in saying "I did" when reflecting on their success in past computer science environments. However, when it came to pursuing further computer science, women were hesitant to say they would be successful in the future. In contrast, men were more likely to express confidence about their future success. This suggests that women may feel the need to prove themselves and could be more afraid of failure than men, which ties into the earlier distinction between internalizing failure (women) versus externalizing it (men). This dynamic may explain why women were less likely to connect their other interests to computer science. Without formal training in how to integrate computer science with their passions, and given that the required courses for a minor likely would not have made those connections, women may have lacked the confidence to see how their interests and computer science could align. This finding aligns with prior literature that found women consistently have lower self-efficacy than men in STEM, despite having just as good if not better performance (MacPhee et al., 2013; Whitcomb et al., 2020).

5.2.1.4 Community and Belonging

Men and women had markedly different perceptions of the computer science field and its community. Women were more attuned to common stereotypes, often noting the male dominance and socially awkward personality types associated with computer science, which impacted their experiences more significantly. They frequently encountered reinforcing situations that made these stereotypes feel pervasive and discouraging, which prior literature has found to be a major factor in women's participation in computer science (Cheryan et al., 2009; Master et al., 2016; Spieler et al., 2020). The male-dominated stereotype, in particular, can negatively impact women's self-efficacy, as one important way self-efficacy develops is through observing similar others succeed, and without visible examples of other women succeeding in the field, women lose a vital source of confidence in their ability to succeed (Bandura & Wessels, 1997). While some women acknowledged their gender identity in the classroom as being highly salient, a commonality for women in male-dominated STEM fields (Van Veelen et al., 2019), they did not always attribute their decision to leave computer science solely to male dominance. However, one participant explicitly stated that being a woman led to different treatment, making the environment feel actively unwelcoming in ways that men did not experience. In contrast, men generally described the computer science community as welcoming, aligning with prior work that has shown men to not understand the additional struggles women face in STEM (Freedman et al., 2018). Women, however, often felt isolated or excluded, and even when they encountered kind individuals, they did not characterize the field as equally welcoming, friendly, or supportive as men did (Cheryan et al., 2020; Widdicks et al., 2021).

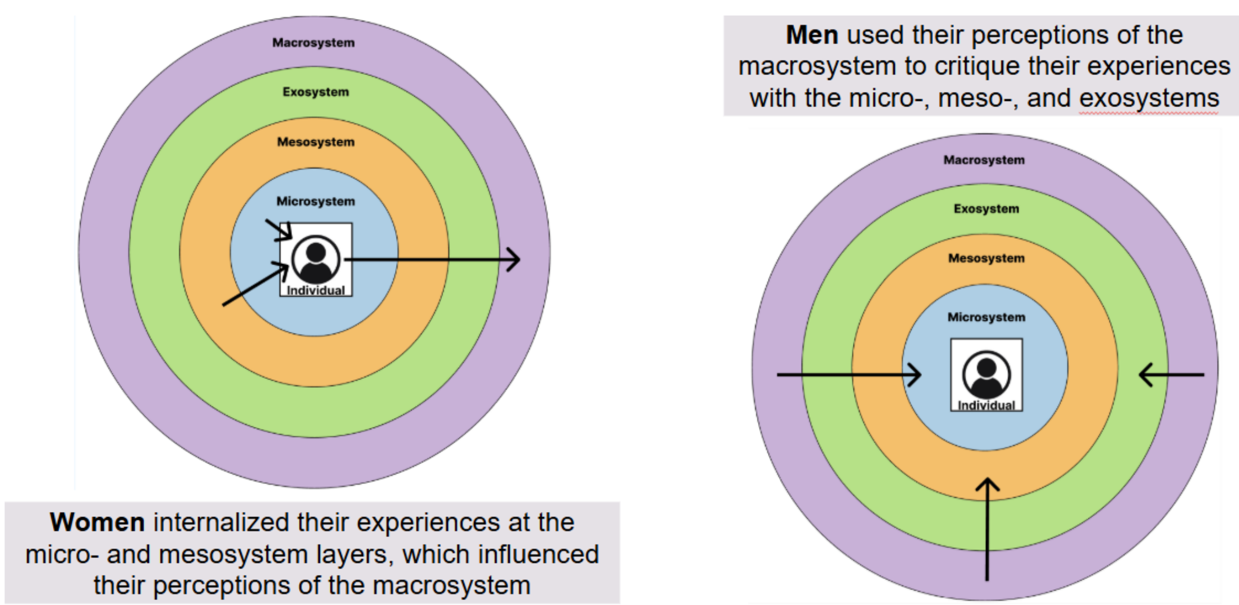
Moreover, while both men and women identified as outsiders to the computer science community, their perceptions of potential inclusion differed. Women tended to define community membership by formal, measurable criteria, such as possessing specific knowledge or earning a degree. Consequently, although they recognized that they could be successful in pursuing these qualifications, they felt excluded because they had not followed that path. Men, on the other hand, saw community membership as more fluid and based on personal choice rather than rigid standards. They believed that if they wanted to be part of the community, integration would be easy. This difference suggests that women perceive more barriers to inclusion than actually exist, potentially limiting their own sense of belonging in computer science, and that men have a higher computing self-efficacy within the field (Beyer, 2014).

These differing views on community shaped how participants made sense of their place in the field. For women, stereotypes, gender identity, and limited interest in the field contributed to a lack of desire to belong. Because they neither identified strongly with computer science nor wanted to fit in with the stereotypical community, their weak sense of belonging did not negatively influence their decision to persist, they simply did not want to belong. Men, on the other hand, tended to view belonging as a matter of personal choice rather than identity. Some felt they belonged, while others did not, but the lack of belonging was irrelevant to their decision about pursuing a minor because those who lacked belonging did not see persistence as a path to community. For both groups, a sense of belonging, or the absence of it, played little role in shaping decisions about continuing in computer science. Instead, these findings point to domain identification as a more significant factor than belonging in influencing persistence decisions (Jones et al., 2016).

5.2.1.5   Agency Within the Field

Overall, men and women navigated computer science spaces in distinctly different ways. In our study, Men tended to act with more agency and confidence, while women often exhibited hesitation and a more passive approach. This difference is evident in several areas: women are more likely to internalize difficulty, face more stereotypes and higher barriers to belonging, and struggle to draw connections between computer science and their other interests (Beyer, 2014; Whitcomb et al., 2020). In contrast, men externalize difficulty, challenge stereotypes, perceive belonging as an easy choice, and find ways to link computer science to fields they care about. In doing so, men tend to blame their environment for any failures and manipulate the environment to their advantage, giving them more agency within the field. Figure 5.2 highlights these differences using Bronfenbrenner's Ecological Systems Theory (Bronfenbrenner, 1979) to show the interactions, as well as their direction, between the various system levels.

Figure 5.2. Gendered Differences in System Level Interactions



These patterns align closely with attribution theory (Weiner, 1985), which has been used to show that men are more likely to attribute successes to their own ability and failures to external, unstable factors, whereas women tend to credit successes to external causes and blame themselves for failures (Beyer, 1998; Rosenthal, 1995). This attributional style reinforces men's confidence and sense of control while undermining women's self-efficacy, fostering a tendency for women to internalize negative experiences. As a result, women often feel more controlled by their environment, encountering additional barriers while holding themselves responsible for their struggles. They are frequently hesitant to embrace confidence, expecting instead that they must adapt to the environment rather than the environment adjusting to them.

This ongoing pattern leads to a sense of value misalignment with the field; yet even when women recognize these issues, they tend to blame themselves rather than question whether the field has failed to support them. For many women, it may feel easier to assume that all computer science spaces are the same and opt to leave the field rather than try to reshape themselves to fit in. Men, however, believing failure stems from external or temporary circumstances, are more likely to stay, test out new computer science spaces, and expect that they can change the environment if needed (Master et al., 2021). This dynamic is further reinforced by cultural messaging suggesting that computer science is not a space for women(Cheryan et al., 2015). While these messages may not always consciously drive women's decisions, they likely contribute to women's lower sense of agency in the field compared to men. Attribution theory helps explain this dynamic: when failure is viewed as internal and stable, as women often do, they are more likely to avoid similar contexts in the future, whereas men's external, unstable attributions for failure make them less likely to disengage from these environments. Together, these patterns help explain persistent gender disparities in computer science participation and persistence.

5.2.2 Influences Across System Levels

While the findings from manuscripts 1 and 2 could be interpreted as being shaped by specific contextual factors due to their limited scope, the results from manuscript 3 point to a broader issue: attrition in computer science is not confined to isolated contexts but is instead a systemic, field-wide problem. Moreover, this issue cuts across all levels of the system, as the reasons for leaving appeared consistently at every stage of departure. By using Bronfenbrenner's Ecological Systems Theory alongside Social Cognitive Career Theory, we can dissect how various system levels influence individuals' decisions to disengage with the computer science field.

At the individual level, several factors emerged across the manuscripts as key influences in participants' decisions to disengage with the field (relevant literature is cited to demonstrate where these findings were consistent with prior research): gender (Spieler et al., 2020), self-efficacy (Whitcomb et al., 2020), prior experiences (Margolis & Fisher, 2002), values and career goals (Eccles & Wang, 2016), sense of belonging (Krause-Levy et al., 2021), interest (Master et al., 2021), emotional and physical well-being (Kiazad et al., 2024), and performance expectations (Beyer, 2014). SCCT helps us interpret how these personal inputs and cognitive processes shape career decision-making.

Starting with personal inputs, manuscripts 1 and 2 demonstrate that gender influences how individuals experience computer science spaces and engage with them. Manuscript 3 further emphasizes the role of health, both mental and physical, as a major determinant in decisions to persist or depart from the field. These personal inputs also mediate how individuals experience and interpret the surrounding systems. In terms of background and environmental influences, manuscripts 1 and 2 highlight the importance of prior programming experience, which shaped learning trajectories and system-level interactions. SCCT also introduces learning experiences as key to understanding career development; in our data, these experiences primarily occurred within the micro- and mesosystem levels in manuscripts 1 and 2, and within the academic struggles theme of manuscript 3. Self-efficacy, a central construct in SCCT, emerged as a major factor across all three manuscripts and at all decision-making stages. It closely interacted with performance expectations, as failure to meet these expectations often led to decreased self-efficacy. Interest, another core SCCT factor, was shaped not only by engagement with computer science but also by exploration of alternative fields, and this factor was influenced by micro-, meso-, and macrosystem interactions. Finally, SCCT's concept of choice goals was found to be interwoven with belonging. Manuscripts 1 and 2 revealed that a lack of desire to belong mitigated the impact of exclusionary experiences. In short, individual-level factors were both shaped by and reactive to dynamics occurring at other system levels.

The microsystem includes direct interactions with individuals within the system. Influential actors in this layer included peers (both inside and outside of computer science) (Barker et al., 2009; DuBow et al., 2017), family members (Tuma et al., 2025), instructors (Barker et al., 2009; DuBow et al., 2017)), teaching assistants (Kabir et al., 2025), managers (Y. Wang, 2024), and co-workers. Manuscripts 1 and 3 showed that negative interactions at this level often influenced individuals' perceptions of the larger computer science environment, contributing to their decision to leave. However, Manuscript 2 added nuance, as it showed not all negative microsystem experiences had broader implications, especially when moderated by personal factors like prior experience.

The mesosystem includes first-order structures and environments where individuals regularly operate, such as classrooms and direct workspaces (Barker et al., 2009; Bunderson & Christensen, 1995). This level was shown to be especially influential: negative experiences here were often the primary reason for leaving, shaped perceptions of the field as a whole, and guided what individuals sought to avoid or change in their subsequent careers. This finding suggests that interventions targeting mesosystem structures, like curriculum design, classroom culture, or work team dynamics, could yield substantial benefits in reducing attrition. However, Manuscript 2 showed that yet, again, prior experience played a mediating role. For some individuals, particularly those with substantial programming or workplace experience, negative mesosystem dynamics were less impactful.

The exosystem encompasses institutional structures and policies that individuals do not directly engage with but that still affect their experiences, such as university administration or corporate policy (Griffith, 2010; Kiazad et al., 2024). In our data, these structures often influenced the mesosystem level. For example in manuscript 3, organizational policies around work-life balance or rigid degree requirements often translated into negative mesosystem experiences that drove people out of the field. Interventions at this level could indirectly but powerfully shape the environments in which individuals make their stay-or-leave decisions.

The macrosystem represents the broadest contextual layer: the overarching culture, values, and assumptions of the computer science field. Key elements influencing participants' decisions included stereotypes about who belongs in computer science and perceptions of job market expectations (Kendall, 2011; Master et al., 2016, 2021). Importantly, participants often interpreted negative experiences at other system levels not as isolated incidents but as reflective of the entire field. Leaving one job or program was not seen as a solution; instead, individuals often concluded that the entire field was not for them. Manuscript 2 underscored that for some, the macrosystem, and its interaction with the individual, was the most influential factor in their departure.

5.2.3 Computer Science and Larger Culture

A major factor influencing individuals' decisions to disengage from the field across all departure stages, identified in manuscript 3, was job dissatisfaction, a theme that also emerged in manuscripts 1 and 2. Additionally, the previous section demonstrated how each layer of Bronfenbrenner's Ecological Systems Theory contributed to participants' decisions to leave computer science, suggesting that attrition results from systemic, field-wide issues rather than isolated circumstances, career stages, or system levels. While these findings highlight important patterns of experience and interaction, they do not fully address the deeper cultural beliefs that may drive these dynamics. Some might contend that challenges such as isolating work, poor work-life balance, and competitive, unsupportive environments are not unique to computer science, but instead reflect broader societal patterns. This raises a critical question: Are these issues inherent to the culture of computer science, or are they manifestations of larger societal forces playing out within computer science contexts?

Many of the challenges participants described, such as declining interest, underperformance, misalignment of values, and poor work-life balance, are not exclusive to computer science (Y. Wang, 2024), though these issues do appear more frequently in computer science than in other fields. Their root causes may be tied to the broader cultural and economic systems in which the field is embedded. For instance, the field's emphasis on constant productivity, individual performance, and competition closely aligns with the values of capitalism (Schwartz, 2007), the economic system in which these studies were conducted. If computer science is particularly entangled in capitalist ideals, this could shape everything from educational and workplace structures to standards for success and ideas about who "fits" or thrives within the field.

If this is the case that findings in prior research are tied more to broader cultural or economic systems and not strictly the field of computer science, it complicates the prospect of solving attrition through CS-specific interventions alone, and could help explain why, despite years of research and reform efforts, progress remains limited. When cultural values like productivity equating to identity, or burnout being seen as a badge of ambition, are deeply embedded in computer science, individuals may be pushed out not because of the technical demands of the field, but because of how success is defined and reinforced socially, culturally, and institutionally.

Qualities that participants valued and sought, such as emotional well-being, collaborative problem-solving, and alignment with personal meaning, are not undervalued only within computer science. Prior work has pointed to similar patterns across the broader STEM landscape (Diekman et al., 2024; Salomone & Kling, 2017; Tan-Wilson & Stamp, 2015), suggesting that these issues may stem from deeper societal norms about what kinds of labor, identities, and ways of working are most valued in today’s cultural system. These insights open important avenues for future inquiry: To what extent are the cultural norms of computer science unique, and to what extent do they mirror dominant societal structures? How might larger societal or economic systems shape experiences of burnout and the narrative of the persistent “leaky pipeline” in computer science? Is meaningful reform within computer science possible without interrogating the larger societal systems in which it operates? Why do some fields with lower attrition rates appear to function outside of these cultural pressures (including some STEM fields), and what can computer science learn from them?

Future research should take this critical lens to the intersections of computer science and broader societal ideologies, exploring how macro-level forces filter down through institutions and into the lived experiences of individuals. A broader systemic perspective may reveal that the issues facing computer science are not field-specific anomalies, but rather symptoms of a culture that permeates many aspects of modern life. If that is the case, the challenge becomes not just how to reform computer science, but how local lower system levels can be built and structured to disrupt and resist influences from the broader societal structures that shape it.

Addressing these larger questions will require the analysis of substantial amounts of data, a task for which generative AI offers promising support. A reflection on the potential and limitations of using generative AI for large-scale qualitative analysis is provided in the section below.

5.2.4 Generative AI for Qualitative Analysis

Across the three manuscripts, I employed both traditional manual thematic analysis and a generative AI-supported workflow, which enabled a comparison of the two analysis methods and an evaluation of the usefulness of generative AI for qualitative analysis. The integration of AI proved helpful in several ways. First, generative AI enabled the identification of more qualitative codes than would typically emerge through manual analysis. This suggests that the AI-supported workflow may detect more nuanced or infrequent patterns across large datasets. For example, the AI was capable of identifying a recurring theme across 20 of 200 data sources, a pattern a human analyst might have missed due to its relatively low frequency. While the large volume of qualitative codes generated by the AI was eventually distilled into a smaller amount and broader themes, its ability to surface uncommon but potentially meaningful ideas reduced the risk of overlooking important insights.

Second, the use of generative AI significantly reduced the time required for the initial phases of data analysis. However, while it did save time, the process still required substantial iteration and human input, much like traditional analysis. One notable advantage was that qualitative code revisions could be applied across the dataset almost automatically, eliminating the need for researchers to manually re-code the data when updating code definitions, a typically tedious and time-consuming task. This allowed more time and cognitive energy to be devoted to higher-order thinking, interpretation, and critique, ultimately resulting in richer and more critical findings. And prior work has identified the value in iterative prompting for more accurate results and researcher reflection (Khan et al., 2024).

Third, when integrated thoughtfully into an iterative workflow, generative AI can act as a thinking partner, offering alternate perspectives during theme development. For instance, AI may suggest a different thematic organization than a researcher might initially choose. While not all AI-suggested structures are appropriate, they prompt critical reflection and invite researchers to view the data from multiple angles (Khan et al., 2024). Much like collaborating with another analyst, this multi-perspective approach can improve the accuracy and depth of the analysis.

However, the use of generative AI is not without limitations. First and foremost, human oversight remains essential. While AI can technically function without human intervention, the results are unlikely to be accurate or meaningful without iterative refinement. In this study, the final codebook was developed through human interpretation of the AI-generated outputs. Relying solely on the raw AI analysis produced weaker and less reliable findings, an observation made by others who have used generative AI for thematic analysis of social media data (Ghali et al., 2025; Khan et al., 2024).

Second, generative AI is more adept at answering descriptive “what” questions than interpretive “why” or “how” questions. While it excels at extracting information, it struggles with deeper analytical tasks such as identifying causal relationships or synthesizing abstract insights. Prior work has drawn similar conclusions, that models trained to summarize large amounts of data offers a wide understanding but not the depth that academic training brings (Breazu et al., 2024). Addressing such questions still requires human judgment and interpretive skill, and future workflows should further develop ways to enhance this capacity.

Third, while AI was less likely to overlook data, it was more likely to fabricate or overextend interpretations. When information was sparse or absent, the AI attempted to force coherence by generating conclusions that went beyond the evidence, which made a human-in-the-loop portion of our methods crucial. Unlike human analysts, generative AI is less inclined to recognize data gaps or to acknowledge that an answer is not present (Breazu et al., 2024). This reinforces the need for ongoing human evaluation throughout the analysis process.

5.3 Recommendations

Our findings offer several insights into how we can address the attrition problem in computer science. Below, I’ve organized these insights by system level and target audience. These recommendations are grounded in findings from all three manuscripts and further supported by prior literature cited throughout the dissertation.

5.3.1 Individual: Are you thinking about disengaging from computer science?

For those who are currently navigating the computer science system, or considering it, but are feeling uncertain or thinking about stepping away at any point, there are several strategies that can help prevent disengagement.

Get early exposure. If you're unsure about computer science, try it out, formally or informally, before you're forced to make a decision. Early experiences can help you make a more informed choice. Our data shows that students with more prior exposure to computer science tend to find courses easier. That early experience can also buffer against negative events that might otherwise negatively impact your perception of the field.

Do not compare yourself to others. If others seem more confident, more interested, or less challenged, do not assume that you're doing something wrong. Everyone engages with computer science differently, and there's no single "right" way to be part of the field. Our data showed that believing you are the only one struggling can negatively influence your self-efficacy, despite still maintaining high performance. Your path is valid, even if it looks different from those around you.

Trust your success, especially women. Our women participants were hesitant about their future success despite their past success, which lead them away from pursuing a formal qualification in the field. Believe in your abilities and do not let your fear of failure turn you away. If you succeed, that success is real. It was not luck or a fluke. You were and are capable. Move from "I did it" to "I can do it." That belief matters, and it is true.

If you're in a computer science job and feeling unhappy, reflect on what's really causing that. The theme of job dissatisfaction was broad and did not always reflect aspects unique to computer science. Ask yourself: Is it the field itself, or is it this particular job? There are many computer science roles out there that are collaborative, have good work-life balance, and are led by supportive management. Try not to project the challenges of one workplace or role (the micro or mesosystem) onto the entire field (the macrosystem). The broader computer science landscape is more diverse than any one experience.

5.3.2 Microsystem: Are you an actor in computer science or engaging with someone from computer science?

For those who are firmly in the computer science system and not considering leaving, or for those who regularly interact with others who might be unsure about their place in the computer science field, there are meaningful ways you can help support retention and foster a more inclusive environment.

Be kind and supportive. This applies to everyone, including faculty, TAs, peers, family members, coworkers, and managers. Our data showed that individuals look to have positive interactions with these individuals and that negative interactions, or a lack of interactions, can cause people to want to leave the field. Build authentic connections, offer support, and lead with kindness. Avoid judgment and create space for others to feel seen and valued.

Value and respect diversity in all forms. This goes beyond gender, race, or ethnicity. Embrace differences in personality, interests, communication styles, and skill sets. Our data showed that not fitting into stereotypes of the field lead to disengagement. To reduce the narrative of stereotypes, challenge the notion of a “stereotypical” computer scientist, and instead, recognize the value of diverse contributions, especially from those who do not fit the traditional mold. Creativity and innovation thrive in difference.

Be mindful of how you talk about the field. The language you use shapes the culture. If you're casually downplaying the difficulty of an intro course after years of prior experience, or consistently centering conversations around certain subfields like AI while dismissing others like social computing, consider the impact. Our data showed that self-efficacy can be negatively influenced by self-comparison to others' perceived difficulty. And that having misperceptions of all the applications of the field contributed to disengagement. What you choose to talk about, and how you talk about it, contributes to what others think the field values. Make sure your words invite others in rather than push them out.

5.3.3 Mesosystem: How can we structure formal computer science spaces?

To better support retention in computer science, formal computer science spaces, both academic and workplace environments, need intentional design. In academic environments, especially at the introductory level, course design plays a critical role in shaping student perceptions and experiences.

Introduce diverse applications of computer science early. Many upper-level courses showcase a broad range of applications, but our data suggest this often comes too late, as our participants chose not to pursue further studies based on experiences in introductory courses that did not showcase diverse applications. Introductory courses should include varied and relatable applications of computer science to spark interest and prevent narrow or inaccurate assumptions about the field.

Scaffold content and provide robust resources. Our participants who had no prior programming experience needed strong classroom support, or they found the course too difficult and lost interest in pursuing further courses in the field. Introductory courses must be well-structured, with clear scaffolding and accessible learning supports. Offering a range of materials, such as textbooks, annotated code examples, lecture slides, and practice problems, helps students engage with the material in different ways, meeting diverse learning styles and backgrounds.

Additionally, incorporating generative AI into teaching practices can help provide 1-1 support for students when human resources and time are scarce.

Be mindful of pacing and prior experience. Our participants without prior experience often found pacing too fast, causing feelings of difficulty that turned them away from the field. Instructors should carefully consider course pacing, allowing time for those new to computer science to grasp foundational concepts. At the same time, courses should be designed to support both beginners and students with prior experience, as our participants who had prior experience often found the course too easy, also leading to disengagement. This means offering flexibility and challenge for all, without catering exclusively to one group.

Regardless of the academic or workplace setting, community-building and well-being must be central. Participants across studies had the desire to interact with peers, and when they were not provided with the opportunity, they turned to other fields to provide it. Encourage collaboration and connection. Create opportunities for students and employees to connect and collaborate, through group projects, classroom activities, team brainstorming sessions, or informal social events. Our findings show that relationship-building fosters a sense of belonging and shared purpose, which is essential for retention.

Prioritize physical and mental well-being. Our data showed that both poor mental health due to stress and overwork and concerns for physical health were common themes attributing to leaving the field. Avoid fostering cutthroat environments, whether in classrooms or teams. Recognize that school or work should not consume an individual’s entire life. Build in moments for rest and recovery, encourage movement, and create a culture where flexibility is possible during times of personal or academic challenge. Support those who may be struggling and normalize asking for help.

5.3.4 Exosystem: What high level policies can reduce computer science attrition?

Policy changes, both in academic institutions and industry, play a crucial role in fostering more inclusive and supportive environments for engagement in computer science. Academic institutions should create more flexible pathways into and through computer science programs to support diverse interests and backgrounds.

Offer flexible prerequisites and minor pathways. Our men participants highlighted how requiring classes that do not help connect computer science to their fields of interest may cause them to lose interest in pursuing minors. Allow for more adaptable prerequisite structures in computer science courses and provide flexible course options for pursuing a computer science minor. This gives students the freedom to explore computer science without committing to a rigid track and enables them to integrate computer science into other fields of interest.

Develop interdisciplinary computer science minors. Our participants have other areas of interest that they want to pursue, but with inflexible pathways may have to choose between computer science and their other field of interest. Programs that combine computer science with areas such as the arts, social sciences, or business can help students see the relevance of computer science in a wide range of contexts. This flexibility supports broader engagement and encourages students from diverse academic backgrounds to participate.

Encourage early exposure without requiring early commitment. While making computer science courses mandatory early on can be logistically difficult, institutions should actively encourage students to take computer science courses early in their academic careers. Some of our participants would have pursued further studies had they taken the introductory course sooner. Early exposure increases the likelihood of continued engagement, especially if a course sparks unexpected interest.

In the workplace, company values and policies should align with the needs and values of employees, not just in principle, but in practice. If a company claims to value work-life balance, collaboration, or community, those values should be clearly reflected in both daily practices and broader policies. For instance, L.L. Bean provides employees with not only vacation time but also “outdoor experience days”, flexible days off that can be used spontaneously to enjoy good weather (*L.L.Bean | Careers | Benefits*, n.d.). Our data showed that individuals are looking for over-all well-being and happiness in their careers. By aligning policies with values, it reflects a commitment to both well-being and work-life balance. Additionally, if collaboration is a core value, it should be embedded into team structures, work rhythms, and even promotion criteria. Dedicate time during the workday for community-building, cross-functional brainstorming, or mentorship. Recognize and reward collaborative behavior, not just individual achievement.

5.3.5 Macrosystem: How should you represent computer science culture?

While direct change to the macrosystem, the overarching culture of computer science, is not directly feasible, it is shaped by the cumulative impact of actions taken at every other system level. These recommendations here focus on how we represent computer science as a field, and how that representation can foster a more inclusive and accurate cultural narrative.

Broaden the representation of computer science careers. Our data showed that having misperceptions on how to use or apply computer science can lead to disengagement. We must highlight the full range of computer science roles and how computer science is integrated across virtually every industry. From healthcare to the arts, environmental science to education, computer science plays a vital role, and people should see that. Some of our participants were deterred by misconceptions about job prospects, but there is a growing number of positions that remain unfilled. Clear, accessible education about the diversity and availability of computer science careers can help counter these barriers and spark interest.

Represent all kinds of people in computer science. As with microsystem-level efforts, the broader computer science culture should reflect the full diversity of the people within it. Representation should include variation in gender, race, ethnicity, interests, personality types, and skill sets. Our data showed that stereotypes that do not reflect diversity can influence individuals' decisions to disengage. The narrative around computer science should be shaped intentionally to communicate that the field is for everyone, not just a narrow subset. By reshaping the way computer science is portrayed and talked about, we contribute to a macrosystem that is more inclusive, more accurate, and ultimately with lower attrition.

5.4 Limitations

This dissertation is not without its limitations. First, there are important considerations when using generative AI for qualitative analysis, as previously discussed, as well as when analyzing social media data, as in Manuscript 3. The AI model's accuracy is not absolute, and key contextual information, such as participant demographics or whether individuals ultimately exited the field, was unavailable. These limitations affect the depth and certainty of the interpretations drawn from that dataset. Additionally, for the analysis in manuscripts 1 and 2, there are the inherent limitations of thematic analysis done by a solo analyst for both the codebook generation and application.

Second, manuscripts 1 and 2 are limited by their focus on a single, institution-specific context, which may affect the generalizability of findings. Specifically, the results of these studies, including the gender comparisons made, are limited to individuals who are non-CS majors enrolled in introductory computer science courses. They do not reflect the experiences of all men and women within the broader field of computer science. Additionally, there is potential for selection bias, as participants self-selected into the study. Those who chose to participate may have had particularly strong opinions, either positive or negative, about their experiences. Moreover, although Manuscripts 1 and 2 focus on gender, the survey used the terms ‘male’ and ‘female’ when asking students to self-identify, terms more commonly associated with biological sex than gender identity, rather than ‘man’ and ‘woman’. However, respondents were also given the options ‘non-binary’ and ‘prefer not to say’, which are more typically aligned with gender self-identification practices.

Third, there are limitations in the cross-manuscript comparisons. While both computer science majors and non-CS majors were included in the analysis and appeared to share similar experiences within comparable contexts, their underlying motivations, interests, or long-term goals may differ in ways not fully captured in this study. Lastly, while Bronfenbrenner’s Ecological Systems Theory and Social Cognitive Career Theory offered valuable frameworks for interpreting participant experiences and decisions, these theoretical lenses are inherently limited. This study did not draw on critical or cultural theories, which may have provided additional insights into systemic, structural, or identity-based influences on persistence in computer science.

5.5 Future Work

While these three manuscripts provided valuable insights into the high attrition rates in computer science, they also lay important groundwork for future research. There are numerous directions in which future studies can build upon these findings. Research going forward should draw on insights from Manuscript 3 to inform the development of interview protocols and survey instruments that better identify the diverse factors contributing to computer science attrition across different stages and contexts. For instance, depression did not emerge as a theme in

Manuscripts 1 or 2, but it is possible that it would have, had it been explicitly included in the interview protocol. Future studies should also seek to quantify the influence of factors identified in Manuscript 3 to determine which are most impactful, and how various factors may interact. Additionally, similar large-scale qualitative studies could be conducted in other disciplines to assess which factors are unique to computer science and which reflect broader societal or cultural influences. To support this work, methods for using generative AI in qualitative analysis should continue to be developed, refined, and validated.

Manuscripts 1 and 2 examined both individual and system-level factors influencing decisions to leave computer science. Future research should delve more deeply into students' initial motivations for enrolling in introductory computer science courses, their pathways into those courses, and how the perceived complexity of their major may influence decisions to disengage. It would also be valuable to study individuals who did not initially intend to pursue a computer science minor but chose to do so after taking an introductory course, in order to explore how their experiences align with or differ from those reported in Manuscripts 1 and 2. Additionally, to improve gender-based comparisons, future sampling should include more interviews with men who lack prior programming experience and women with more intensive programming backgrounds, which would help disentangle the effects of gender from those of prior exposure. Finally, longitudinal studies are needed to examine how engagement with computer science evolves over time for individuals outside the traditional computer science pathway, particularly as they progress through different stages of their careers.

5.6 Conclusion

Through three distinct but interrelated manuscripts, the purpose of this dissertation was to address the high attrition rates in computer science and to examine factors that contribute to the large gender gap by examining the experiences of understudied populations within the field. This work provides a holistic understanding of why individuals disengage from computer science, highlighting both gender-specific and shared factors across various stages of academic and professional development.

Manuscript 1 explored the experiences of high-achieving women enrolled in introductory computer science courses for non-majors, focusing on why they chose not to pursue a computer science minor. Manuscript 2 expanded this inquiry to include high-achieving men in the same course context, offering a critical comparison that revealed both overlapping and gendered factors influencing disengagement. Using Bronfenbrenner's Ecological Systems Theory, findings showed that women reported more negative experiences at the micro- and mesosystem levels, such as classroom interactions and peer dynamics, which they then extrapolated to broader perceptions of the computer science field (macrosystem). In contrast, men's disengagement was more directly influenced by their perceptions of the macrosystem, which shaped how they interpreted their micro- and mesosystem experiences. Additionally, men were more likely to integrate their personal interests with computer science, while women often saw computer science as incompatible or in conflict with their other passions. Notably, neither group expressed a strong desire to belong to the computer science community.

Manuscript 3 expanded the investigation by analyzing large-scale social media data from individuals at multiple stages in their computer science pathway. This study not only reinforced the themes from Manuscripts 1 and 2, but also uncovered additional factors contributing to later-stage attrition, including job dissatisfaction, shifting interests, emotional and academic struggles, health issues, and broader concerns about the tech industry. These factors were present across all departure points, underscoring that attrition is not confined to early academic experiences. In addition to these substantive findings, Manuscript 3 contributed a methodological framework for using generative AI in large-scale qualitative thematic analysis.

Together, these three studies offer a multi-layered, intersectional view of disengagement from computer science. They underscore that attrition is not a matter of individual failure, but often results from misalignments between individuals and the systems they engage with, systems that must be reimagined to support a broader range of identities, pathways, and values. By surfacing diverse perspectives and identifying actionable factors, this dissertation contributes to both scholarship and practice. It provides empirical insights that can inform the creation of more inclusive curricula, as well as more supportive academic and workplace cultures. Ultimately, reducing attrition and addressing the gender gap in computer science requires sustained, multi-level efforts across individual, institutional, and societal levels to ensure that all individuals feel they belong and can thrive within the field of computer science.

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Appendix

Interview Protocol (Manuscript 1 and Manuscript 2)

Tell us a bit about yourself
Tell us what is your major, what class standing you have?

Tell us about your experience in the course you took

- Which course are you taking?
- Is this your first CS course at VT?
- Why did you decide to take any of these courses?
    - o Was it just the computing requirements?
    - o Did you take with any friends?
- Did you take any computer courses in high school? Tell us more about that? Did you participate any computer related extracurricular activities?

- Was there any unexpected surprises in the course?
    - o What did you like in the course? were you fascinated by any topics
    - o Anything that turned off?
    - o How engaged were you with the material?
    - o Was the course demanding compared to other courses?

- Tell us about the most interesting part or least interesting part of the course?
- Has their perception of CS or programming changed after taking this course?
- Do you think real life experiences in CS field would be like this?

Future plans

Are you planning to take more CS courses? If senior, I guess
Tell us more about how you came to this decision.
If you were not graduating, would you take more courses?
If you are graduating, what are you doing afterwards?

CS Community

- Tell us how you feel about the CS community and your CS classmates
    - o Class environment (tell us more)
    - o Classmates
    - o Teacher attitude/TAs helpfulness and support
        - ▪ tell us more, can you give me a specific example of the behavior)
        - ▪ what kind of interactions did you have with them)
    - o Role model
    - o Expectation of future professional community

We noticed that a lot of students felt neutral about being an insider in the CS community.

- Who do you think is part of the CS community?
- Do you feel like an insider or outsider in the CS community?
- Do you want to fit in? is that important to you to be part of this community or be associated with it?

- How does your peers/friends/family feel about CS community or you taking part in CS courses?

Codebook Manuscript 1

Code	Definition	Example
Background information	Discussion of participant's personal background information (class standing, major, etc.)	P4: I'm a senior and graduate student in four plus one program for public administration. My major is smart and sustainable ci ties. My minors are data, data decisions, and political science
Prior programming experience	Discussion of participant's prior experience with programming (or lack thereof)	P5: I did an after school program in the fourth grade, but I did not take any courses.
Reason for taking course	Discussion of participant's reason or motivation for taking introductory CS course	P6: It's required for my major. I specifically decided to do Python just because I heard S 11 14. Intraosftware design was a really hard class, especially someone with not that much programming experience
Reason for K-12 engagement	Discussion of why individuals engaged with CS (or not) in K-12	P3: At the time, I was trying to apply to the college of Engineering here at Tech. And so I was trying to make my application as strong as it could.
Prior experience influence	Discussion of how participant's prior programming experience (or lack thereof) influenced their experiences in introductory course	P1: So again, even that little bit of background that I had come in with really did help even in those first few weeks. And I feel like if I had not had that little bit of background, I would have already started this semester struggling. But since I had some knowledge, I was able to start the assignments and keep up right from the beginning, which made things easier going into the rest of the semester.
Impact of course (course impact)	Discussion of how the course has impacted participant's perceptions, skills, and feelings around CS	P1: I am more confident in recreating code now, not just copying it, but being able to recreate my own personal code.

Course pace	Discussion of difficulty of course at different points in the semester	P4: I do think and they had a good like week of review and I was like, this is easy like this is good. I know all of this stuff. And then like it was the pace. I think because like he did pick up like the first 2/3 weeks, I was like, okay, like this is fine, like nice. And then all of a sudden it kind of like went zero to 100. At least I felt like it did. It probably didn't like, know what it was about it. It was just the pacing was hurt me the most. Because once you don't grasp one topic, I feel like that point on, I did not get a single thing.
Course set up	Discussion of logistics of course (assignments, flow, instructor, mode, class size, etc.) in a neutral or factual way	Did you have any team projects? P5: I don't believe so.
Course difficulty	Discussion of what the participants found easy or hard about the course	P2: Honestly, the course itself was challenging because I heard that there was like a high rate of cheating for that specific class last semester. So they like beefed it up I feel like way too much this semester to the point where it was just like, you know, I think we were kind of like just supposed to feel out like the new changes. And I'm pretty sure they made a lot of tweaks for the next semester because I don't think a lot of that worked out. P3: It was pleasantly smooth sailing compared to some of like, even like stupid management classes and stuff have given me more of a headache than the coding class.
Course changes	Discussion of things participant wished was different about course	P7:I would say honestly, like only th ing different would be like just not throwing a huge project at you when all you've been doing is reading about code and

		then doing like two lines of code and then five exercises like every Sunday.
Self-reflection	Reflection of participant of how their actions influenced performance in course	P3: I should have just reached out to the professor. In hindsight for help. That probably would've been better so they could teach it to me a little bit better than they did
Course positives	Discussion of things participant liked about course	P6:One thing I loved was the office hours. There were so many office hours for that class, there were 1 million PAs. And it was amazing because I would honestly not even start on a project until I went to office hours
Course negatives	Discussion of things participant did not like about course	P7: the way the class was structured is that we would have readings. Then we would have like after every week on Sunday, we would have these little Python ac tivities we had to do that were like two lin es long. But then we would have projects that were like 80 lines of code. It was just a lot. And whenever like I would get an error message, I would just like not know what to do or because it would be like so much . And I was like always like have to get help. That would probably be the only thing that I didn't like, but it's also part of the course
Future plans	Discussion of future plans generally (not specific to CS) or lack thereof	P4: I think I'm going to go into law. I want to because my degree is Public Administration

		or my Master's will be Public Admi nistration. And from there I wanted to get my LSAT taken in th e next year, 18 months, and then go from there and pursue law school .
Future CS engagement	Discussion of future plans to engage with CS or not	Are you planning to take any more computer science courses? P5: I am not.
Usefulness of coding	Discussion of how participant finds coding useful in their future, in general, or how it would have helped them in the past had they had more experience, or how they wish the usefulness was covered more in class	P2: And it's a good tool to have, especia lly with the day and age that we're at, like where I feel like I feel it's only going to grow more an d more.
Male stereotype	Discussion of stereotype CS being male dominated and not welcoming to women	P6: there's like the stigma with like women coding as well. And again, I'm sure if I were a guy and at least said like one thing in general about like, oh, like coding would be cool. They would be like, oh, take a codi ng class. Like you should do that. But I didn't really get like that push and I wish that I did a little bi t, especially since I was always strong in like math and scien ce. Like as a kid it would have been useful
Isolating	Discussion of not talking with people in the course, not having group projects, or seeming to make friends (or negative examples that are unique)	P1: the environment of having so many students, is that like every time I came, even though I was sitting in the same section, I was sitting next to different people, so I never really got to talk to those around me. Or make friends, or like have study buddies like I would for any other class. P2: The class environment was basically just like sit down and be quiet and

		listen.
Instructor interactions	Discussion of interacting with course instructor or TAs	P2: Yes, Lewis. I can remember he was the Dr. Yeah, he was cool. Anytime I like because one time my computer like gave out on me and I couldn't get it fixed. But it was like during the middle of a quiz. So like all everything was just lost. He was very understanding about that. And then another time, the submission wasn't working for one of the essays on canvas. And I feel like as long as you address it right away and don't wait, like the day of when something is due or something, he'll be understanding.
Anti-social stereotype	Discussion of stereotypes that CS is an anti-social field or people are socially awkward in cs	P7: CS, people aren't very emotionally intelli gent. That's like a really weird answer. I'm just better at talking to people than spitting code out and making c ode.
Value-experience misalignment	Discussion of participant's experiences in CS field and their misalignment with personal values, desires, or needs	P1: Is that like just for example in my field, I, in my senior design project, I was talking to doctors, patients, people with specific illnesses. It was a very collaborative approach. And I, I'm a very social person and I like the collaborative thing. And I found that at least with the computer science class I'd taken in high school and all my other computer science experience is that like for example in this class there was no teamwork or no team project. Everything was completely individual. I was doing the projects and the

		assignments and the exercises in my home, in my room, just sitting in front of my computer. And I found that I wasn't getting the collaborative or like the teamwork aspect that I wanted from the field.
Insider/outsider	Discussion of participant's feelings or desires related to being an insider or outsider to the CS community or why people may identify as one way or the other	P6: I think like the only reason like I would personally feel like an outsider is if like they pull up li ke a coding project and I have no idea what they're doing.
CS community	Definition of who belongs in CS community and what it is like	P6: I would definitely say like CS majors
Non CS interest	Discussion of being interested in something other than CS	P6: I always been interested, but I was editor in chief of my school newspaper for two years and also on my dance team and was super involved with that. And then also dance outside at like studio. So there was just like literally no ti me. More of a time constraint rather than like lack of interest
CS interest	Discussion of liking or being interested in CS	P3: But I guess I am fascinated by what you can do and how many things you can import to Python and work with and so many different plug ins and things like that. Just, I mean the sky is the limit
No CS interest	Discussion of not liking or not being interested in CS	P2: I didn't like coding. I was like, I don't like all aspects of coding, so I didn't want to be in the field of where it's just that I like diversity and things like that.

Stereotype origin	Discussion of where stereotypes around CS come from or are influenced by	P2: I don't know, ask for where it came from, I guess because some of the CS classes are, can be kind, kind of rough. And so most most people have to, you know, really take their time to actually like study and get ready for it. And so that's, I guess the less social part of it. Plus some people in CS, even though it may not like, again, a stereotype are gamers and things like that. So they do prefer to be by themselves. I feel like every major has their little stereotypes. Yeah. How they came about doing like cane, like pinpoint the accepts
CS misperceptions	Discussion of not having a clear understanding of what the CS field does or what you could do with CS degree and how that influenced decision	P5: Honestly, I realized computer science was not for me. […] I really like dealing more on the data analysis end versus the cleaning of the data.
Difficult culture	Discussion of CS being known as a difficult field	P4: I was like, this is for non majors, like we're all just here. Like, I don't know because obviously we go to Virginia Tech, like we know engineers are like som etimes snobbish because they're like pretentious with how, because their degree is really hard.
COVID impact	Discussion of how course experiences were influenced by COVID	P1: And then also because like my freshman year was cut pretty early on into spring semester and I was taking my second fundamentals engineering class. And we're supposed to do more with MATLAB in solid works. And that was just cut. Like when we went online, my engineering professor literally said, forget about all of that stuff. You're only assignment for the rest of the semester is an essay.

Extracurricular CS	Discussion of participants' involvement with extracurricular activities related to CS	P2: I was on the Corp of Cadets cybersecurity team. [...] I was very, very busy. I could barely make a meeting, but I think it was like every Wednesday, something like that. But it wasn't very beneficial for me because I felt like it was it wasn't just for beginners, like it wasn't like rudimentary, like intro to programming stuff. It was literally for the people that knew what they were doing. They're like, hey, we're going to introduce something new. But like for people like me that had absolutely no experience at that time, because I didn't take these introductory, you know, Python courses or anything like that until literally this year. It was, it was kind of like a foreign language. Just literally just nod my head acting like I knew what was going on when I didn't.
Peer support	Discussion of how having peers or friends in the course was helpful in participant's success, or how it would have been helpful	P2: It would help if you had a buddy because if you got lost anywhere, it would be very hard to get caught up, especially if you're me. Because I would get lost in various places. And then I did have a buddy and then she was like, oh this is wrong I'm like, oh, okay. So it's like good to like piggyback off each other, things like that.
Stereotype influence	Discussion of how stereotypes in general influenced the decision to stay or leave rather than a specific stereotype	P2: But you know, II wouldn't let that be something that like defines me or deters people what I want to do. That definitely wasn't a factor. Why left I or anything
Course effort	Discussion of the effort put into the course or how engaged a student was with course material	P3: But when we had like a project or something, I did try to do it really well. I didn't just do the bare minimum. I tried to do as much as like the extent of my knowledge and some of my engineering friends knowledge would allow to try to

		make it look good. That I would get for sure 100, maybe some extra credit points here and there. But no, I didn't do any personal projects.
Family support	Discussion of participant's family and the role they play in supporting or not their engagement with CS	P3: I remember so vividly my parents telling me about how the horrors of when they had to take this C plus plus class back in the day. They was trying to make this tick tack toe board and my mom couldn't figure it out for the life of her. So I know they have extreme respect for people in the CS community that have that knowledge that for some reason just did not come easily. Then my dad hires a lot of CS majors. He owns a small contracting company that does intelligence work as well. He hires a lot of CS majors because he can't do what they do. He has all the respect for him. So they were then he knows if I know a language and things like that, that it's also very valuable and something that employers definitely look for. They've always encouraged me.
Self-efficacy	Discussion of participant having high or low self-efficacy about computing	P4: I wish I could have learned more, but like I felt like I was inadequate to learn it.

Themes Manuscript 1

Theme	Definition	Code	Definition

Negative Course Experiences	Participants' negative experiences and perceptions of their introductory computer science courses, including challenges they faced, their assessment of the course difficulty, and how these experiences shaped their feelings, beliefs, and perceptions, ultimately influencing their decisions to disengage with the field.	Instructor interactions	Discussion of interacting with course instructor or TAs
		Course changes	Discussion of things participant wished was different about course
		Course negatives	Discussion of things participant did not like about course
		Isolating	Discussion of not talking with people in the course, not having group projects, or seeming to make friends (or negative examples that are unique)

		Value-experience misalignment	Discussion of participant's experiences in CS field and their misalignment with personal values, desires, or needs
		Impact of course (course impact)	Discussion of how the course has impacted participant's perceptions, skills, and feelings around CS
		Self-efficacy	Discussion of participant having high or low self-efficacy about computing
		Prior experience influence	Discussion of participant's prior programming experience (or lack there of) influenced their experiences in introductory course

		Course pace	Discussion of difficulty of course at different points in the semester
		Course difficulty	Discussion of what the participants found easy or hard about the course
		Male stereotype	Discussion of stereotype CS being male dominated and not welcoming to women
		Anti-social stereotype	Discussion of stereotypes that CS is an anti-social field or people are socially awkward in cs

		Stereotype origin	Discussion of where stereotypes around CS come from or are influenced by
		CS misperceptions	Discussion of not having a clear understanding of what the CS field does or what you could do with CS degree and how that influenced decision
		Difficult culture	Discussion of CS being known as a difficult field
		Stereotype influence	Discussion of how stereotypes in general influenced the decision to stay or leave rather than a specific stereotype
Interest	Participants' interest or non interest in CS and other fields of hobbies and how it influenced their decision	Non CS interest	Discussion of being interested in something other than CS
		CS interest	Discussion of liking or being interested in CS
		No CS interest	Discussion of not liking or not being interested in CS
Community Belonging	Participants' beliefs about who is involved in the CS community and whether or not they feel as though they belong	Insider/outsider	Discussion of participant's feelings or desires related to being an insider or outsider to the CS

	in the community and why and how it influenced their decision		community or why people may identify as one way or the other
		CS community	Definition of who belongs in CS community and what it is like
Participant Personas	Background and personal information about participants that give an overview of their unique situation and provide context in interpreting other themes	Future CS engagement	Discussion of future plans to engage with CS or not
		Background information	Discussion of participant's personal background information (class standing, major, etc.)
		Prior programming experience	Discussion of participant's prior experience with programming (or lack there of)
		Reason for taking course	Discussion of participant's reason or motivation for taking introductory CS course
		Reason for K-12 engagement	Discussion of why individuals engaged with CS (or not) in K-12
		Future plans	Discussion of future plans generally (not specific to CS) or lack there of

		Extracurricular CS	Discussion of participants' involvement with extracurricular activities related to CS

Codebook Manuscript 2

Code	**Definition**	**Example**
Background Information	Discussion of participants' background info (major, year standing, course taken, etc.)	P5: I'm a junior currently. I am a Cybersecurity management analytics major in Pamplin. I do a lot of sports, play a lot of video games. I'm in RA, on campus.
Reason for taking course	Discussion of why participant took the CS course	P4: I had to take a science and engineering el ective. And I think there are 16 op tions, eight of which being denote d as civil, and then the other eight are kind of random, they are applied to civil engineering as well. And I took some Python classes in high school. Actually, I thought that this

		would be something relativel y easy
Prior experience	Discussion of computing experience in K-12	P3: I took advanced Python in high school. Okay. I also had about three or four years of experience in Python beforehand. Were in high school. Yeah, and that's about it. I also went to a academy t hat did cybersecurity and also went depth into bash and other c odes. So I don't know if cybersecurity or like physical computer parcast as yes, but I I do have this experie nce.
Course set up	Discussion of how the course was structured, including space where class was held, with neutral or factual tone	P2: There's always one project a t the very end. There's one project that is t eam oriented except for 1114. Didn't have any of that.
Course challenges	Discussion of specific aspects of the course were difficult or challenging for the participant	P4: But the projects were definitely the hardest part, not to say that you can't do them in a single day. But that's if you go to offic e hours for several hours and you get a lot of extra help. I don't know how people w ho didn't go to office hours did them at all. I don't know if they would get higher 70

Questioning course design	Questioning if how the course was designed was the best or critique of course design or set up or discussion of what they would change about the course	P1: The quizzes were fairly challenging because you had to you didn't have any reference material when you were doing them, so you had to do it all from memory, which on the one hand is understandable, but I feel like it's also not really indicative of a development environment.
Course approach	Discussion of how participant approached completing course assignments	P1: I mean, if you're doing your homework, you can just look up the programming library for Python. And if you have a question on this function, I was about to say method, goodness, how is this function used in Python? You can just look up the reference document and you'll find it there. If you look further, you might even see people saying. If you try to pass these arguments through this, it can end up with these kind of problems.
Impact of prior experience	Discussion of how prior computing experience influenced their experience in their course	P3: Yes, It was super easy. Everything they taught, I alr eady knew
Social nature of course	Discussion of course environment in terms how it supports or does not support social interactions	P2: But like I said, I think with the size of clas ses, you'll get a lot of people w ho just don't, they don't engage with the class. Because most of the class is not meant for engagement . It's meant for doing the wor

		k by yourself outside and then you're sub mitting it.
Course positives	Discussion of course aspects that participant liked	P1: the TA's and the professor were all extremely helpful and very f riendly
Instructor interaction	Discussion of how instructor or TA interacted with participant (does not include what instructor did in class unless it specifically was targeted as a 1-1 interaction)	P3: People the TA's there were helpful and they were usuall y, they usually didn't give all t he answers, but they would get hints. So it was really helpful for both classes.
Course negatives	Discussion of things participant did not like about the course	P2: I really hated because of agreed bef ore Sophia. I don't know if you're famil iar with that. Okay. The CS department u ses this thing or they don't use it anymore. This thing in house IDE cal led green for four Sophia which is horribl e. I had to get a dual boot on my Max so that I could use it because it didn't run on Ma x. That was horrible.
Course impact	Discussion of how the course influenced participants (perception of cs field, self-efficacy, career goals, skills, etc.)	P4: I don't know if it changed my perspective on it. I think it stayed the same.
Course buddies	Discussion of having friends or individuals in class who you the participant can interact with	P1: Now, the interaction I had with other people takin g

		a class was basically strictly the friend group that I came in with and we sat on opposite sides of the roo m. So we only talked outside o f class
Future CS engagement	Discussion of future plans to engage with CS and why	P2: There is a class that I want to take that I probably will not take
Future plans	Discussion of future plans outside of CS engagement	P3: I want to become a data scientist. I have worked for the fire department as a data analysis intern last s ummer. I enjoyed it and I want to continue doing that in the f uture
CS community	Discussion of how participant defines who is in the CS community	P6: I would say for the most p art, the community probably con sists of mainly computer science ma jors, just straight off the bat, as well as I'd say anyone that has like a really strong drive to learn about computer scie nce, like me, I enjoy it, I'm not going to pursue it. Maybe learn some stuff her e or there.
Insider/outsider	Discussion of if the participant feels like an insider or outsider to the CS community, why, and if they feel a desire to be part of the community	P3: I feel like I feel like I'm in the CS co mmunity
Family influence	Discussion of how family has influenced or	P4:

	not engagement with CS	My family didn't really pres sure me, but they would more so encourage, explore, and see.
CS interest	Discussion of interest or passion or not in CS	P4: When I used Mat Lab I found it to be so helpful and interesting. It made me like computer science a little mo re. I know it's not fully comput er science, but it is really just coding. The application of coding to something like civil engi neering, where you could see graphs come out and really just make it do whatever you want. That was really c ool. I genuinely enjoy that cours e
Outside CS adjacent classes	Discussion of taking CS like classes in non CS departments and their experiences and opinions of these classes	P4: I also took a class called Computer Applications in Ci vil Engineering. And that's where we did Ex cel BDA. And not Python, but Matt L ab
Usefulness of coding	Discussion of how having CS or computing knowledge is useful and can be applied to so many areas	P6: just like in the amount of things that I figured out that I could d o with it, even in some of the smallest, like outside tas ks, use it like you wouldn't real

		ly think of
Course difficulty	Discussion of overall course difficulty	P5: Compared to other classes. Not super demanding. Let's say around the middle
Field difficulty	Discussion of the difficulty nature of the CS field	P2: someone who experienced a little bit of CS in college, I don't know. Yeah, it's difficult. I'd say like a lot of getting everything to work together is really complex.
Friendly community	Discussion of how kind and friendly and welcoming those in the CS field are	P3: Most of the time it is like, well, I just talked to people about CS. They're just really open to talk and they're just really open to talk about an y, about projects or any problems they have with code. They are really talk about just like the fundamen tals of like programming like thi s, code is bad, I prefer that whatnot. They're really engaging
Self-efficacy	Discussion of participants' computing self-efficacy	P2: pressure in terms of getting better? No. I think if that were the case, then I would have to be no t as good.
Friend influence	Discussion of how friends have influenced or not engagement with CS	P3: My friends, they don't peer pressure me to do anything. They're really open.

		There they are like CS maj ors, but we don't talk about
CS stereotypes	Discussion of there being stereotypes about CS	P4: I don't know how exactly to describe it, but engineering also has that type of connotation wh ere they're just more introverted and I think it's just more of an extreme in CS like, if you can think right code with perfect logic and all th at, you have a special type of brain I think. But there are trade offs like if you're good at one thing you might lack like sociability or something.
Misperception of cs	Discussion of a misperception of the cs field	P6: So there's a lot more room for variability within the econ field than the computer science field. Honestly, I just think that it 's because computer science is newer t han econ.
Non CS-interest	Discussion of choosing something other than CS due to having an interest in that other area	P6: Econ just fit more what I wanted.

Themes Manuscript 2

Theme	Def	Code	Definition
Course Experiences	Participants' experiences in their introductory CS courses that did not enjoy, including their assessment of course difficulty, and how they influenced their	Course challenges	Discussion of specific aspects of the course were difficult or challenging for the participant

	feelings, beliefs, and perceptions and decision to disengage	Impact of prior experience	Discussion of how prior computing experience influenced their experience in their course
		Course difficulty	Discussion of overall course difficulty
		Questioning course design	Questioning if how the course was designed was the best or critique of course design or set up or discussion of what they would change about the course
		Social nature of course	Discussion of course environment in terms how it supports or does not support social interactions
		Course negatives	Discussion of things participant did not like about the course
		Self-efficacy	Discussion of participants' computing self-efficacy
Community Belonging	Participants' beliefs about who is involved in the CS community and whether or not they feel as though they belong in the community and why and how it influenced their decision	CS community	Discussion of how participant defines who is in the CS community
		Insider/outsider	Discussion of if the participant feels like an insider or outsider to the CS community, why, and if they feel a desire to be part of the community

		Friendly community	Discussion of how kind and friendly and welcoming those in the CS field are
Interest	Participants' interest or non interest in CS and other fields of hobbies and how it influenced their decision	CS interest	Discussion of interest or passion or not in CS
		Outside CS adjacent classes	Discussion of taking CS like classes in non CS departments and their experiences and opinions of these classes
		Future CS engagement	Discussion of future plans to engage with CS and why
		Non CS-interest	Discussion of having interest in something other than CS
		Course impact	Discussion of how course influenced participant (perception of cs field, self-efficacy, career goals, skills, etc.)
Participant Personas	Background and personal information about participants that give an overview of their unique situation and provide context in interpreting other themes	Background Information	Discussion of participants' background info (major, year standing, course taken, etc.)
		Reason for taking course	Discussion of why participant took the CS course
		Prior experience	Discussion of computing experience in K-12
		Future plans	Discussion of future plans outside of CS engagement

List of SubReddits Pulled From
["AskAcademia", "AskanEngineer", "AskEngineers", "AskReddit", "AskScience", "Education", "Engineering", "EngineeringGradSchool", "GradSchool", "Grad_School", "HigherEducation", "Jobs", "LadiesofScience", "Resumes", "Science", "compsci", "programming", "learnprogramming", "coding", "cscareerquestions", "webdev", "softwaredevelopment", "AskComputerScience", "computerscience", "gradadmissions"]

Prompt 1 (summarizing posts)
You are an expert text analyst reading {data_type}s collected in {data_collection_context}. I am going to send you part of one of these {data_type}s. I need you to use your expertise to analyze the provided {data_type} in the <{data_type}> tag below and summarize it in an enumerated list. Follow the instructions in the <instructions> tag to complete your task. Be aware that your instructions include task instructions and formatting instructions. The {data_type} for you to analyze will be provided after the instructions.

<instructions>
Part 1. Task Instructions.
You should perform your summary task by providing several short descriptive phrases that summarize each idea discussed in the {data_type}. The goal is to capture the main points in the {data_type}.

Part 2. Formatting Instructions.
Regarding formatting, when you suggest multiple items in your summary, separate each item in your response with a new line. Start your response with "My expert summary:". Use plain text without any markdown or additional formatting. We simply need your numbered list of summary points. Providing a numbered list will make parsing your response easier for downstream analysis.
</instructions>

Here is an example of input and desired output from a different context when there are only two topics, but remember that you can suggest as many topics as you think are necessary for the text you summarize.
Example input: "Jared did a great job responding quickly to emails and turning in good work."
Example output: "My expert summary:
1. Responded quickly to emails
2. Turned in good work".
Notice how the output summary did not make up information that was not in the input. You must NEVER make up information that is not in the input text you receive because there is a severe penalty for that. If the {data_type} you receive is very short and says very little, do not make up new things. If you feel compelled to write something in that situation, you can say "too little information in this {data_type}". This concludes your instructions.

Here is the {data_type} for you to summarize:
<{data_type}>

{text}
</{data_type}>
Take a moment to collect your thoughts and observations. When you are ready, begin your summarization using this template:
SUMMARIZATION TEMPLATE
My expert summary:
[your numbered list of summary points goes here]
Prompt 2 (filtering posts)

Act as if you are the world's best text analyst specializing in screening text for analysis. You make decisions based on content and its relevance to downstream studies. Analyze the summary of the {data_type} provided to you according to the instructions below in the <instructions> tag. The summary of the {data_type} for you to analyze will be provided in the <summarized_data_to_analyze> tag after your instructions.

<instructions>

TASK INSTRUCTIONS
Evaluate the summary of the {data_type} from {data_collection_context} in the <summarized_data_to_analyze> tag to determine its relevance to our study on individuals considering leaving the field of computing. Use the following two inclusion/exclusion criteria to determine whether or not we should keep the {data_type}:

Criteria 1: Relevance to Computing. The person writing the {data_type} MUST be talking about the field of computing. The field of computing includes: computer/information analysts, programmers, computer scientists, software engineers/developers, network architects, web developers, etc.
Criteria 2: Departing Computing. The {data_type} MUST be about totally departing from any computing-related work or study. This criterion means the following do not qualify:
a) Changing roles within computing
b) Moving between computing areas
c) Changing industries while staying in computing
d) Moving between academia and industry within computing
e) Pursuing further education in computing

Here are some other aspects of the {data_type} for you to consider in your analysis.
- Leaving the computing field means exiting all computing-related work/study for an unrelated field (e.g., healthcare, education, hospitality, agriculture, arts, trades)
- The {data_type} can be about leaving as a student, professional, hobbyist, or other role
- The {data_type} should be a personal story/experience, and not an advertisement
- If ambiguous, analyze context carefully for clear indicators of complete departure

Your analysis should include initial observations, including relevant points you have observed. Then, you should evaluate the summarized {data_type} along each of the two inclusion/exclusion criteria I gave you above. Finally, you should write your final recommendation (the options are keep, discard, or undetermined), including your confidence in your recommendation and justification for your recommendation.

FORMATTING INSTRUCTIONS
Your analysis should be presented in the following JSON format:

```
{{
  "expert_analysis": {{
    "initial_observations": [
      "Observation 1",
      "Observation 2"
    ],
    "computing_analysis": "Discussion of whether the post is discussing the computing field",
    "departure_analysis": "Discussion of whether the post is about departing the computing field",
    "additional_context": "Any other contextual information that influences your recommendation
to include or exclude the {data_type}"
  }},
  "conclusion": "keep {data_type}|discard {data_type}|unable to determine",
  "confidence_level": "1-5",
  "justification": "Brief justification for your decision and confidence level"
}}
```

</instructions>
Now that you have studied your instructions, here is the summary of the {data_type} for you to analyze:
<summarized_data_to_analyze>
{text}
</summarized_data_to_analyze>

Take a moment to gather your expert thoughts. When you are ready, begin your analysis using the specific JSON formatting. As a reminder, that formatting is provided again below.

```
{{
  "expert_analysis": {{
    "initial_observations": [
      "Observation 1",
      "Observation 2",
      // Add more observations as needed
    ],
    "computing_analysis": "Discussion of whether the post is discussing the computing field",
    "departure_analysis": "Discussion of whether the post is about departing the computing field",
    "additional_context": "Any other contextual information that influences your recommendation
to include or exclude the {data_type}"
  }},
  "conclusion": "keep {data_type}|discard {data_type}|unable to determine",
  "confidence_level": "1-5",
  "justification": "Brief justification for your decision and confidence level"
```

}}

Prompt 3 (information extraction)

You are an AI assistant analyzing Reddit posts about career decisions in the computing field.

Definition: In this context, "decision factors" are elements that a person is actively considering or weighing as they contemplate their career in computing. These factors can be both positive (reasons to stay) and negative (reasons to leave), and may include aspects of their current job, potential opportunities, personal circumstances, or industry trends.

Examples of decision factors:
- Work-life balance (could be a pro or con depending on their current situation)
- Career growth opportunities (in or outside of computing)
- Salary and benefits (current or potential)
- Job satisfaction or passion for the work
- Industry trends or job market outlook
- Personal interests or skills alignment
- Workplace culture or environment
- Geographic location or remote work options
- Educational or retraining requirements
- Long-term career goals

These differ from simple "reasons for leaving" as they represent a more holistic view of the person's career considerations.

Please review the following post in the <reddit_post> XML tag and provide a JSON response with these three elements:

1. "considering_career_change": (true/false) - Is the person actively weighing whether to stay in or leave the computing field?
2. "decision_factors_mentioned": (true/false) - Did they explicitly mention factors they're considering in this decision?
3. "decision_factors": [list of factors] - If both 1 and 2 are true, list the factors the person is considering in their decision. For each factor, indicate whether it's a "pro" (reason to stay), "con" (reason to leave), or "neutral" (could go either way). If factors are not explicitly stated but can be inferred, include them and note that they are inferred.

Here's the post to analyze:
<reddit_post>
{text}
</reddit_post>

Please provide your analysis in the following JSON format:

{{

"considering_career_change": "true|false",
"decision_factors_mentioned": "true|false",
"decision_factors": [
{{
"factor": "Factor 1",
"type": "pro|con|neutral",
"explanation": "Brief explanation of how this factor is being considered"
}},
{{
"factor": "Factor 2 (inferred)",
"type": "pro|con|neutral",
"explanation": "Brief explanation of how this factor is being considered"
}},
{{
"factor": "Factor 3",
"type": "pro|con|neutral",
"explanation": "Brief explanation of how this factor is being considered"
}}
]
}}

Begin your analysis when you are ready.

Prompt 4 (codebook generation)

Act as if you are the world's best qualitative data analyst with expertise in generating qualitative codebooks for thematic analysis. You specialize in creating parsimonious codebooks with non-overlapping and non-redundant codes. A codebook in this setting is a collection of labels and definitions for those labels that can be used to describe pieces of data in a qualitative research study. I need your help to create a qualitative codebook to analyze {data_type}s from {data_collection_context}. We are interested in answering the research question "{research_question}". To aid you in this process, I am going to send you instructions in the <instructions> XML tag. You must follow these instructions using your expertise and data to analyze in the <data_to_analyze> XML tag. I will provide you the instructions first and then the data to analyze afterward. Be aware that your instructions contain task instructions, evaluation criteria, and formatting instructions, each in their respective XML tags.

<instructions>
<task_instructions>
We are working diligently to determine whether or not an exsiting qualitative codebook is sufficient for analyzing excerpts from {data_type}s that you will be given in the <excerpts> XML tag below. Your important task is to analyze excerpts from {data_type}s collected in the context of {data_collection_context} and determine if the themes discussed in the {data_type} exercpts are already covered by the codes in an existing codebook that will be given to you in the <existing_codebook> XML tag or if instead the codebook needs one or more new codes to cover

the theme in the {data_type} excerpts. You should complete your task by following these six steps:
Step 1: Read existing codebook.
Examine the existing codebook given to you in the <existing_codebook> tag. Describe what these codes are discussing.
Step 2: Read the excerpts of the {data_type}s.
Read the excerpts from the {data_type}s given to you in the <excerpts> XML tag and identify the main theme discussed in the excerpts.
Step 3: Try to use existing codebook.
Attempt to describe the main theme of the {data_type} using one or more of the existing codes in the existing codebook. Think at a high level of abstraction and consider if any new themes could be subcategories of existing codes. If you determine that there is no need to create a new code, say "No new codes needed". Remember, creating unnecessary codes can negatively impact the analysis. Your primary goal is to use existing codes whenever possible.
Step 4: Create new code if needed.
If in step 3 you discover that you are unable to use the current codes to describe the main theme in the excerpts of the {data_type}s that you are analyzing, determine whether the existing codebook needs new labels to describe the excerpts in the <excerpts> XML tag. You should complete this determination by reasoning step-by-step. If you determine that a new code is necessary, explicitly justify why existing codes or combinations thereof are insufficient. Finally, generate a new code (or codes, if multiple ones are absolutely necessary) that captures the main concepts or themes discussed in the {data_type}s that you review. Remember, you specialize in creating parsimonious codebooks and avoid creating redundant codes. Your goal is to use the least number of new codes possible while still accurately representing the data.
There is a VERY significant penalty for creating redundant or unnecessary codes, so you should only create a new code if you are **absolutely** certain the existing ones are insufficient, even when combined or broadened. If you decide to generate a new code, you should provide:
- The code (a short phrase).
- A brief definition of what the label represents.
Step 5: Evaluate your suggestion.
To guide your work, you must consider the following four evaluation criteria. These four evaluation criteria in the <evaluation_criteria> XML tag will be used by other famously strict expert qualitative data analysts to evaluate the quality of your work. In the self-evaluation step, you must check whether you have satisfied each of these four criteria:

<evaluation_criteria>
Evaluation Criteria 1. Parsimony: Have you made every effort to use existing codes or combinations of existing codes before proposing a new one? If the answer is no, then it is necessary to reconsider the code.
Evaluation Criteria 2. Abstraction Level: Is any proposed new code at an appropriate level of abstraction, consistent with existing codes? If the answer is no, it is not a good code.
Evaluation Criteria 3. Relevant to Research Question: Are any proposed codes relevant to answering the research question: "{research_question}"? If the codes is not relevant to answering the research question then it should not be included in your final recommendation.

Evaluation Criteria 4. Non-Redundancy: Have you avoided creating codes that significantly overlap with existing ones? Only non-redundant codes should be included in your final recommendation.

To help illustrate what I mean by non-redundancy, here is an example of redundant codes and an explanation of their redundancy:
{redundancy_example}

It is CRUCIAL TO REMEMBER that if you do not think a new code should be created, you must say "No new codes needed". Only codes that satisfy all four of these evaluation criteria should be included in your final recommendations.
</evaluation_criteria>
Step 6: Final recommendation.
Present your final logical recommendation about any codes after your self-evaluation to decide whether to create a new code or whether none are needed.
</task_instructions>
Use the evaluation criteria and these task instructions to help you in your reasoning and execution of each of the steps given to you in these instructions.
<formatting_instructions>
I will give you a template to use for your response. The template uses XML tags to structure your response. The main parts of the template are the following.
Response Part 1: Your analysis of the existing codebook. You should place your analysis in the <existing_codebook_analysis> XML tag.
Response Part 2. Your analysis of the excerpts. You should place this in the <excerpts_analysis> XML tag. Your anlayis notes should be succinct and formatted in a numbered list rather than long prose. This means that each step in your step-by-step reasoning should get its own line as if it were a premise in a proof. These notes should be logical, adhere perfectly to your task instructions, be concise, and be in a numbered list.
Response Part 3: Try to use the existing codebook to summarize or describe the excerpts. Your analysis should be in the <existing_codes_coverage_analysis> XML tag.
Response Part 4: Make an initial recommendation on whether or not to create a new code based on your initial analysis of whether the existing codes cover the topics in the excerpts. You should place this recommendation in the <initial_recommendation> XML tag. Your recommendations can either be "No new codes needed" if no new codes are needed or the actual codes you suggest adding to the codebook. If you do think one or more new codes should be created, your response should start 'Code: ' followed by your code, then on a new line 'Definition: ' followed by your definition for that code.
For example:
Code: <code 1>
Definition: <definition 1>
Response Part 5: You should evaluate your initial recommendation using the guidelines given about in the <evaluation_criteria> XML tag. You should place your evaluation of your initial recommendation in the <self_evaluation> tag. You should be sure to demonstrate your expertise and reputation for creating parsimonious codebooks in this step.
Response Part 6: Based on your initial recommendation and self-evaluation, you should create a final recommendation. The final recommendation can either be "No new codes needed" or the

code(s) and definition(s) you recommend adding to the codebook. This should be placed in a <final_recommendation> XML tag.
</formatting_instructions>
This concludes your task and formatting instructions.
</instructions>

Now that you have studied your instructions, here are the data for you to analyze.

<data_to_analyze>
<existing codebook>
{codes}
</existing codebook>
And here are the excerpts from the {data_type}s for you to analyze.
<excerpts>
{text}
</excerpts>
</data_to_analyze>

Now that you have meticulously studied the data to analyze using your task instructions, formatting instructions, and evaluation criteria, take a moment to gather your expert thoughts and observations. When you are ready, begin your flawless and logical step-by-step analysis using the instructions and evaluation criteria outlined above. Be sure to display your expertise in creating parsimonious codebooks and minimizing redundancy and use the full analysis template, provided below. Be sure to use spaces in any codes you write rather than concatenating words together (e.g., say "example code" rather than "examplecode"). Here is the template to use for your analysis. Begin your expert analysis when you are ready.
FULL ANALYSIS TEMPLATE:
<existing_codebook_analysis>
[your step 1 notes describing the existing code go here]
</existing_codebook_analysis>
<excerpts_analysis>
[your step 2 notes go here to identify the main theme in the {data_type}s]
</excerpts_analysis>
<existing_codes_coverage_analysis>
[your step 3 notes to describe the main theme in the {data_type}s with existing codes here]
</existing_codes_coverage_analysis>
<initial_recommendation>
[your step 4 notes considering whether to create new code here, favoring parsimony and avoiding unnecessary code creation]
</initial_recommendation>
<self_evaluation>
[your critical self-evaluation reflection notes here, reviewing the four evaluation criteria of parsimony, non-redundancy, appropriate abstraction, and relevance to the research question]
</self_evaluation>
<final_recommendation>

[logical recommendation based on expert step-by-step reasoning about whether or not to create zero, one, or more than one new codes. These notes will reflect your reputation for only creating essential codes]
</final_recommendation>

Prompt 5 (theme identification)

You are an expert qualitative researcher specializing in thematic analysis. Your task is to analyze a list of codes that will be given to you below in the <codes> tag and identify potential themes following the guidance of Braun and Clarke. The goal is to identify themes that help to answer the research question "{research_question}". Please follow these steps outlined in the <instructions> tag carefully.

<instructions>
Step 1. Review the list of codes provided below in the <codes> tag below. These codes are being used to analyze {data_type}s from {data_collection_context}.
Step 2. Look for patterns and shared meanings among the codes. Consider how different codes might be combined based on underlying concepts or features of the data.
Step 3. Identify overarching narratives that might represent broader themes or sub-themes.
Step 4. Remember that themes don't simply "emerge" from the data. Actively construe relationships among the codes and examine how these relationships inform potential themes.
Step 5. Consider the importance and salience of potential themes. Remember, the number of codes supporting a theme is less important than whether the pattern communicates something meaningful that helps answer the research question(s). On that note, remember that the research question for this research is {research_question}.
Step 6. Aim for themes that are distinctive yet coherent with the overall analysis. Themes may even be contradictory to each other.
Step 7. Be willing to let go of codes or potential themes that don't fit the overall analysis. Consider creating a "miscellaneous" category for codes that don't fit elsewhere.
Step 8. Strive for a balance in the number of themes - not so many that the analysis becomes unwieldy, but enough to fully explore the depth and breadth of the data.
Step 9. For each theme, prepare a structured description including the theme name, its underlying concept, associated codes, and how these codes relate to each other and the overall theme.
Step 10. Reflect on your analysis considering: themes that seem too broad or narrow, contradictions or unexpected patterns, need for subthemes, and codes that don't fit well into the current themes.
Step 11. Organize your analysis into a structured format with initial observations, an array of suggested themes (each as an object with name, concept, codes, and relationship), and your reflection.
</instructions>

Now that you have studied your instructions carefully, here is the list of codes to analyze to identify themes related to the research question "{research_question}":
<codes>
{labels}
</codes>

Proceed with your expert analysis, explaining your reasoning at each step. Present your analysis in JSON format with the following structure:

```
{{
 "initial_observations": [
   "observation1"
 ],
 "suggested_themes": [
   {{
     "theme_name": "Theme 1",
     "concept": "Brief description of the underlying concept or narrative",
     "codes": [
       "Code 1"
     ],
     "relationship": "Brief explanation of how these codes relate to each other and the overall theme"
   }}
 ],
 "reflection": {{
   "broad_or_narrow_themes": "Discussion of any themes that seem too broad or too narrow",
   "contradictions_or_unexpected_patterns": "Description of any contradictions or unexpected patterns",
   "potential_subthemes": "Discussion of any need for subthemes within the main themes",
   "unclassified_codes": "List of any codes that were not included in the proposed themes"
 }}
}}
```

Use this JSON structure I have given you as a template. Expand on the template by adding as many observations, themes, and codes as necessary based on your analysis. Ensure that your response remains a valid JSON object. Do not include any text outside of this JSON structure.

Now that you have thoroughly read your task instructions, formatting instructions, and the codes to analyze, take a moment to gather your expert thoughts. Begin your analysis when you are ready.