Mixed Methods Study of Experiences of Non-Computer Science Majors in Introductory Computer Science Courses

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(ABSTRACT)

With the unprecedented growth of the Computer Science field, there is an underlying assumption that undergraduate students would naturally gravitate towards Computer Science courses or acquire related skills, irrespective of their career interests. However, this research challenged that assumption, focusing on the experiences and attitudes of Non-Computer Science majors enrolled in Computer Science courses. The objective of this study is to gain a comprehensive understanding of the experiences and attitudes of Non-Computer Science majors taking Computer Science courses. The research questions seek to uncover the factors influencing their engagement in Computer Science. This research employs a mixed-method study, starting with a quantitative phase followed by a qualitative one. Quantitative data is analyzed using factor analysis and inferential statistics, followed by thematic analysis on the qualitative data. The findings reveal that stereotypes associated with the Computer Science field are established as early as high school. These stereotypes, particularly affecting females, sometimes act as barriers, discouraging further pursuit of Computer Science. Addressing these stereotypes becomes crucial for fostering inclusivity in the field. To counteract these stereotypes, it is proposed that Computer Science and its applications should be promoted as early as freshmen year of high school. By introducing students to the field early, we can potentially mitigate the impact of stereotypes and encourage a diverse range of individuals to pursue Computer Science. Further exploration into the experiences of Computer Science majors is recommended to deepen our understanding and inform targeted interventions.

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(GENERAL AUDIENCE ABSTRACT)

As Computer Science gains popularity, the assumption that all students, regardless of their career goals, naturally gravitate towards it is challenged. This study delves into the experiences and attitudes of Non-Computer Science majors taking Computer Science courses. This research aims to understand what influences Non-Computer Science majors' engagement in Computer Science, and the factors that shape their experiences and attitudes. Using a mixed-method approach, we first collect quantitative data through a survey, measuring various aspects. We then gather qualitative insights through interviews. Analyzing the quantitative data involves factor analysis and inferential statistics, while qualitative data is explored through thematic analysis. Our findings indicate that stereotypes about Computer Science are established as early as high school, often discouraging females from pursuing further education in the field. Addressing these stereotypes is crucial for fostering inclusivity. To counteract stereotypes, we propose promoting Computer Science from the freshman year of high school. By introducing students early, we can mitigate the impact of stereotypes and encourage a diverse range of individuals to explore Computer Science. Further exploration into the experiences of Computer Science majors is recommended to inform inclusive interventions.

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Chapter 1

Introduction

1.1 Motivation

Computer Science (CS) has become a highly sought-after skill for this generation, creating a surge in the number of students eager to acquire these skills and delve into the discipline. A personal motivation drives this study. During my undergraduate studies in Computational Modeling and Data Analytics, with a minor in CS, I faced challenges feeling fully integrated into the CS community, despite being actively engaged in the field with experiences and skills. This research focuses on non-CS majors who enroll in CS courses, either as a requirement or because they recognize the need for such skills in their respective careers. My personal experiences have propelled me to explore the experiences of students who have encountered similar challenges and circumstances.

1.2 Objective

The main objective of this study is to understand the experiences of non-CS majors enrolled in introductory CS courses. To achieve this objective, we conducted a survey among students enrolled in these introductory courses, coupled with interviews to gain a more in-depth understanding of their experiences.

1.3 Research Questions

The main research questions of this thesis are as follows:

RQ1. Is the instrument chosen for the quantitative study valid and reliable?

RQ2. Do we see any difference between Non-CS major female and male students in their sense of belonging, interest, and group inclusion? Do we see any difference based on other demographic information?

RQ3. Are there any other factors affecting the experiences of the students in these introductory courses?

1.4 Structure of Thesis

In Chapter 2, a comprehensive review of the literature is presented, delving into relevant research and exploring instruments of interest. Chapter 3 details the methods employed in the study, categorized into quantitative and qualitative sections. The findings of the quantitative study and their discussion are presented in Chapter 4, while Chapter 5 focuses on the results and discussions stemming from the qualitative study. Chapter **??** offers a broader discussion of the overall results, additional observations, and outlines potential future directions. Finally, Chapter 6 serves as the conclusion, summarizing the thesis and proposing potential solutions.

Chapter 2

Review of Literature

Several studies across different disciplines and cultures have looked at engineering education from the perspective of the students (sociology and psychology) and programs (assessment, research, and evaluation). This section highlights findings of such papers as well as discusses some methods that have been used to conduct quantitative and qualitative research.

Holloman et al. (2021) [13] explores the presence of an assessment cycle in the literature related to broadening participation in engineering. The authors conducted a systematic literature review to gather insights on this topic. The paper discusses the importance of publishing research related to broadening participation in engineering and CS, and highlights the need for a systematic assessment cycle to evaluate the effectiveness of interventions and initiatives aimed at increasing diversity and inclusion in these fields. While assessment is a critical component, challenges abound. Issues such as the adequacy of existing assessment tools, the potential for bias in evaluation, and the need for culturally sensitive metrics emerge as recurrent themes. The literature underscores the necessity of continually refining assessment strategies to ensure they align with the evolving landscape of broadening participation. The authors illuminate the multifaceted landscape of assessment in initiatives aimed at broadening participation in engineering and CS. From redefining success metrics to acknowledging the intersectionality of student experiences, the insights gleaned underscore the need for a comprehensive and evolving approach to assessment.

Astin (1984) [1] explores the role of student involvement in higher education and presents a comprehensive development theory. The paper asserts that the degree of student engagement significantly influences academic success, personal development, and overall satisfaction during the college years. Astin's theory emphasizes that student involvement goes beyond academic achievements, encompassing personal and social development. Active engagement in both co-curricular and extracurricular activities contributes to a more enriching and holistic educational experience. While recognizing the importance of academic success, Astin's model extends the concept to include critical thinking skills, intellectual curiosity, and a sense of personal responsibility. The paper highlights that student involvement positively correlates with various dimensions of academic achievement. Astin distinguishes between co-curricular and extracurricular involvement, arguing that both are crucial for a well-rounded education. Co-curricular activities are seen as integral to academic development, while extracurricular activities contribute significantly to social and personal growth. The theory has implications for diversity and inclusivity, promoting an inclusive environment by recognizing and valuing the contributions of students from diverse backgrounds. Astin's work encourages universities to provide a range of involvement opportunities that cater to the diverse needs and interests of all students. The paper has had a profound impact on higher education practices. It has influenced curriculum design, the structuring of extracurricular programs, and the development of student support services. However, challenges include balancing academic rigor with extracurricular opportunities and ensuring equitable access to involvement opportunities for all students. Astin's theory remains a cornerstone in the study of student engagement and development, guiding research and shaping educational practices. As higher education institutions adapt to evolving student needs, the theory continues to offer a valuable framework for fostering meaningful student engagement and growth.

Hoegh and Moskal (2009) [12] investigate the attitudes of science and engineering students toward CS, shedding light on important findings and insights. As a part of their research, the authors conducted an attitude asking question under five different constructs: Confidence(C), Interest(I), Gender(G), Usefulness(U), and Professional(P). The study reveals a diversity of attitudes among science and engineering students regarding CS. It identifies a spectrum of sentiments, ranging from enthusiastic interest to potential aversion, suggesting that students' perceptions of CS are not uniform within these disciplines. The authors find that students' prior experiences with CS significantly shape their attitudes. Those who have prior exposure through coursework or other activities generally express more positive attitudes, highlighting the impact of early exposure on shaping perceptions. The paper uncovers gender differences in attitudes toward CS. It discusses how stereotypes and societal expectations may contribute to these differences, and emphasizes the importance of addressing gender-related barriers to foster more inclusive attitudes among all students. The authors identify challenges in altering negative perceptions. Addressing these challenges requires not only curricular adjustments, but also a concerted effort to create inclusive learning environments that dispel stereotypes and encourage diverse student participation. Hoegh and Moskal emphasize the necessity of adopting inclusive practices within CS education. This includes promoting diversity, addressing gender disparities, and creating an environment that welcomes students from various backgrounds. In summary, Heigh and Moskal's study provided a valuable insights into the attitudes of science and engineering students toward CS. The findings help understand the factors influencing students' perceptions and suggest strategies for fostering a more inclusive and positive environment for learning CS within these disciplines.

Stirling (2001) [2] introduces thematic networks as an analytic tool for qualitative research, offering a comprehensive methodological approach. The paper emphasizes the utility of thematic networks in structuring and analyzing qualitative data, providing a framework for researchers to identify patterns, relationships, and themes within their data. The paper highlights the role of thematic networks in facilitating the organization of qualitative data. By categorizing data into themes and sub-themes, researchers can create a structured representation that aids in the interpretation and synthesis of complex information. Thematic networks support an iterative process of analysis. Researchers can refine and modify the network structure as they progress through the data analysis, allowing for a dynamic and responsive approach that captures the evolving insights from the data. Thematic networks serve as a tool for data reduction and synthesis. The method allows researchers to distill large volumes of qualitative data into manageable and meaningful themes, supporting the generation of concise and insightful summaries. Thematic networks enable researchers to integrate contextual factors into the analysis. By considering the relationships between themes, researchers can better understand the contextual nuances that influence the interpretation of qualitative data. Stirling argues that thematic networks contribute to rigorous qualitative analysis. The method provides a transparent and systematic process, enhancing the reliability and validity of the findings derived from qualitative data. In summary, the paper establishes thematic networks as a valuable ad versatile tool for qualitative researchers.

Jansen et al. (2014) [14] introduce a new conceptual framework for understanding the inclusion and utilized it as a foundation for creating and validating a scale to assess perceptions of inclusion. Building upon existing research on inclusion and incorporating insights from optional distinctiveness theory and self-determination theory, the paper suggests that inclusion is a two-dimensional concept with hierarchical qualities, encompassing perceptions of belonging and authenticity. Furthermore, the paper proposed that in the inclusivity process, the primary agency lies with the group rather than the individual. Based on this conceptualization, the authors developed and validated the Perceived Group Inclusion Scale (PGIS), a 16-item instrument. The findings from two different samples supported the proposed structure of inclusion, indicating that PIS is a reliable measure of inclusion with both nomological and predictive validity. The authors also believe that this conceptualization can be translated to other group contexts without any theoretical obstacles. This study contributes to refining the conceptual understanding of inclusion and provides researchers with a reliable and valid tool for future investigations into inclusion.

Ceci et al. (2014) [6] investigate the evolving status of women in academic science. The study contributes to the understanding of challenges faced by women in academic science, providing insights into the potential barriers and suggesting ways to foster a more inclusive environment. The authors discuss the changing landscape of women's representation in academic science and highlight trends over time. The authors analyze the educational trajectory of women and men in STEM fields from the mid-1980s to 2011, highlighting a consistent trend of women comprising over 50% of bachelor's degree recipients by 2010. Noteworthy disparities between GEEMP (geoscience, engineering, economics, mathematics/CS, and physical science) and LPS (life science, psychology, and social science) fields emerge, with women receiving only 25% of bachelor's degree in GEEMP fields in 2011, contrasting sharply with their substantial overrepresentation, reaching almost 70%, in the LPS fields. The gender gap in transitioning from undergraduate major to PhD has decreased in GEEMP fields from early 1990s to 2007-2011. The authors examine potential explanations for the under-representation of women in academic GEEMP careers. While acknowledging the established under-representation of women in math-intensive fields, the causes are debated between economists and psychologists. Economists focus on comparative advantage and market forces, considering productivity and discrimination as potential factors. In contrast, psychologists emphasize early socialization practices, biases, stereotypes, and biological differences. The paper also notes the agreement among economists and psychologists that early socialization and potential biological differences contribute to variations in comparative advantage, affecting career choices. In LPS fields, the focus shifts to post-bachelor's drop-offs, with economists emphasizing rational choices related to work-family balance, and psychologists highlighting sec differences in occupational interests. The discussion traces potential explanations from prenatal hormones through childhood socialization, cognitive aptitude, and achievement, to academic-career outcomes, evaluating evidence at each stage. Despite initial differences, the perspectives of economists and psychologists on women's migration from LPS fields appear to converge over time.

Cheryan et al. (2013) [7] address the under-representation of women in CS, attributing it to stereotypes that may discourage women from pursuing the field. The study focuses on U.S. undergraduates' stereotypes of computer scientists, emphasizing the gendered nature of these stereotypes of computer scientists, emphasizing the gendered nature of these stereotypes. Stereotypes include perceiving computer scientists as technology-oriented, singularly focused on computers, lacking interpersonal skills, intelligent, physically distinctive, and predominantly male with masculine interests. The research aims to investigate the spontaneous generation of these stereotypes among college undergraduates and explores the potential consequences on women's interest in CS. The study also considers the role of media, particularly newspapers, in perpetuating and transforming these stereotypes. The findings suggest that altering stereotypes could impact women's interest in CS, highlighting the importance of media in shaping perceptions and the need for diverse representations in the field. The studies presented offer an explanation for the persistent challenge of recruiting women into CS, attributing the difficulty to stereotypical portrayals of computer scientists. These stereotypes, depicting computer scientists as highly intelligent but socially unskilled individuals singularly obsessed with technology, contribute to deterring women from pursuing the field. The research emphasizes the power of media, especially print representations, in manipulating these stereotypes and influencing women's interest in CS. Contrary to the belief that women's disinterest in CS is inherent, the findings suggest that media representations can significantly impact preferences for majoring in the field. The study challenges the notion of college major choices as "free" decisions, revealing their constraint by prevalent stereotypes. The research underscores the crucial role of media in attracting under-represented groups to specific domains, and calls for efforts to diversify representations of computer scientists to increase women's participation in the field. Ultimately, altering stereotypes through media outlets may prove essential in achieving a more inclusive and varied image of CS, fostering increased interest among women.

Cheryan et al. (2017) [8] note that while some STEM fields, such as biology, have achieved a more balanced gender representation at the undergraduate level, others, like CS, continue to witness significant under-representation of women. This paper seeks to explore and explain the disparities in women's participation among various STEM fields. Unlike prior research that often treated STEM as a uniform category, this study focuses on the differences between STEM fields to understand why certain fields attract and retain women more effectively than others. The analysis, both theoretically and practically, aims to identify the underlying causes of current under-representation, highlighting, for instance, that gender differences in math ability do not explain the gender imbalance in CS. The findings offer insights into which fields may require immediate attention, pinpoint the factors contributing to existing disparities, and provide recommendations for effecting changes to reduce gender imbalances in STEM participation. The paper also discusses some factors that are less likely to explain the variability in gender participation — the authors rebut claims downplaying the role of gender discrimination in women's under-representation in STEM, emphasizing that evidence indicates discriminatory obstacles persist across STEM fields, affecting women more than their white male counterparts. Contrary to assertions, the review contents that discrimination remains a significant issue even in STEM fields where women have achieved greater representation, like biology and chemistry. The pervasive nature of discrimination against girls and women is stressed, emphasizing its presence across various STEM disciplines. Furthermore, the authors discuss different efforts that will help reduce under-representation of women. Efforts to address gender disparities in STEM fields have primarily focused on encouraging girls to enter field where they are already well-represented, such as biology and chemistry. However, challenges in CS, engineering, and physics persist, demanding targeted strategies. The under-representation of women in these fields begins before college, emphasizing the need to recruit girls early on. A model identifies three factors contributing to the gender gap: masculine cultures, insufficient early experience, and gender gaps in self-efficacy. Initiatives to mandate early and sustained experience, change stereotypes, and provide diverse role models have proven effective in increasing female participation in CS programs. While making CS mandatory in schools is a step forward, careful implementation is crucial to avoid reinforcing gendered stereotypes. The importance of experiences that offer learning opportunities, support, and diverse role models is highlighted, as they significantly impact women's success in STEM. The research suggests that emphasizing the importance of STEM fields alone may not close gender gaps. Successful inventions at institutions like Harvey Mudd, Carneige Mellon, and the University of Washington involved changes in departmental policies, curriculum, and the creation of supportive environments, illustrating the need for a multifaceted approach. The analysis recognizes the interplay of internal and external factors influencing women's choices in STEM fields, challenging arguments about inherent interests and emphasizing the role of cultural forces in shaping women's perceptions and preferences.

Yücel and Rızvanoğlu (2019) [20] discuss how gender has consistently been considered a controlled variable in usability and playability tests, yet there is a lack of consensus on how gender differences should influence the design of digital environments. They conduct a qualitative study, conducted with 16 middle school children in Turkey, aged 11 to 14, using the

“Code Combat” learning game, aims to shed light on the existing gender stereotypes and prescribed identities on females despite equal access to computer technology. The study’s results highlighted significant gender differences across nine attributes, including perceived computer competence, coding difficulty, identification, game difficulty, success perception, enjoyment, anxiety levels, likelihood of replay, and willingness to try new features. Both qualitative and quantitative findings consistently revealed that female participants exhibited lover perceived computer competence, reduced self-efficacy, higher perceived coding difficulty, and elevated anxiety levels, contrasting with their male counterparts. Females, after playing the coding game, reported negative feelings towards the coding concept, suggesting the influence of negative gender stereotypes. The study affirmed that perceived computer confidence and coding difficulty significantly impacted participants’ attitudes and performance, correlating with their gender identity. The perpetuation of stereotypes, such as “coding experts need to be male” or “coding is for boys”, discouraged females, hindering their identification with coding and increasing anxiety during the game. In-depth interviews uncovered that female participants associated their interest or success in coding deviating from traditional gender roles, creating a distinct social identity. Exposure to coding in a game featuring violence reinforced male-positive stereotypes, diminishing female participants’ perceived success and comfort. Females were more likely to perceive coding as a weak point due to the male-centric game environment, leading to frustration and voluntary exclusion. The study supported hypotheses indicating that perceived computer competence and lower perception of coding and game difficulty predicted game engagement, feature exploration, and enjoyment. The findings suggested that intrinsic and extrinsic barriers hindered females from developing computational thinking abilities and realizing their full potentials. Overall, the study underscored the pervasive impact of gender stereotypes on females’ attitudes toward coding and the importance of addressing these stereotypes to foster inclusivity and equitable participation in computational fields.

Bandalos and Finney (2019)[3] discuss the tasks researchers should perform to successfully conduct factor analysis, a quantitative method commonly used in Social Sciences. They structure the tasks into exploratory and confirmatory factor analysis sections. The section relevant to this study is primarily Exploratory Factor Analysis (EFA). First, the literature emphasizes the role of theory and prior research in guiding decisions during EFA. While EFA is exploratory, researchers often have some theoretical basis or expectations, even if rudimentary, guiding their analysis. The argument against theory reliance if considered implausible, as variables are rarely chosen randomly, suggesting an underlying theory. Second, the distinction between exploratory and confirmatory analyses need to be addressed. The authors suggest that EFA is suitable when minimal research has been conducted on the construct, whereas Confirmatory Factor Analysis (CFA) may lead to misfit. A guideline is provided, suggesting EFA for newly developed or unexplored variables, and CFA when previous EFA has been conducted on independent data. Third, the authors discuss the importance of understanding measured variables in EFA. The number and nature of factors depend on the observed variables. A clear presentation of each observed variable is crucial for interpreting the factor solution. Fourth, it is important to describe the sampling method and sampling size in EFA. While EFA is exploratory and not inferential, the sample's makeup should be detailed for readers to gauge generalizability. The authors recommend a sample size of at least 100 if three factors are measured by three or more variables, each with a communality of at least 0.7. If the communility is less, a larger sample size is recommended. Next, the authors recommend performing tests for tests the suitability of the data to perform factor analysis. Next, the authors discuss the critical method of extraction in Factor Analysis, distinguishing it from component analysis. Various extraction methods (for factor extraction), such as Principle Axis (PA) and Maximum Likelihood (ML) are discussed. The choice of extraction method should be justified rather than arbitrary. The next step involves the determination of the number of factors, classifying methods as statistically, mathematically or heuristically based. Statistical methods like Barlett's test and Velicer's MAP procedure, as well as mathematical methods like the eigenvalue greater than one rule, are discussed. The importance of using theory and previous research to inform decisions about the number of factors is emphasized. The next step delved into the method of rotation, emphasizing the choice between orthogonal and oblique rotations, The need for justifying the rotational procedure is highlighted, and the distinction between various rotation methods is emphasized. The next step involves variable elimination. This allows cautioning against arbitrary decisions and encouraging researchers to carefully consider the validity of construct removal. If variables are eliminated, the model must be reanalyzed, and justifications for deletions should be provided. The next step emphasizes on observing the different values of results of factor analysis. Parameter values, detailing the importance of providing and discussing commonalities, structure coefficients, pattern coefficients, and factor correlations are crucial. The next step in determining the number of factors involved discussing the percentages of variance, emphasizing the importance of reporting and interpreting the variance explained by the solution and each factor before and after rotation. Lastly, the authors highlight the interpretation of factors, incorporating different coefficients, correlations and theoretical knowledge. The importance of factor naming, and achieving a simple structure is emphasized, along with the need for replication and integration into the theoretical framework for a comprehensive understanding.

Lastly, the recent literature on women in STEM and CS education sheds light on various aspects of gender disparities and retention challenges in higher education. Blackburn's (2017) [4] comprehensive review highlights the status of women in STEM from 2007 to 2017, emphasizing the need for ongoing research and interventions. Giannakos et al.(2017) [10] delve into the factors influencing student retention in computer science education, identifying the crucial role of the learning environment, perceived gains, barriers, and perceived usefulness of the field. Tellhed et al.(2018) [17] contribute insights into the factors shaping adolescents' first educational choices, emphasizing the role of ability beliefs and acetic vs. communal career goals, providing explanations for gender imbalances. Finally, Yates and Plagnol's (2022) [19] qualitative exploration focuses specifically on female CS students in the UK. Their study delves into the lived experiences of studying CS at the university level, providing valuable qualitative data to complement quantitative findings. Together, these works underscore the multifaceted nature of gender gap in STEM and CS education, acknowledging the importance of addressing factors such as educational environment, perceived gains and barriers, ability beliefs, and career goals to promote gender balance and enhance the experiences of women in these fields. The synthesis of these studies call for a holistic approach that combines quantitative analysis, statistical insights, and qualitative narratives to inform strategies aimed at fostering inclusivity and promoting the success and retention of women in STEM disciplines, particularly in CS education.

Chapter 3

Methods

3.1 Research Questions

The main research questions of this thesis are as follows:

RQ1. Is the instrument chosen for the quantitative survey valid and reliable?

RQ2. Do we see any difference between female and male students in their sense of belonging, interest, etc.? Do we see any difference based on other demographic information?

RQ3. Are there any other factors affecting the experiences of the students in these introductory courses?

Mixed Methods

Mixed methods research is a systematic approach that combines with quantitative and qualitative research methodologies within a single study. This methodological strategy is employed to provide a more comprehensive and holistic understanding of a research question or phenomenon by leveraging the strengths of both quantitative and qualitative data. By integrating numerical (quantitative) and narrative insights (qualitative), mixed methods research seeks to offer a more nuanced and complete perspective than either method could achieve in isolation. The rationale behind employing mixed methods lies in the recognition that certain research questions are best addressed through numerical measurements and statistical analyses, while others require deeper exploration of context, meaning, and participant experiences. The combination of these approaches allows researchers to triangulate findings, validate results, and provide a more robust foundation for drawing conclusions. The mixed methods approach typically involves a sequential or concurrent design. In a sequential design, one phase of research (quantitative or qualitative) is conducted first, and the subsequent phase builds upon or informs the results of the initial phase. In a concurrent design, both quantitative and qualitative data are collected simultaneously, allowing for a more integrated analysis.

Sequential Exploratory Strategy

One of the sequential procedures is the Sequential Exploratory Strategy, and this is the approach used to conduct this research. As defined by Creswell (2018), "sequential explanatory strategy is a popular strategy for mixed methods design that often appeals to researchers with strong quantitative leanings. It is characterized by the collection and analysis of quantitative data in a first phase of research, followed by the collection and analysis of qualitative data in a second phase that builds on the results of the initial quantitative results." [9] Emphasis is placed on quantitative data, and the integration of data takes place when the initial quantitative findings guide subsequent qualitative data collection. As a result, these two types of data remain distinct but interconnected. The overall procedure may or may not be influenced by an explicit theory. This strategy is commonly employed to elucidate and interpret quantitative findings through the collection and analysis of subsequent qualitative data. It is proven to be particularly valuable when unexpected results emerge from a quantitative study, allowing for a more in-depth examination of these surprising outcomes through qualitative data collection. The simplicity of this strategy is a notable strength, facilitating easy implementation due to distinct, separate stages. However, the main drawback lies in the extended time required for data collection across the two separate phases, especially if equal priority is assigned to both stages.

3.2 Quantitative Study

This section describes all the methods used in the quantitative study of this mixed method research, including instruments/measure being used, data collection and statistical tests being used to analyze the quantitative data.

3.2.1 Instrument and Measures

Derived from pertinent literature and existing studies in the field, our instrument was crafted, drawing primary inspiration from two seminal papers: "Examining Science and Engineering Students' Attitudes Toward CS (2019)" authored by Hoegh and Moskal [12], and "Inclusion: Conceptualization and Measurement (2014)" authored by Jansen et al. [14]. Hoegh and Moskal's (2019) work aligns with a similar target audience, specifically focusing on science and engineering students outside the realm of CS. The instrument employed in their study comprises five constructs—Confidence, Interest, Gender, Usefulness, and Professional—aimed at comprehending the experiences of the students.

Out of these constructs, our study selectively focused on evaluating Confidence, Interest, and Gender. Additionally, we sought to explore an aspect not explicitly measured in Hoegh and Moskal's study—Inclusion. To address this, we turned to the study conducted by Jansen et al. (2014), whose target audience consists of psychology students, focusing on the assessment of inclusion and inclusion initiatives in that domain. Upon examination of their instrument, we found it to be sufficiently generic, allowing for its adaptation to understand inclusion in a different field (CS). Consequently, we adopted the instrument from Jansen et al. (2014) for our study.

As a result, the instrument developed and employed in this study comprises four measures: Confidence (C), Interest (I), Gender (G), and Group Inclusion (GI). The constructs of Confidence, Interest, and Gender were adapted from the study conducted by Hoegh and Moskal, while the Group Inclusion construct was taken from the research conducted by Jansen et al.

- Confidence (C) : students' confidence in acquiring skills related to CS
- Interest (I) : students' interests in CS
- Gender (G) : students' views on CS being a male-dominated field
- Group Inclusion (GI): students' views on being an insider/outsider in the CS community

Each of these measures encompasses a distinct number of items, or survey questions, as detailed in the tables below. These items are replicated from Hoegh and Moskal [12] for Confidence, Interest, and Gender constructs, and from Jansen et al. [14] for the Group Inclusion construct. Tables 3.1, 3.2, 3.3, and 3.4 list the items for each of the measures used in this study.

Confidence
C1. I am comfortable with learning computer science concepts
C2. I have little self-confidence when it comes to computer science classes
C3. I do not think I can learn to understand computer science concepts
C4. I can learn to understand computer science concepts
C5. I can achieve good grade (C or better) in computer science classes
C6. I am confident that I can solve problems by using computer science applications
C7. I am not comfortable with learning computer science problems
C8. I doubt that I can solve problems by using computer science applications

Table 3.1: Confidence Measure and Items

Interest
I1. I would not take additional computer science courses if I were given the opportunity
I2. I think computer science is boring
I3. I hope that my future career will require the use of computer science concepts
I4. The challenge of solving problems using computer science does not appeal to me
I5. I like to use computer science to solve problems
I6. I do not like using computer science to solve problems
I7. The challenge of solving problems using computer science appeals to me
I8. I hope that I can find a career that does not require the use of computer science concepts
I9. I think computer science is interesting
I10. I would voluntarily take additional computer science courses if I were given the opportunity

Table 3.2: Interest Measure and Items

Gender
G1. I doubt that a woman could excel in computing courses
G2. Men are more capable than women at solving computing problems
G3. Computing is an appropriate subject for both men and women to study
G4. Women and men can both excel in careers that involve computing
G5. It is not appropriate for women to study computer science
G6. Men produce higher quality work in computing than women
G7. Men are more likely to excel in careers that involve computing than women are
G8. Women produce the same quality work in computing as men
G9. Men and women are equally capable of solving computing problems
G10. Men and women can both excel in computer science courses
G11. Non-binary person can excel in careers that involve computing
G12. It is not appropriate for a non-binary person to study computer science
G13. Men produce higher quality work in computing than non-binary person

Table 3.3: Gender Measure and Items

Group Inclusion
GI1. Gives me the feeling that I belong
GI2. Gives me the feeling that I am part of this group
GI3. Gives me the feeling that I fit in
GI4. Treats me as an insider
GI5. Likes me
GI6. Appreciates me
GI7. Is pleased with me

GI8. Cares about me
GI9. Allows me to be authentic
GI10. Allows me to be who I am
GI11. Allows me to express my authentic self
GI12. Allows me to present myself the way I am
GI13. Encourages me to be authentic
GI14. Encourages me to be who I am
GI15. Encourages me to express my authentic self
GI16. Encourages me to present myself the way I am

Table 3.4: Group Inclusion Measure and Items

As presented above, Confidence has 8 items, Interest has 10 items, Gender has 13 items, and Group Inclusion had 13 items. These items have been replicated word for word from the literatures mentioned above. Each item employed a five-point Likert-type scale, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), to elicit participant responses. The Confidence, Interest, and Gender measures encompass both positive and negative statements. Therefore, a higher average score for the positive statements (e.g., **C1, C4, C5, C6** for **Confidence**) implies students exhibiting greater confidence, whereas a higher average for negative statements (**C2, C3, C7, C8**) suggests lower confidence levels. In contrast, the Group Inclusion measure exclusively comprises positive sentiments. Consequently, a higher average score for the entire measure indicates a heightened sense of inclusion or feeling included, while a lower average implies a diminished sense of inclusion.

Moving forward, our examination will delve into the correlation between each item within the Confidence, Interest, and Gender measures, followed by an exploration of descriptive statistics for each item. It is noteworthy that these measures incorporate a mix of positive and negative statements, prompting a detailed scrutiny of the descriptive statistics for individual items within each category.

Confidence

	C1	C2	C3	C4	C5	C6	C7	C8
Mean	3.81	2.70	2.04	4.03	4.24	3.80	2.11	2.12
Std	1.05	1.25	1.06	0.85	0.96	1.01	0.99	0.96
Median	4.00	2.00	2.00	4.00	4.00	4.00	2.00	2.00

Table 3.5: Mean, Standard Deviation and Median for Items in Confidence

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1.00	-0.39	-0.41	0.65	0.68	0.57	-0.46	-0.38
C2	-0.37	1.00	0.57	-0.29	-0.23	-0.34	0.59	0.58
C3	-0.41	0.57	1.00	-0.38	-0.25	-0.36	0.61	0.52
C4	0.65	-0.29	-0.38	1.00	0.64	0.73	-0.44	-0.39
C5	0.68	-0.23	-0.25	0.64	1.00	0.63	-0.38	-0.31
C6	0.57	-0.34	-0.36	0.73	0.63	1.00	-0.46	-0.57
C7	-0.46	0.59	0.61	-0.44	-0.38	-0.46	1.00	0.72
C8	-0.38	0.58	0.52	-0.39	-0.31	-0.57	0.72	1.00

Table 3.6: Correlation between Items in Confidence

An observation stemming from the correlation analysis of the items indicates that positive statements (**C1, C4, C5, and C6**) exhibit higher correlation among themselves, and similarly, negative statements (**C2, C3, C7, C8**) demonstrate a similar pattern. Additionally, there is a negative correlation between the positive and negative statements.

Interest

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Mean	2.33	1.99	2.99	2.25	3.24	2.25	3.19	2.43	3.63	3.06
Std	1.33	1.11	1.43	1.21	1.34	1.10	1.35	1.25	1.36	1.47
Median	2.00	2.00	3.00	2.00	3.00	2.00	4.00	2.00	4.00	3.00

Table 3.7: Mean, Standard Deviation and Median for Items in Interest

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
I1	1.00	0.68	-0.05	0.63	0.12	0.64	0.17	0.69	0.22	-0.16
I2	0.68	1.00	-0.02	0.69	0.18	0.61	0.19	0.70	0.16	-0.03
I3	-0.05	-0.02	1.00	-0.04	0.81	0.06	0.75	-0.05	0.76	0.81
I4	0.63	0.69	-0.04	1.00	0.12	0.76	-0.01	0.78	0.24	0.00
I5	0.12	0.18	0.81	0.12	1.00	0.07	0.81	0.09	0.80	0.73
I6	0.64	0.61	0.06	0.76	0.07	1.00	0.15	0.78	0.28	0.08
I7	0.17	0.19	0.75	-0.01	0.81	0.15	1.00	0.11	0.79	0.69
I8	0.69	0.70	-0.05	0.78	0.09	0.78	0.11	1.00	0.24	0.04
I9	0.22	0.16	0.76	0.24	0.80	0.28	0.79	0.24	1.00	0.77
I10	-0.16	-0.03	0.81	0.00	0.73	0.08	0.69	0.04	0.77	1.00

Table 3.8: Correlation between Items in Interest

Similarly, correlation of the items for Interest indicate that positive statements (**I3, I5, I7, I9, I10**) exhibit higher correlation among themselves, and similarly, negative statements (**I1, I2, I4, I6, I8**) demonstrate a similar pattern. Additionally, there is a negative correlation between the positive and negative statements.

Gender

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13
Mean	1.04	1.19	3.98	4.03	1.06	1.16	1.37	3.84	3.99	4.00	3.93	1.23	1.29
Std	0.63	0.85	1.78	1.76	0.71	0.87	1.06	1.79	1.75	1.76	1.75	0.97	1.01
Median	1.00	1.00	5.00	5.00	1.00	1.00	1.00	5.00	5.00	5.00	5.00	1.00	1.00

Table 3.9: Mean, Standard Deviation and Median for Items in Gender

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13
G1	1.00	0.79	0.45	0.48	0.80	0.74	0.64	0.40	0.46	0.47	0.44	0.71	0.63
G2	0.79	1.00	0.39	0.40	0.70	0.91	0.75	0.29	0.34	0.37	0.32	0.68	0.73
G3	0.45	0.39	1.00	0.94	0.35	0.37	0.38	0.91	0.95	0.94	0.93	0.30	0.38
G4	0.48	0.40	0.94	1.00	0.43	0.37	0.35	0.93	0.97	0.98	0.96	0.34	0.35
G5	0.80	0.70	0.35	0.43	1.00	0.68	0.56	0.37	0.41	0.43	0.42	0.75	0.55
G6	0.74	0.91	0.37	0.37	0.68	1.00	0.80	0.25	0.31	0.34	0.29	0.66	0.78
G7	0.64	0.75	0.38	0.35	0.56	0.80	1.00	0.29	0.34	0.33	0.31	0.54	0.65
G8	0.40	0.29	0.91	0.93	0.37	0.25	0.29	1.00	0.95	0.93	0.95	0.27	0.26
G9	0.46	0.34	0.95	0.97	0.41	0.31	0.34	0.95	1.00	0.97	0.97	0.33	0.32
G10	0.47	0.37	0.94	0.98	0.43	0.34	0.33	0.93	0.97	1.00	0.96	0.34	0.35
G11	0.44	0.32	0.93	0.96	0.42	0.29	0.31	0.95	0.97	0.96	1.00	0.29	0.27
G12	0.71	0.68	0.30	0.34	0.75	0.66	0.54	0.27	0.33	0.34	0.29	1.00	0.60
G13	0.63	0.73	0.38	0.35	0.55	0.78	0.65	0.26	0.32	0.35	0.27	0.60	1.00

Table 3.10: Correlation between Items in Gender

Similarly, correlation of the items for Gender indicate that positive statements (**G3, G4, G8, G9, G10, G11**) exhibit higher correlation among themselves, and similarly, negative statements (**G1, G2, G5, G6, G7, G12, G13**) demonstrate a similar pattern. Additionally, there is a negative correlation between the positive and negative statements.

Group Inclusion

	GI1	GI2	GI3	GI4	GI5	GI6	GI7	GI8	GI9	GI10	GI11	GI12	GI13
Mean	2.46	2.47	2.47	2.41	2.64	2.54	2.61	2.54	2.69	2.73	2.66	2.79	2.64
Std	1.45	1.49	1.43	1.40	1.47	1.41	1.42	1.43	1.46	1.49	1.44	1.51	1.44
Median	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Table 3.11: Mean, Standard Deviation and Median for Item in Group Inclusion (G1 — G13)

	GI14	GI15	GI16
Mean	2.66	2.59	2.62
Std	1.44	1.40	1.41
Median	3.00	3.00	3.00

Table 3.12: Mean, Standard Deviation and Median for Items in Group Inclusion (G14 — G16)

	GI1	GI2	GI3	GI4	GI5	GI6	GI7	GI8	GI9	GI10	GI11	GI12	GI13
GI1	1.00	0.95	0.95	0.90	0.89	0.92	0.90	0.91	0.88	0.86	0.86	0.84	0.88
GI2	0.95	1.00	0.95	0.92	0.92	0.92	0.91	0.90	0.90	0.88	0.89	0.86	0.88
GI3	0.95	0.95	1.00	0.91	0.93	0.93	0.92	0.90	0.89	0.88	0.88	0.85	0.90
GI4	0.90	0.92	0.91	1.00	0.91	0.93	0.91	0.92	0.88	0.87	0.87	0.84	0.87
GI5	0.89	0.92	0.93	0.91	1.00	0.95	0.95	0.94	0.94	0.94	0.93	0.92	0.92
GI6	0.92	0.92	0.93	0.93	0.95	1.00	0.96	0.94	0.93	0.92	0.91	0.89	0.93

GI7	0.90	0.91	0.92	0.91	0.95	0.96	1.00	0.94	0.93	0.93	0.93	0.91	0.94
GI8	0.91	0.90	0.90	0.92	0.94	0.94	0.94	1.00	0.93	0.91	0.91	0.89	0.92
GI9	0.88	0.90	0.89	0.88	0.94	0.93	0.93	0.93	1.00	0.95	0.94	0.92	0.94
GI10	0.86	0.88	0.88	0.87	0.94	0.92	0.93	0.91	0.95	1.00	0.95	0.95	0.94
GI11	0.86	0.89	0.88	0.87	0.93	0.91	0.93	0.91	0.94	0.95	1.00	0.95	0.93
GI12	0.84	0.86	0.85	0.84	0.92	0.89	0.91	0.89	0.92	0.95	0.95	1.00	0.92
GI13	0.88	0.88	0.90	0.87	0.92	0.93	0.94	0.92	0.94	0.94	0.93	0.92	1.00

Table 3.13: Correlation between Items in Group Inclusion (G1 — G13)

	GI14	GI15	GI16
GI14	1.00	0.96	0.95
GI15	0.96	1.00	0.97
GI16	0.95	0.97	1.00

Table 3.14: Correlation between Items in Group Inclusion (G14 — G16)

Finally, concerning the Group Inclusion measure, notable correlations exist between its items. It's noteworthy that no negative correlations are observed in this measure, as all the statements are positive in nature. The subsequent section delves into a more detailed exploration of the procedures employed, and the students involved in the quantitative study.

3.2.2 Procedure and Participants

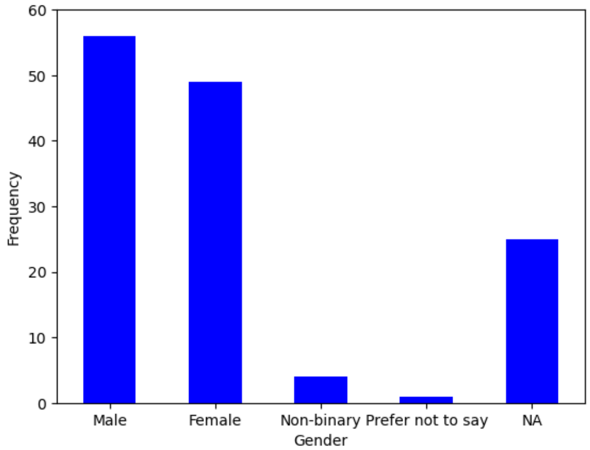
A survey, created using Question Pro, served as the primary mode of data collection for the quantitative study. A recruitment strategy was devised, involving the creation of e-brochures distributed to instructors teaching specific introductory courses exclusively designed for non-CS majors. These courses included CS 1014: Introduction to Computational Thinking, CS 1044: Introduction to Programming in C, CS 1054: Introduction to Programming in Java, CS 1064: Introduction to Programming in Python, and CS 2064: Intermediate Programming in Python during the Spring 2023 semester. These introductory courses were deliberately chosen, being open to all majors and serving as an ideal source for participants matching the target population of non-CS students. With instructors facilitating the distribution of the survey, we successfully reached participants within our specified demographic. Additionally, the survey collected supplementary information, including class standings, other CS courses taken, and background and demographic details from the participants.

During the Spring 2023 semester, data was collected from 159 students who were enrolled in the specified introductory CS courses, as previously mentioned. The objective of the data collection, conducted towards the end of the semester, was to capture a comprehensive range of experiences and potential shifts in attitudes throughout the term. Subsequently, the data obtained from the survey platform, Question Pro, underwent meticulous filtering and processing to ensure the accuracy of responses. The applied criteria for this purpose were:

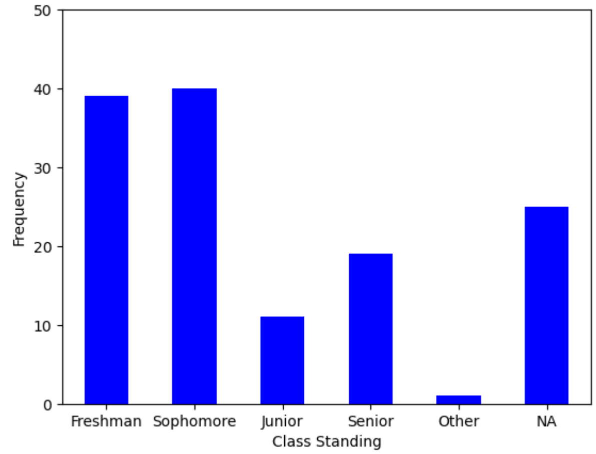
- Non-Null Response IDs (generated by the survey platform) (0 responses dropped)
- Elimination of duplicate IP addresses (9 responses dropped)
- Exclusion of responses with completion times less than 1 minute (15 responses dropped)

Following the application of the aforementioned criteria, a total of 135 responses remained. These responses encompass both complete and incomplete submissions, with incomplete responses indicating instances where participants commenced the survey but discontinued at various points. In instances where applicable, these incomplete responses were retained for factor analysis. However, during the execution of inferential statistics, such incomplete responses had to be omitted.

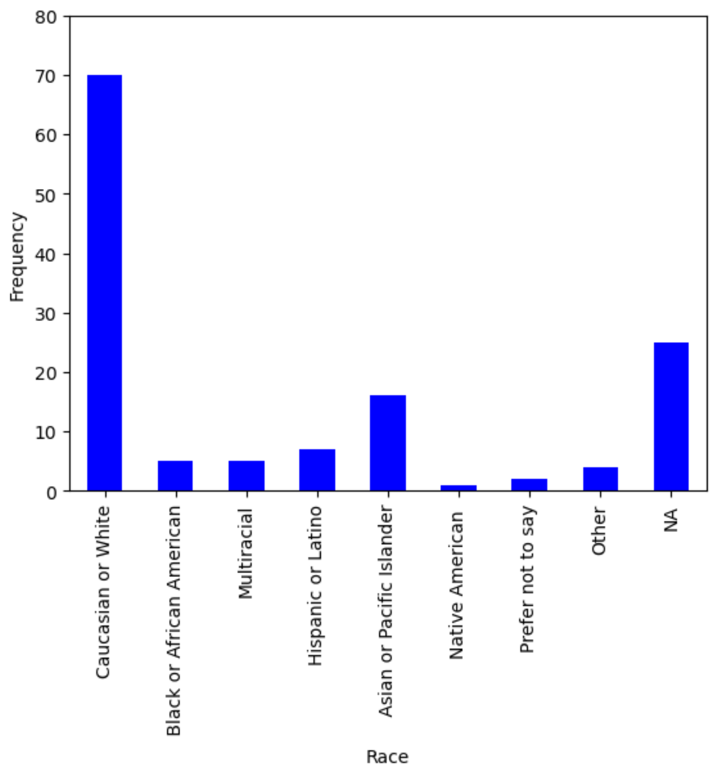
Roughly 80 percent of the participants self-identified as non-engineering majors. Although a significant portion of the sample comprised Freshman and Sophomore students, there was a substantial representation of Junior and Senior standings as well, i.e., the sample sizes were comparable. The bar charts below provide visual representations of the participant distribution across various criteria:



(a) Bar Chart for Gender (Category)



(b) Bar Chart for Class Standing



(c) Bar Chart for Race

Figure 3.1: Bar Chart for the Demographic Categories, where X-axis represents categories and Y-xis shows the frequency of participants in each category

For each of the mentioned demographics, **NA** bars, indicate null data (result of incomplete responses), and were excluded before conducting inferential statistics tests. Tables with percentage for each of the variables are presented below:

Category	Frequency	% of Total
Male	56	41.48
Female	49	36.30
Non-Binary	4	2.96
Prefer not to say	1	0.74
NA	25	18.52

Table 3.15: Distribution by Gender

Category	Frequency	% of Total
Freshman	39	28.89
Sophomore	40	29.63
Junior	11	8.15
Senior	19	14.07
Other	1	0.74
NA	25	18.52

Table 3.16: Distribution by Standing

Category	Frequency	% of Total
Caucasian or White	70	51.85
Black or African American	5	3.70
Multiracial	5	3.70
Hispanic or Latino	7	5.19
Asian or Pacific Islander	16	11.85

Native American	1	0.74
Prefer not to say	2	1.48
Other	4	2.96
NA	25	18.52

Table 3.17: Distribution by Race

A key observation from these tables is that if the frequency of any given sample falls below an acceptable sample size of 10, that particular sample is excluded from the inferential statistics, as detailed further in the subsequent section. For instance, considering the sample size for "Non-Binary" is 4, it will be omitted from any Gender-focused statistical test, given that the sample size is not comparable to that of the other categories—Male: 56 and Female: 49.

3.2.3 Statistical Tests

Following the completion of the data collection phase, a series of tests and analytical techniques were employed to scrutinize the quantitative data. All analyses described below were conducted using Python and relevant modules/packages. The initial phase involved validating the instrument utilized for our dataset, with a particular focus on factor analysis.

Before delving into factor analysis, the assumptions associated with this method were tested. The Kaiser Meyer Olkin (KMO) test, a statistical measure within the realm of multivariate analysis, played a crucial role in this assessment. The KMO test evaluates the dataset's appropriateness for factor analysis by assessing the sampling adequacy for each variable. The resulting KMO value ranges from 0 to 1, with higher values signifying greater suitability for factor analysis. In this study, a threshold as defined by Kaiser as "middling" — 0.7 will be used. [11] [5] The KMO test returned a robust value of 0.9118, which would be considered "marvelous" based on the original definitions. This high KMO est value affirms the dataset's suitability for exploratory factor analysis (EFA), providing a sold foundation for proceeding with the subsequent analytical phase. Furthermore, the KMO test values for each of the measures also returned values greater than 0.7. This was checked in the case that factor analysis is performed at the measure-level as well. The KMO values are as follows — Confidence: 0.834, Interest: 0.797, Gender: 0.913, and Group Inclusion: 0.959.

Upon confirming the reliability of the dataset, factor analysis was initiated. Factor analysis serves as a statistical method aimed at uncovering latent factors that elucidate patterns of correlations among variables. Its primary purpose is to reduce the dimensionality of the data by identifying latent constructs responsible for observed variance. This analytical approach unveils the inherent structure within the data, revealing associations between observed variables and their common factors.

In this study, the analytical approach of choice is exploratory factor analysis (EFA). EFA is a specialized application of factor analysis, especially beneficial when researchers confront a lack of predefined hypotheses regarding the underlying structure of the data. By permitting patterns to naturally emerge from observed variables, EFA plays a crucial role in formulating hypotheses or theories related to latent constructs within the dataset [3].It is pertinent to note that factor analysis is conducted at the measure level in this study, meaning that all the items within each measure are loaded into the factor analysis simultaneously. Consequently, four independent factor analyses are performed, each corresponding to one of the four measures.

Within the realm of EFA, Principal Axis Factoring (PAF) was employed. PAF operates under the assumption that observed variables share common factors, contributing to the correlations among them. This assumption aligns with situations where researchers believe that observed variables are influenced by underlying latent factors. PAF is particularly effective when the data exhibit a correlation structure and when a set of variables is expected to be interrelated. It aids in understanding the common factors contributing to these interrelationships.

Taking into account the distribution and correlation tables, Principal Axis Factoring (PAF) stands out as a robust choice for Exploratory Factor Analysis (EFA) in this study. Its suitability becomes evident in scenarios where variables are expected to exhibit interdependencies, and the method is specifically designed to unveil the common factors underlying these relationships. Furthermore, the simplicity of interpreting PAF results and its adherence to a simple structure contribute to its favorability in conducting factor analysis for this study.

To perform Principal Axis Factoring (PAF), three distinct methods were employed to determine the number of factors to be extracted—Scree Plots, Minimum Average Partial (MAP), and Parallel Analysis, as recommended by Bandalos [3].

The use of these three methods aimed to avoid reliance on any specific extraction method, considering the absence of a predetermined theory before the analysis. A factor analysis using PAF, incorporating the number of factors extracted by each method, was then conducted. The results were compared based on factors such as factor loading, cumulative variance, and correlation between factors to determine the final number of factors.

After performing EFA, a Cronbach's Alpha coefficient is used to check the reliability of the factor analysis. A high Cronbach's alpha value, typically above 0.7 indicates a reliable and internally consistent factor, reinforcing the validity of the factor analysis results. Once the reliability and validity of our instrument is confirmed, some inferential statistics are performed.

Analysis of Variance (ANOVA) was conducted on the dataset based on gender and other demographic information collected, namely Gender, Standing, Major, and Race. ANOVA is a statistical test designed to assess whether there are statistically significant differences in means across multiple groups. It aids in determining if variations in the dependent variable can be attributed to the differences between the groups being compared. ANOVA is applied individually for each factor and measure.

The Likert-type scale responses were transformed into a numerical scale, ranging from 1 for "Strongly Disagree" to 5 for "Strongly Agree." These values were then averaged for each factor. The independent variables for these tests encompass demographic categories (Gender, Standing, Major, and Race), while the dependent variables are the four measures (Confidence, Interest, Gender, and Group Inclusion). The objective is to discern if there are significant differences in the experiences of samples concerning different measures.

Before conducting ANOVA, an assumption testing phase was implemented. This involved the Shapiro-Wilk Test to check if the variables follow a normal distribution. For samples that did not meet the assumptions of ANOVA, the Kruskal-Wallis Test, a non-parametric alternative to ANOVA, was employed.

3.3 Qualitative Study

3.3.1 Questionnaire

After analyzing the quantitative data, a structured questionnaire was developed for participants who expressed interest in further interviews. The questionnaire aimed to gather detailed insights into their backgrounds (mainly in CS), and included inquiries about their interests in the field and sense of inclusion/belonging to the community.

3.3.2 Procedure and Participants

Qualitative data collection focused on participants (who had expressed interest in being interviewed from the survey) identified through the Likert scale results (from the quantitative data collection) — specifically, females exhibiting high confidence and interest but low sense of inclusion/belonging, aligning with the research focus. Four participants, two STEM-majors (non-computer-related engineering) and two non-STEM majors, were selected for Zoom interviews. These sessions were recorded and transcribed for subsequent in-depth analysis. The participants were compensated with an e-gift card for their time.

Four female participants were chosen from the sample that had a high confidence and interest, but lower sense of inclusion/belonging. These participants were interviewed through Zoom. Some brief context for each participant is provided below -

Student	Standing	Major	Prior Exposure to CS
Student 1	Senior	Biomedical Engineering	Took AP CS
Student 2	Sophomore	Industrial & Systems Engineering	Took CS courses in community college
Student 3	Senior	Cybersecurity Management and Analytics (Business)	Took AP CS
Student 4	Senior	Public Administration	No exposure

Table 3.18: Qualitative Procedure Participant Information

3.3.3 Thematic Analysis

Thematic analysis served as the primary method for analyzing qualitative data. Widely used in qualitative research, thematic analysis involved identifying, analyzing, and reporting patterns (themes) within textual data, such as interview transcripts. The process entailed systematic coding to reveal recurring themes and key concepts, offering a comprehensive and flexible approach to unravel complex narratives. This method facilitated a nuanced understanding of the participants' experiences and perspectives in the context of the study.

Chapter 4

Quantitative Results and Discussion

This chapter details the analyses conducted on the quantitative dataset. Following the data exploration process, several preparatory steps were taken, including data cleaning procedures such as eliminating duplicates and removing responses from participants with a response time of less than one minute. These meticulous steps resulted in a refined dataset consisting of 135 responses, forming the basis of our subsequent analyses.

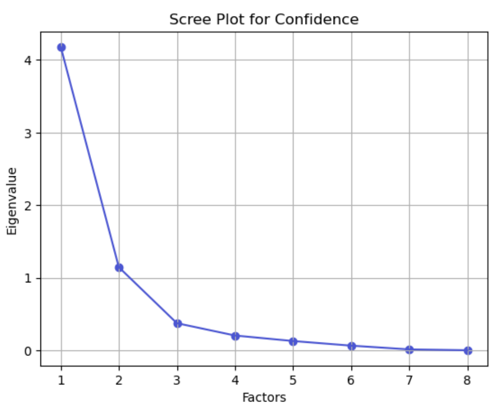
4.1 Validation of the Instrument

In this section, we discuss the results for each step of the factor analysis, providing explanations of different design and parametric choices.

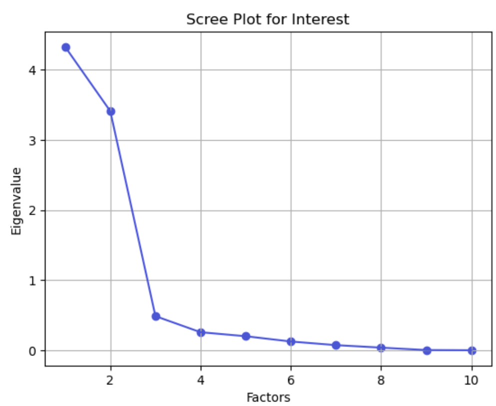
4.1.1 Extraction of Factors

Various factor extraction techniques, including the scree plot, Velicer's minimum average partial (MAP), and Horn's parallel analysis, were employed to determine the number of factors for each of the four measures. An oblique method of rotation was employed for each extraction method. An oblique rotation is recommended when there are no specific theories regarding the correlation or lack thereof among factors, which was our case. Furthermore, oblique rotation is also justified in this context as they yield more reasonable presentations of data, especially considering that dimensions underlying measures in social or behavioral sciences typically exhibit correlations. [3] To inform this decision, an initial exploratory factor analysis (EFA) was conducted.

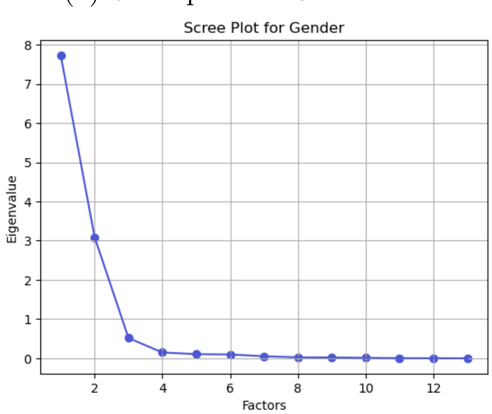
The scree plot, a visual method, facilitates the identification of factors with eigenvalues greater than 1, which are considered significant in factor analysis. The scree plot, depicting the eigenvalues of the initial solution, was utilized to identify factors with eigenvalues greater than or equal to 1. Eigenvalues exceeding 1 were considered, as they signify the variance accounted for by a single factor, The scree plots for each measure are presented below in 4.1.



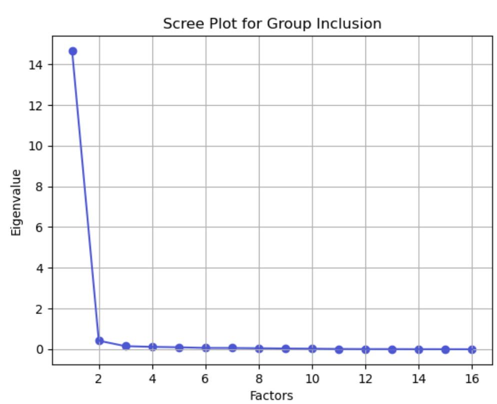
(a) Scree plot for Confidence



(b) Scree plot for Interest



(c) Scree plot for Gender



(d) Scree plot for Group Inclusion

Figure 4.1: Scree plots for all four measures

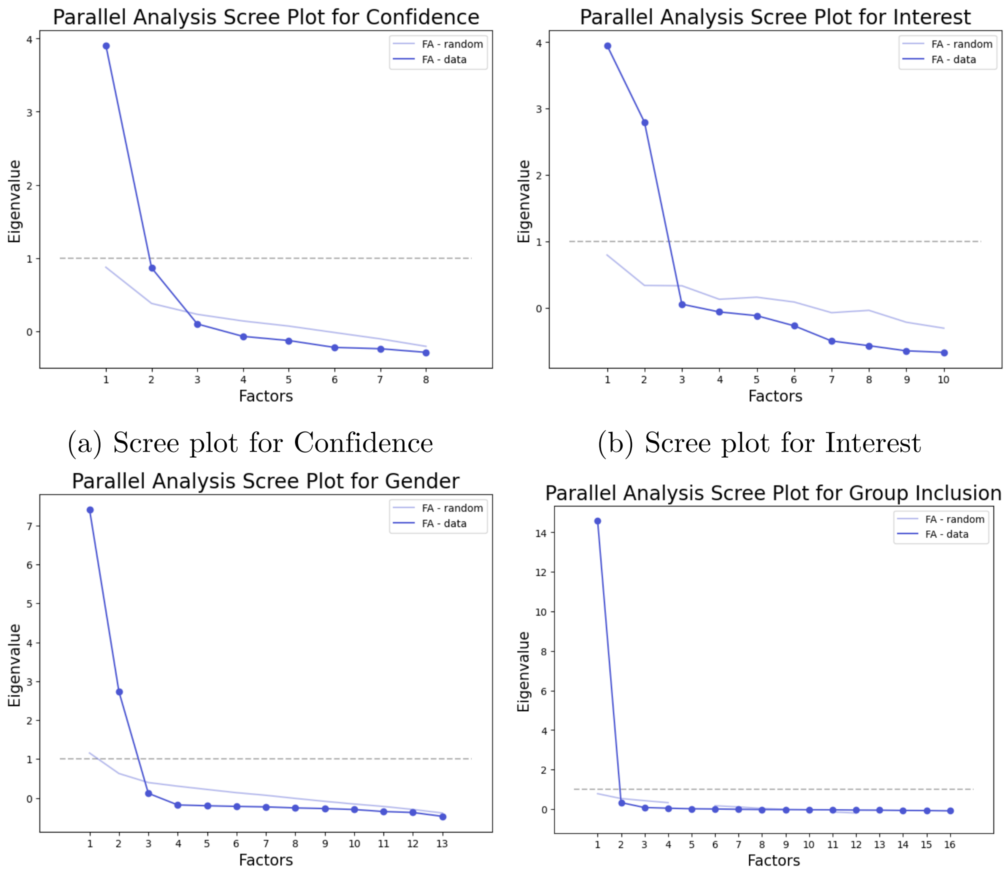
The application of the traditional elbow method for factor/component analysis, which suggests retaining factors/components with an eigenvalue of at least 1, was employed in this study. Upon examining the Scree plots (see Figure 4.1), and applying the traditional elbow method, it is apparent that Confidence, Interest, and Gender each extracted two factors, while Group Inclusion only extracted one.

Furthermore, Velicer's minimum average partial (MAP) procedure was utilized for factor extraction. MAP is a recursive process that computes the average of partial correlations for different numbers of factors, ranging from 1 to n, where n is the number of items used in the factor analysis. The result of MAP is the number of factors with the lowest partial correlation. [18] A lower partial correlation implies greater preservation of individual variability. The results of the MAP test, conducted using Python, are presented in the table below (see Table 4.1).

Measure	Number of factors
Confidence	2
Interest	2
Gender	3
Group Inclusion	3

Table 4.1: MAP test results

The next factor extraction method of Horn's parallel analysis. Parallel Analysis relies on Monte Carlo simulation. This algorithm generates a random dataset identical to the input data in sample size and the number of variables. Eigenvalues for variables are recorded over multiple iterations and averaged. Factors are retained if their eigenvalues exceed the 95th percentile of the simulated values. This method ensures that factors are retained only if their eigenvalues are greater than those obtained at random. The scree plots from this analysis are presented below: Fig. 4.2



(a) Scree plot for Confidence

(b) Scree plot for Interest

(c) Scree plot for Gender

(d) Scree plot for Group Inclusion

Figure 4.2: Parallel Analysis Scree plots for all four measures

The table below summarizes the results of all three of the factor extraction methods -

Measure	Eigenvalue > 1	Scree plot	MAP	Parallel Analysis
Confidence	2	2	2	1
Interest	2	2	2	2
Gender	2	2	3	2
Group Inclusion	1	1	3	1

Table 4.2: Number of Factors from each Factor Extraction Method

4.1.2 Factor Analysis

Following this, a factor analysis was conducted on each of the measures, employing the determined number of factors through various extraction methods, as specified in Table 4.2. The subsequent series of tables showcase the factor loadings for the different numbers of factors. The factor loading matrix illustrates the relationship of each variable to the underlying factor, displaying the correlation coefficient for the observed variable and factor, as well as the variance explained by the observed variables. These factor loadings were derived from a Principal Axis Factoring (PAF) factor analysis utilizing an oblique rotation.

Within each table, loadings equal to or exceeding 0.7 are highlighted in bold. A loading of 0.7 or higher indicates that the factor extracts a significant amount of variance from the corresponding variable [16]. We conducted factor analysis for each measure, and therefore we will look at the results for one measure at a time.

Confidence

Item (Question)	**Factor 1**	**Factor 2**
C1	**0.705097**	-0.118276
C2	0.084949	**0.794629**
C3	-0.003304	**0.722456**
C4	**0.829031**	-0.018458
C5	**0.885254**	0.122726
C6	**0.712813**	-0.154553
C7	-0.064293	**0.808003**
C8	-0.064505	**0.757578**

Table 4.3: Factor Loadings for Confidence with 2 Factors

Item (Question)	**Factor 1**
C1	-0.726953
C2	0.603537
C3	0.628341
C4	-0.733275
C5	-0.645625
C6	-0.768371
C7	**0.751823**
C8	**0.713681**

Table 4.4: Factor Loadings for Confidence with 1 Factor

Tables 4.3 and 4.4 present the factor loadings for Confidence using 2 factors and 1 factor in the factor analysis. Upon examining the bolded loadings, it becomes evident that the results from the 2-factor analysis are more promising. In this case, each item demonstrates a correlation with a factor, whereas in the 1-factor analysis, only items C1 and C2 exhibit loadings that meet the threshold of 0.7.

Next, attention is directed towards assessing the percentage of variance explained by each factor. The objective is to determine the number of factors that yield the highest cumulative variance. The tables below provide insights into the cumulative variance for each factor and measure.

	Factor 1	**Factor 2**
Cumulative Variance	0.488378	
Cumulative Variance	0.311469	0.615650

Table 4.5: Variance for Confidence

Table 4.5 illustrates that 2 factors can account for a higher cumulative variance in our data for Confidence. Based on the factor loadings and variance analysis, there is a preference for using 2 factors for confidence.

Taking a closer look at the survey questions in Table 3.1, it's insightful to understand why certain items had higher loadings for a specific factor. Items **C1, C4, C5, and C6** exhibit higher loadings for Factor 1, while **C2, C3, C7, and C8** have higher loadings for Factor 2. Notably, items with higher loadings for a factor share the same sentiment. For instance, **C1, C4, C5, and C6** are positive statements, and they all demonstrate higher loadings for Factor 1.

Interest

Item (Question)	**Factor 1**	**Factor 2**
I1	-0.018647	**0.788445**
I2	0.016154	**0.787204**
I3	**0.914106**	-0.130605
I4	-0.027931	**0.868648**
I5	**0.891742**	0.037949
I6	0.051761	**0.831303**
I7	**0.854554**	0.050242
I8	-0.008298	**0.902067**
I9	**0.875597**	0.174872

I10	**0.862133**	-0.109610

Table 4.6: Factor Loadings for Interest

Since, all methods of extraction from 4.2 extracted 2 factors for Interest, we look at the loadings with 2 factors. We can observe that each item is 0.7 or higher for a factor.

	Factor 1	**Factor 2**
Cumulative Variance	0.387514	0.743943

Table 4.7: Variance for Interest with 2 Factors

For Interest, the cumulative variance is about 74%. Items **I3, I5, I7, I9 and I10** have higher loadings for Factor 1 and **I1, I2, I4, I6 and I8** have higher loadings for Factor 2. Similar to Confidence, the items with higher loadings for a factors share a similar sentiment, either positive or negative.

Gender

Item (Question)	**Factor 1**	**Factor 2**
G1	0.127224	**0.805578**
G2	-0.040189	**0.948500**
G3	**0.931819**	0.045933
G4	**0.963599**	0.049472
G5	0.102049	**0.750341**
G6	-0.076668	**0.966391**
G7	0.013609	**0.777374**

G8	**0.985026**	-0.065871
G9	**0.989445**	-0.002160
G10	**0.972743**	0.027028
G11	**0.991907**	-0.030098
G12	0.002533	**0.769621**
G13	0.000530	**0.781900**

Table 4.8: Factor Loadings for Gender with 2 Factors

Item (Question)	**Factor 1**	**Factor 2**	**Factor 3**
G1	0.121117	0.344256	0.549719
G2	0.000433	**0.805980**	0.171113
G3	**0.955610**	0.201730	-0.176864
G4	**0.962565**	0.045961	0.012355
G5	0.046688	0.015091	**0.914808**
G6	-0.027351	**0.980017**	0.010658
G7	0.058431	**0.802471**	-0.014260
G8	**0.975537**	-0.081726	0.026455
G9	**0.982691**	-0.027492	0.037765
G10	**0.967180**	-0.003399	0.043746
G11	**0.979314**	-0.098005	0.087172
G12	-0.014729	0.257367	0.615246
G13	0.041671	**0.753190**	0.043277

Table 4.9: Factor Loadings for Gender with 3 Factors

Likewise, tables 4.8 and 4.9 present factor loadings for Gender with 2 factors and 3 factors, respectively. Upon examination, it is observable that while most of the loadings in table 4.9 meet the established threshold, items G1 and G12 fall short of the threshold. In contrast, the loadings with 2 factors demonstrate high loadings with one factor each.

	Factor 1	**Factor 2**	**Factor 3**
Cumulative Variance	0.439268	0.813427	
Cumulative Variance	0.436503	0.672359	0.794831

Table 4.10: Variance for Gender with 3 Factors

For Interest, it's evident from the cumulative variance analysis in Table **??** that 2 factors yield a higher cumulative variance than 3 factors. Consistent with the patterns observed in other measures, items sharing a similar sentiment exhibit higher loadings for a specific factor. Specifically, items **G3, G4, G8, G9, G10, G11** display higher loadings for Factor 1, while **G1, G2, G5, G6, G7, G12, and G13** have higher loadings for Factor 2.

Group Inclusion

Item (Question)	**Factor 1**
GI1	**0.929456**
GI2	**0.938173**
GI3	**0.944253**
GI4	**0.927495**
GI5	**0.968220**
GI6	**0.966026**
GI7	**0.972336**

GI8	**0.959129**
GI9	**0.967156**
GI10	**0.963102**
GI11	**0.962123**
GI12	**0.943122**
GI13	**0.967702**
GI14	**0.959827**
GI15	**0.956211**
GI16	**0.958802**

Table 4.11: Factor Loadings for Group Inclusion with 1 Factor

Item (Question)	**Factor 1**	**Factor 2**	**Factor 3**
GI1	**0.892799**	0.281218	-0.034901
GI2	**0.915105**	0.198629	-0.093026
GI3	**0.915795**	0.222055	-0.054453
GI4	**0.916722**	0.120163	-0.126764
GI5	**0.987036**	-0.068264	-0.159085
GI6	**0.963837**	0.048146	-0.107232
GI7	**0.978319**	-0.023566	-0.066672
GI8	**0.960074**	0.014613	-0.079356
GI9	**0.975301**	-0.064462	0.021917
GI10	**0.986422**	-0.145576	-0.010507
GI11	**0.980624**	-0.123066	0.010762
GI12	**0.967188**	-0.161017	0.038758

GI13	**0.964325**	-0.014397	0.116156
GI14	**0.963952**	-0.063291	0.136368
GI15	**0.941718**	0.036467	0.268086
GI16	**0.957037**	-0.031613	0.162121

Table 4.12: Factor Loadings for Group Inclusion with 3 Factors

In the case of Group Inclusion, the examination of loadings with 1 factor and 3 factors is presented in tables 4.11 and 4.12. It is apparent from the tables that the loadings obtained using only 1 factor are superior to those with 3 factors. This is evidenced by the fact that all the items exhibit high loadings for only 1 factor in the 1-factor analysis.

	Factor 1	**Factor 2**	**Factor 3**
Cumulative Variance	0.912588		
Cumulative Variance	0.911177	0.927614	0.940671

Table 4.13: Variance for Group Inclusion with 3 Factors

The cumulative variance explained 3 factors is higher than that by 1 factor. However, in tables 4.12 and 4.11, we can observe that the loading for Factors 2 and 3 are below our threshold of 0.7. Furthermore, all the items in Group Inclusion measure have a positive sentiment.

Finally, the table below presents the ultimate number of factors for each measure. These were determined based on the loadings and the cumulative variance, as presented in the tables above. The reasoning behind choosing the number of factors is detailed in the discussion section below.

Measure	Number of Factors
Confidence	2
Interest	2
Gender	2
Group Inclusion	1

Table 4.14: Number of Factors for each Measure

Continuing the analysis, it's noteworthy that the factors have been renamed based on the items they represent.

Measure	Factors	Factor Name	Cronbach's Alpha
Confidence	Factor 1	Confident	0.877
Confidence	Factor 2	Lack of Confidence	0.852
Interest	Factor 1	Interested	0.943
Interest	Factor 2	Lack of Interest	0.919
Gender	Factor 1	Positive	0.991
Gender	Factor 2	Negative	0.934
Group Inclusion	Factor 1	Feeling Included	0.994

Table 4.15: Cronbach's Alpha for Each Factor and Measure

Utilizing the number of factors outlined in 4.14, a reliability assessment was conducted for each of the factors through the application of Cronbach's Alpha (with a threshold set at 0.7 or higher). Table 4.15 presents the values of this assessment for each factor and measure. The table above provides a clear indication that each of these factors meets our established threshold of 0.7, thereby contributing to the assessment of the reliability of the factors.

Subsequently, a reliability assessment was conducted for each measure. This involved iteratively removing each item (question in this context) from the measure and examining the resulting Cronbach's alpha. A decrease in Cronbach's alpha compared to the original value would indicate that the item contributes to the measure/instrument. For each measure, removing any item did cause the alpha value to decrease, therefore no items will be removed for further analysis.

Lastly, a validity assessment on each measure was conducted, i.e., the correlation between the factors. The obtained correlations for each measure were as follows (Group Inclusion only had one factor) —

Measure	**Correlation between Factors**
Confidence (Confident and Lack of Confidence)	-0.55775798
Interest (Interested and Lack of Interest)	0.10955274
Gender (Positive and Negative)	0.4154138

Table 4.16: Correlation between Factors

The correlations presented in Table 4.16 may appear low; however, it is crucial to reiterate that the factors for each measure captured different sentiments. Hence, the observed low correlations are not only feasible but also reasonable given the distinct focus of each factor. Following these assessments, it can be affirmed that the instrument demonstrates both reliability and validity.

4.2 Inferential Statistics

In order to derive inferences from certain demographic information, mainly *Gender*, *Class Standing*, *Major* and *Race*, inferential statistics were employed. ANOVA was conducted for

Gender (Female and Male) and *Major* (Engineering and Non-Engineering), *Class Standing* and *Race*. The Likert scale was transformed into a numbered scale, ranging from 1 for "Strongly Disagree" to 5 for "Strongly Agree", each measure was averaged before conducting the statistical tests. The primary hypothesis question is outlined below:

Hypothesis The different samples, based on demographic categories, have different sense of confidence, interest, gender, and inclusion

The visualizations 3.1 created for each demographic category, illustrating the count for each, aided in assessing the numerical feasibility of comparing the samples. Since the Major field collected several values, the counts were: Engineering — 25 and Non-Engineering — 85.

In the Gender category, due to Non-Binary having fewer than 10 values (as seen in 3.1, the tests were executed on the two primary samples — Male and Female. Similarly, in the Class Standing category, the "Other" classification was removed before running the tests. Concerning Race, ANOVA was applied across all distinct samples. However, considering the variance in sample sizes, all groups with counts less than 30 were amalgamated as URM (Underrepresented Minorities). Furthermore, following our analysis from before, the samples were further divided by factors.

4.2.1 Gender

Gender	Factor	Mean	Std
Female	Confident	3.877551	0.727300
Male	Confident	4.075893	0.824235
Female	Lack of Confidence	2.387755	0.911531

Male	Lack of Confidence	2.120536	0.817411
Female	Interested	3.383673	0.826475
Male	Interested	3.614286	0.872078
Female	Lack of Interest	2.575510	0.898733
Male	Lack of Interest	2.296429	0.763714
Female	Positive	4.897959	0.258683
Male	Positive	4.315476	0.850240
Female	Negative	1.148688	0.273487
Male	Negative	1.645408	0.758864
Female	Feeling Included	3.107143	0.665608
Male	Feeling Included	3.220982	0.782530

Table 4.17: Mean and Standard Deviation by Gender and Factor

The table above shows the mean and standard deviation for our two samples, Male and Female for each factor. We can see that the difference is means is not significant, however the table below will show the results of an ANOVA test to be certain if the difference is significant.

Factor	P-Value	Omega-Squared(ω^2)
Confident	0.196848296	0.006504
Lack of Confidence	0.116321680	0.01416
Interested	0.169011870	0.008672
Lack of Interest	0.0884001594	0.01416
Positive	0.000012	0.161695
Negative	0.000033	0.145185

Feeling Included	0.427405744	-0.00349

Table 4.18: ANOVA Results for Gender (Category)

At a significance level of 0.05 and F(1, 103), the p-values for the Confidence, Interest, and Group Inclusion constructs do not provide sufficient evidence to reject the null hypotheses. This implies that males and females have similar experiences in these measures. However, for the Gender measure, there is statistical evidence to conclude that males and females have different attitudes.

Furthermore, considering the effect sizes (ω^2 values), a value greater than or equal to 0.14 is considered a large effect size [15]. The effect size is a measure of the association between the effect (main or interaction) and the dependent variable. The presence of a large effect size in the Gender construct further reinforces that males and females have distinct experiences in this particular measure. Males (std = 0.85) were statistically significantly more than females (std = 0.26) in the Positive factor. Similarly, Males (std = 0.76) were statistically significantly more than females (std = 0.27) in the Negative factor.

4.2.2 Class Standing

Standing	Factor	Mean	Std
Senior	Confident	4.105263	0.756067
Junior	Confident	4.068182	0.775330
Sophomore	Confident	4.012500	0.776147
Freshman	Confident	3.878205	0.796522
Senior	Lack of Confidence	2.171053	0.731497

Junior	Lack of Confidence	2.431818	1.151580
Sophomore	Lack of Confidence	2.256250	0.943071
Freshman	Lack of Confidence	2.250000	0.805001
Senior	Interested	3.536842	0.866802
Junior	Interested	3.763636	0.880083
Sophomore	Interested	3.370000	0.803263
Freshman	Interested	3.512821	0.825635
Senior	Lack of Interest	2.357895	0.860436
Junior	Lack of Interest	2.418182	1.071278
Sophomore	Lack of Interest	2.605000	0.849117
Freshman	Lack of Interest	2.343590	0.689697
Senior	Positive	4.508772	0.837902
Junior	Positive	4.621212	0.789131
Sophomore	Positive	4.741667	0.486206
Freshman	Positive	4.512821	0.783030
Senior	Negative	1.526316	0.680224
Junior	Negative	1.389610	0.838100
Sophomore	Negative	1.292857	0.479785
Freshman	Negative	1.443223	0.673892
Senior	Feeling Included	3.269737	0.598048
Junior	Feeling Included	2.95454	0.636206
Sophomore	Feeling Included	3.176563	0.709636
Freshman	Feeling Included	3.078526	0.809930

Table 4.19: Mean and Standard Deviation by Standing and Factor

Based on the mean and standard deviation of samples for each factor, there seems to be no significant differences. Having said that we perform ANOVA below to get significant statistical results.

Factor	P-value	Omega-Squared(ω^2)
Confident	0.7162194	-0.015305
Lack of Confidence	0.89362029	-0.022407
Interested	0.54980712	-0.008124
Lack of Interest	0.50972848	-0.006193
Positive	0.46641517	-0.003976
Negative	0.55223218	-0.008238
Feeling Included	0.63597599	-0.011976

Table 4.20: ANOVA Results for Class Standing

At a significance level of 0.05 and F(3, 150), the p-values for Confidence, Interest, Gender, and Group Inclusion constructs fail to reject the null hypotheses, i.e., students in different standings have similar experiences in those measures. Therefore, we have strong evidence that standing of students don't affect their experiences and attitudes across different measures. Consequently, the omega-squared values are negative and considered to be small [15]. Further, reinstating our conclusion that standing does not affect experiences of participants in different measures.

4.2.3 Major

Major	Factor	Mean	Std
Engineering	Confident	4.23000	0.52500

Non-Engineering	Confident	3.926471	0.826301
Engineering	Lack of Confidence	2.00000	0.71078
Non-Engineering	Lack of Confidence	2.320588	0.910105
Engineering	Interested	3.480000	0.716473
Non-Engineering	Interested	3.510588	0.870963
Engineering	Lack of Interest	2.520000	0.797914
Non-Engineering	Lack of Interest	2.416471	0.832215
Engineering	Positive	4.593333	0.571467
Non-Engineering	Positive	4.609804	0.730366
Engineering	Negative	1.400000	0.600453
Non-Engineering	Negative	1.394958	0.634162
Engineering	Feeling Included	3.252500	0.518373
Non-Engineering	Feeling Included	3.120588	0.78642

Table 4.21: Mean and Standard Deviation by Major and Factor

The table above shows means and standard deviations for Engineering and Non-Engineering majors and each factor. WE don't observe significant differences, however this is established more in the ANOVA results below.

Factor	P-Value	Omega-Squared(ω^2)
Confident	0.08586731	0.0179
Lack of Confidence	0.10813853	0.014554
Interested	0.87300408	-0.008937
Lack of Interest	0.58225953	-0.006364
Positive	0.9176108	-0.009075

Negative	0.97186267	-0.009163
Feeling Included	0.43216506	-0.003451

Table 4.22: ANOVA Results for Major

At a significance level of 0.05, with F(1, 108) degrees of freedom, the p-values for the Confidence, Interest, Gender, and Group Inclusion constructs do not provide enough evidence to reject the null hypotheses. This implies that students, irrespective of being in engineering or non-engineering majors, have similar experiences in these measures. Therefore, there is strong evidence to conclude that majors do not significantly impact their experiences and attitudes across different measures.

Furthermore, the low omega-squared values further emphasize that majors do not have a substantial effect on the experiences of the participants.

4.2.4 Race

As mentioned in the Methods Chapter 3, the samples with a low sample size have been combined as Under-represented minorities (URM) - Black or African American, Hispanic or Latino, Asian, Native American, Multiracial.

Major	Factor	Mean	Std
White	Confident	4.128571	0.711885
URM	Confident	3.757353	0.880094
White	Lack of Confidence	2.117857	0.823919

URM	Lack of Confidence	2.492647	0.918013
White	Interested	3.542857	0.831372
URM	Interested	3.429412	0.875432
White	Lack of Interest	2.394286	0.794161
URM	Lack of Interest	2.50000	0.89341
White	Positive	4.680952	0.666511
URM	Positive	4.495098	0.696897
White	Negative	1.344898	0.611191
URM	Negative	1.457983	0.602796
White	Feeling Included	3.248214	0.686632
URM	Feeling Included	2.988971	0.836896

Table 4.23: Mean and Standard Deviation by Race and Factor

In the table above, we can observe some difference in Confidence and Group Inclusion constructs. To get more statistically significant results, we will look into ANOVA results below.

Factor	P-Value	Omega-Squared(ω^2)
Confident	0.023177	0.039831
Lack of Confidence	0.038578	0.031587
Interested	0.522585	-0.00569
Lack of Interest	0.542506	-0.006061
Positive	0.191706	0.006945
Negative	0.376068	-0.002019
Feeling Included	0.096198	0.017193

Table 4.24: ANOVA Results for Race

At a significance level of 0.05, with $F(1, 102)$ degrees of freedom, the null hypotheses for the Interest, Gender, and Group Inclusion constructs are not rejected. However, for the Confidence construct, there is statistical evidence to reject the null hypothesis. Hence, there is significant evidence to conclude that individuals identified as "White or Caucasian" and those classified as "URM" (Underrepresented Minority) have different experiences in the Confidence construct.

Additionally, the low omega-squared values for all constructs indicate that the association between the effects and variables is low across the board.

Upon careful examination of the inferential statistics results and analyses, it becomes apparent that the outcomes are suboptimal. In other words, the data does not provide a comprehensive insight into the experiences and attitudes of the participants.

4.3 Discussion

The following summarizes our findings from the quantitative study:

- A mixed method study being used starting with a quantitative phase, followed by a qualitative phase.
- An instrument was created using the instrument used by Hoegh and Moskal [12] and Jansen et al. [14]. The items from these literatures were replicated. The four measures being used in this study are — Confidence, Interest, Gender, and Group Inclusion.
- A survey used to collect data regarding the experiences of Non-CS majors taking introductory CS courses.
- In alignment with the literature by Bandalos and Finney [3], as no specific theory

regarding the correlation or lack thereof among factors was present, an oblique rotation was employed.

- The use of oblique rotation is also justified in our context as they yield more reasonable presentations of data, especially considering that dimensions underlying measures in social or behavioral sciences typically exhibit correlations.

- In conducting the factor analysis, the number of factors was determined by considering results from all three extraction methods, avoiding reliance on a specific method. This approach was deemed reasonable in the absence of a predefined theoretical framework, allowing for a comprehensive exploration of factor analysis outcomes with varying number of factors.

- The final determination of the number of factors was based on the loadings, percentage of variance, and correlations, providing a comprehensive assessment to ensure robust and meaningful factor extraction. The loadings as presented in Tables — 4.3, 4.5, 4.6, 4.10, 4.11, 4.12 help determine the number of factors for each measure. The loadings greater than 0.7 are considered high. The loading paired with the percentage of variance helped determine the number of factors. The number of factors that had a higher cumulative variance was determined as the final number of factors for each measure.

- The selection of the final number of factors was further supported by an examination of the survey questions. In the measures of Confidence, Interest, and Gender, questions encompassed a mix of positive and negative sentiments. Conversely, Group Inclusion consisted solely of questions with positive sentiment. This sentiment analysis was crucial in confirming the appropriateness of the chosen number of factors, as each factor within a measure exhibited uniform sentiments across all its respective items.

- The reliability and validity assessments of the factors yielded impressive results. Notably, the correlations between the factors were observed to be low. This, however, aligns with the earlier discussion, where it was emphasized that the two factors within each measure present positive and negative sentiments. Consequently, the observed low correlation between these factors is consistent with the nature of the survey design.

- Despite the instrument passing all tests of reliability and validity for factor analysis, the results from inferential statistics were not deemed impressive. This discrepancy leads us to believe that the survey may not accurately measure the true experiences of the students. Furthermore, the study from which the instrument was replicated, only utilized a factor analysis. We could therefore imply that the instrument does not accurately collect data that is statistically rich.

- Additionally, there are other potential reasons for the lackluster results in inferential statistics: a) The small sample size might have compromised the statistical power, making it challenging to detect real effects, b) A possible measurement error, indicating that the Likert scale might not accurately reflect the experience or attitudes, thereby diminishing the ability to identify real effects.

4.3.1 Future Work

Several potential future directions for this study could significantly enhance the depth and accuracy of understanding participants' experiences and attitudes. One promising avenue is the incorporation of qualitative data, achieved through interviews with students. This approach aims to capture nuanced insights that may not be fully elucidated by quantitative measures alone. For example, given the observed difference in the Gender construct between males and females in the inferential statistics, conducting interviews with individuals from these groups could offer a richer understanding of this discrepancy.

To further augment the results of the quantitative study, exploring alternative measurement scales, such as a numeric 1-10 scale, could be considered. This adjustment may provide a more refined and detailed assessment of participants' sentiments.

Additionally, broadening the survey audience to include CS majors could offer valuable insights. This expansion is particularly relevant considering the limited variations observed in Non-CS majors. Including CS majors in the study could illuminate potential differences in experiences and attitudes within this specific academic discipline.

Chapter 5

Qualitative Results and Discussion

This chapter discusses the outcomes of the qualitative study conducted after the analysis of the quantitative study. A thorough thematic analysis was executed on the qualitative data, leading to the detailed exploration of themes outlined below.

5.1 Theme 1: Perception of stereotypes in CS

The perception of stereotypes within the CS field is a prevalent theme among students, reflecting a combination of personal experiences and societal expectations. The recurring sentiment across students responses revolves around the lack of a social and collaborative environment within CS courses, contributing to the perpetuation of stereotypes. Students emphasize the auditorium size of these CS courses, highlighting the absence of a social aspect. The large class size hinders personalized support and fosters an environment where individual work prevails over teamwork. The mention of "awkward classmate interactions" and the characterization of CS as "Male-dominated" Suggests a perceived lack of diversity and inclusivity, contributing to a stereotype of introverted and awkward individuals. Additionally, students articulated the notion of a non-social environment within CS courses, linking it to the class size, which they perceived as hindering community building. The description of the class environment as one where students are expected to "sit down and be quiet" reinforces the notion of a rigid and antisocial atmosphere. The stereotype of CS individuals as "loner" further solidifies the idea of a community-deficient field. Furthermore, students responses add a layer to the theme by stating that typical CS students are perceived as "snobbish". This negative stereotype suggests a perception of arrogance or exclusivity within the CS community. The use of such descriptors indicates a broader societal stereotype that may contribute to the alienation of potential students who do not fit this mold.

> *"I know this is not a secret that it's (CS) a very male-dominated class and field, unfortunately. I mean, 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 kind of impact how I felt about taking the course because I came into it knowing that it was going to be male-dominated..." — Student 1*

The theme of stereotypes in CS is multifaceted, encompassing the lack of social and collaborative aspects, the prevalence of a male-dominated environment, and the environment, and the association with negative personality traits. The students' responses highlight the impact of class size, class environment, and societal perceptions on the formation and perpetuation of stereotypes within the CS field. Addressing these concerns and promoting a more inclusive and collaborative learning environment could contribute to breaking down these stereotypes and fostering a more diverse and welcoming CS community.

5.2 Theme 2: Misperception of the Field based on Limited Early Exposure

The theme of the misperception of the CS field based on limited early exposure is evident in the experiences and perspectives shared by students. The common thread running through the students' responses is the realization that early exposure often fails to capture the diversity and breadth of opportunities within the CS field. Student 1 highlights a narrow exposure to CS through friends in web development and a CS seminar that solely showcased coding. The limited exposure to these aspects may contribute to a skewed perception of the entire CS field. The absence of exposure to the diversity to the CS field, beyond web development, suggests that early encounters may not provide a comprehensive understanding of the range of opportunities within CS. Student 2 builds on this notion by expressing that most CS majors they interacted with were engaged in similar pursuits, sharing similar interests and mindsets. The observation that CS lacked variety not only in degrees but also in people and opportunities, with a predominant focus on gaming, game design, and security, indicates a need for more diverse representations of the field from the outset. The desire for exposure to the real-world application of CS, underscores the importance of practical, hands-on experiences in shaping perceptions, The suggestion that if exposed to the real-world applications, they would have pursued CS more intently implies that early, practical exposure can significantly influence students' choices and interests.

> *You know, just showing kids the real-world application they can do with this(CS). It's just, they are not just saying and listening into the stereotypes of either doing gaming or software engineering or like there is all types of CS majors like you don't necessarily have to be always locked in your room anti-social, it is not that...*
> *— Student 2*

The theme of misperception based on limited early exposure in the CS field is manifested through students' accounts of narrow representations, lack of diversity in pursuits, and yearning for exposure to real-world applications. These narratives highlight the need for a more comprehensive and diverse introduction to the CS field at an early stage, ensuring that students are exposed to a broader spectrum of opportunities and applications, fostering a more accurate understanding of the field's depth and versatility.

5.3 Theme 3: Lack of interest in CS and non-CS interest

The theme of lack of interest in CS and the influence of non-CS interests is noticeable in the shared experiences and perspectives of the students. The common thread in their statements is a sense of disconnect or disinterest stemming from limited exposure to the diverse facets of CS and a perception of homogeneity within the field. Student 1 (biomedical engineering) indicates a lack of interest in CS, possibly due to a narrow exposure limited to web development. The engineering seminar's exclusive focus on coding may have contributed to a perception of CS as a monolithic and uninteresting field. The absence of exposure to the diverse aspects of CS suggests that early encounters might not have appealed to a broader range of interests, potentially leading to disinterest. Building on this, Student 2 (Industrial & Systems Engineering) emphasizes that most CS majors they interacted with shared similar interests and mindsets, engaging in comparable activities. The perceived lack of variety in both degrees and the people within the field contributes to a sense of monotony. The mention of a desire for exposure to different paths within the CS field indicates that diversifying experiences through first-year experience courses can pique interest by showcasing the breadth of opportunities available. Student 2's perspective on CS lacking variety not just in degrees but in people's interests and opportunities aligns with Student 1's narrative, underlining a consistent perception of homogeneity within the field. The mention of a predominant focus on gaming, game design, and security suggests a need for showcasing the diverse applications of CS to cater to a broader range of interests.

> *I wish I was more open, but I don't feel the need to be on the inside of it (CS community). It is just not something that I am like, I don't feel like I need to be in that community to be like to know stuff about computers and like to have friends who know things about computers... — Student 4*

The theme of a lack of interest in CS and non-CS interests emerges through students' accounts of limited exposure, perceived homogeneity within the field, and the misclassifications of certain CS-related areas. These narratives underscore the importance of providing diverse and comprehensive representations of the CS field to cater to a broader range of interests and dispel misconceptions that may contribute to disinterest.

5.4 Theme 4: CS Community at Large — Insider or Outsider

The theme of CS community and the dynamics of insiders and outsiders is a recurring topic among the students, highlighting a complex interplay of passion, stereotypes, imposter syndrome, and the perceived exclusivity of the community. Student 1 provides insight into the nuanced perspective of someone who, while not an outsider, does not feel deeply rooted in the CS community. The mention of patience as a requirement for those who "belong" suggests that the community might have its own set of challenges and intricacies. The lack of a deep-seated passion is identified as a factor that differentiates insiders from those who may be considered on the periphery. The notion that the CS community did not feel like hers reflects a sense of not fully identifying with or being embraced by the larger CS community. Student 2 introduces the idea of "unicorns" in the CS community, implying that those who are in CS purely to learn and not necessarily for a career are rare and perhaps not fully understood or accepted. The stereotypical image of gamers and programmers being more accepted within the community than those with a casual interest in learning is a noteworthy observation. Feeling like an outsider due to misaligned interests highlights a potential challenge for individuals who may fit the perceived mold of a typical CS community member. Student 3 expresses a profound sense of imposter syndrome, emphasizing the disparity between her perceived lack of connection to CS and the stereotypical image of someone deeply immersed in coding languages and carious CS domains. The acknowledgement of the advantage held by the CS community due to their knowledge, and the respect she expresses for their abilities, further accentuates the perceived hierarchy and expertise within the community. Student 4 delves into the exclusivity of the CS community, suggesting that it is tightly sealed around specific majors, such as CS and computer-related engineering. The idea that knowing about computers does not automatically grant one insider status challenges the assumption that knowledge alone can bridge the gap between insiders and outsiders. The acknowledgement that there is some alienation of people outside specific majors implies a potential barrier to entry into the CS community.

> *I think people who would fall under the CS umbrella just because it is like, I don't know, a stereotype that I have heard or grown up with as anybody who definitely is really, really handy with all of the coding languages and people who dabble in AI and all that type of stuff... — Student 3*

The thematic analysis of the CS community and insider/outsider dynamics reveals a range of perspectives, from those who feel a lack of deep-rooted passion to individuals experiencing imposter syndrome. Stereotypes within the community and perceptions of exclusivity based on interests or majors contribute to a complex landscape where individuals may feel either embraced or excluded. These narratives shed light on the multifaceted nature of the CS community and the intricate dynamics that shape the sense of belonging or outsider status among students.

5.5 Theme 5: Experience in CS courses

The theme of experience in CS courses emerges as a multifaceted narrative, reflecting the challenges, learning opportunities, and varying perceptions of students within the discipline.

Student 1 provides a detailed account of the challenges faced in an auditorium-size class, emphasizing the struggle with time management, the lack of teamwork, and the overwhelming complexity of the coursework. The impact of the class size on personalized support becomes apparent, especially with a mention of a helpful TA who, unfortunately, is too busy due to the large number of students. The influence of external factors, such as the pandemic and isolation, further compounds the difficulties. Despite the hardships, the student acknowledges the learning gained but underscores the need for more personalized support and smaller class sizes. Student 2 shares an experience marked by challenges, emphasizing the impact of cheating in the previous semester, which led to an intensified curriculum. The importance of projects in applying learned concepts is highlighted, with a recognition of the positive influence of having s study buddy and productive office hours. The shift in the course's trajectory, especially in the third project, is noted, illustrating the dynamic nature of the learning experience. The student's preference for problem-solving and practical application underscores the importance of hands-on projects in enhancing understanding.

Student 3 presents a contrasting experience, describing the class as easier than expected, with open-book and open-internet exams. The enjoyment derived from the course is attributed to the seamless understanding of different syntaxes, particularly Python. The appreciation for a supportive community and responsive feedback from instructors and TAs emphasizes the role of a positive learning environment in shaping a student's experience. The student's active engagement, doing more than the bare minimum, suggests a genuine interest in the subject. Student 4 articulates the challenges faced in a intermediate class, highlighting a shift from a well-guided introductory course to one with less structure. The difficulty in following the intermediate class curriculum, along with the perceived lack of guidance, leads to a withdrawal from the course. The contrasting experiences between the introductory and intermediate courses, particularly in the professor-student interaction and the pacing of the course, demonstrate the potential impact of instructional style on student outcomes. The student's struggle with the assumption of prior knowledge by the professor highlights the importance of clear communication and alignment of expectations.

> *I really like that they make non-majors take this class. That is a core requirement that Tech (Virginia Tech) requires. I think it is valuable considering the way the world is going...-Student 3*

The thematic analysis of the experience in CS courses reveals a spectrum o challenges, learning styles, and perceptions. The impact of class size, external factors, project-based learning, community support, and instructor guidance all play integral roles in shaping students' experiences within the CS discipline. These diverse narratives underscore the need for adaptability, personalized support, and a positive learning environment to enhance the overall quality of the CS educational experiences.

5.6 Theme 6: Shift or Change in Mindset and Attitude Towards Computing Post-Course

The theme of a shift or change in mindset and attitude towards computing post-course completion is evident in students' reflections on their experiences with CS. The responses provide insights into how exposure to the field, collaborative opportunities, and course challenges have influenced their perceptions and future considerations. Student 1 highlights a relation of collaborative options within CS. The observation of friends who are social in the CS field suggests a departure from the stereotype of introverted individuals. The exposure to classmates working on user-side projects, particularly in data-informatics and visualization, indicates a broader understanding of the diverse application and roles within the field. This suggests that the course has broadened the student's perspective beyond initial perceptions. Student 2 recounts a significant shift in perspective, starting with considering a minor in CS at the beginning. However, the challenges faced, particularly in the third project while taking the introductory class, led to a complete turnaround, resulting in the decision not to pursue a minor. This illustrates how course experiences, especially when they prove challenging, can significantly impact a student's commitment and interest in the field. Student 3 describes a change in perception from finding CS daunting to considering it more approachable. The firsthand experience of the field had made it less intimidating, leading the student to explore more technical cybersecurity courses. The expressed interest in delving deeper into Python and an appreciation for the CS requirement for non-majors suggest a newfound curiosity and recognition of the practical value of computing skills. Student 4 articulates a substantial transformation in the perception of CS. The shift from viewing it as a "big scary monster" to realizing that one does not need to be as smart as initially thought reflects a decrease in perceived barriers. The student expresses interest in taking more CS courses, driven by the recognition that computer programming is becoming increasingly relevant across various job sectors. This suggests a shift in attitude from intimidation to a recognition of the importance of CS skills in the evolving job market.

> *I think I briefly mentioned seeing my other senior design teams and their projects like data informatics and visualizations, where they had that user side of it(CS). Seeing that now, and also seeing how much it connects to my field (biomedical engineering). I think if I had known that earlier than there would have been a chance of like doing something computer science based or at the very least taking more computer science classes... — Student 1*

The thematic analysis reveals a pattern of changing attitudes towards computing after completing a CS course. Experiences of collaboration, exposure to diverse applications, overcoming challenges, and recognizing the practical value of programming skills contribute to a more positive and open mindset. The students' evolving perceptions reflect the transformative impact of education on their attitudes toward CS, dispelling initial fears and stereotypes and fostering a more approachable and appreciative stance towards the field.

5.7 Discussion and Future Direction

This section delves into various observations, including those related to personal contexts. Firstly, a notable observation is the influence of family in motivating students to pursue CS, irrespective of their academic level. Student 3, for instance, expressed an initial interest in engineering due to her family background but eventually embraced the closest alternative—CS. Similarly, Student 4, encouraged by siblings involved in the broader CS field, opted for an intermediate CS class to gain technical skills, despite it being beyond her primary career choice. These responses underscore the role of early exposure in enhancing students' understanding of the field. Another intriguing observation pertains to the insider/outsider perspectives within the CS community. The responses highlight that the CS community is often perceived as a population adept at coding, aiming to build a career in the field. However, merely having an interest and a desire to learn is deemed insufficient for entry into this perceived "tightly sealed" community of computer-related majors. Some students express a lack of alignment with the community's interests, while others, despite an eagerness to be part of it, feel like outsiders due to a perceived lack of skills and experience. These perspectives contribute to the perpetuation of stereotypes ingrained in society, suggesting that comprehensive experience and skills with computers are prerequisites for community membership.Lastly, a common recognition among students is that, even if they do not foresee an immediate pursuit of CS in the near future or during their college years, they anticipate acquiring additional skills because it aligns with the evolving trends of their generation.

5.7.1 Future Direction

In this study, our primary focus was on exploring the experiences of non-majors in CS courses, particularly emphasizing the perspectives of female students. However, a promising avenue for future research lies in incorporating the viewpoints of male students. Given the enduring prevalence of gender stereotypes in STEM fields, conducting a comparative analysis of experiences from both genders could enhance our overall understanding. Additionally, delving into the experiences and attitudes of CS majors might provide valuable insights into their motivations for persisting in the field, especially considering the challenges inherent in the curriculum. Lastly, employing a different instrument to assess students' experiences and attitudes could yield more accurate results, potentially enhancing the overall impact of the analysis.

Chapter 6

Conclusions

6.1 Research Questions

- **Is the instrument chosen for the quantitative study valid and reliable?**

  In summary, our extensive research, which included factor analysis, reliability and validity assessments, as well as inferential statistics, has yielded a clear and nuanced understanding of the instrument utilized in our quantitative study. The factor analysis successfully identified distinct factors that can effectively measure participants' experiences across various measures. Despite the absence of significant results in inferential statistics, our thorough evaluation confirms the validity and reliability of the instrument. Although inferential statistics did not yield conclusive results, it played a crucial role in informing the design of the qualitative study.

- **Do we see any difference between female and male students in their sense of belonging, interest, and group inclusion? Do we see any difference based on other demographic information?**

  Noteworthy distinctions emerged in the Gender and Confidence constructs, revealing disparities in experiences between male and female participants and variations among different racial groups, mainly "White" and "Under-represented Minorities". Surprisingly, variables such as Standing and Majors did not exert significant influence on student experiences and attitudes.

- **Are there any other factors affecting the experiences of the students in these introductory courses?**

  The qualitative study served as a valuable complement to our insights, revealing crucial factors that significantly influence participants' experiences and attitudes in computer science (CS). Key findings include the pervasive impact of stereotypes, misconceptions about the nature of the field, and the substantial influence of familial exposure on participants' perceptions. Another noteworthy aspect was the identification of stereotypes and misperceptions influencing participants' behavior even before engaging in CS classes. These stereotypes and misperceptions emerged as substantial barriers, affecting participants' sense of belonging and inclusion within the CS community. Collectively, these qualitative findings contribute to a more comprehensive understanding of the intricate factors shaping student experiences and attitudes in CS. The insights garnered provide valuable guidance for future research endeavors and educational initiatives in the field, facilitating a more informed and targeted approach to fostering a positive and inclusive environment in computer science education.

In conclusion, we adopted a mixed-method approach to explore the factors influencing the experiences and attitudes of non-CS majors enrolled in CS courses. Employing an instrument with four measures—Confidence, Interest, Gender, and Group Inclusion—we conducted a survey to gather quantitative data. The quantitative phase involved factor analysis, revealing distinct positive and negative sentiments within each construct. Additionally, we performed inferential statistics, including t-tests on demographic categories like Gender, Race, Standing, and Major. Despite yielding less than optimal results, these quantitative findings guided our qualitative investigation. The qualitative phase comprised interviews with four female participants, uncovering themes related to stereotypes, misconceptions, changing attitudes, and a sense of insider/outsider dynamics in the CS community. The findings highlighted students' desire to learn more about the broad applications of CS, challenging stereotypes associated with specific roles in the field. Therefore, this study emphasizes the significance of early exposure to CS to foster diversity and counter societal stereotypes, suggesting interventions at the high school level to encourage broader engagement with the field.

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Appendices

Appendix A

Survey Questions

The survey questions presented below were used to collect data for the quantitative study.

Hello,
You are invited to participate in our survey to Understand the Experiences of Non-CS majors in Introductory Computer Science courses. In this survey, non-CS major students will be asked to complete a survey that asks questions about their experiences in introductory CS classes. It will take approximately 10 minutes to complete the questionnaire. Your participation in this study is completely voluntary. There are no foreseeable risks associated with this project. However, if you feel uncomfortable answering any questions, you can withdraw from the survey at any point. It is very important for us to learn your opinions. Your survey responses will be strictly confidential and data from this research will be reported only in the aggregate. Your information will be coded and will remain confidential. If you have questions at any time about the survey or the procedures, you may contact Dr. Sara Hooshangi (shoosh@vt.edu) or Khushi Parajuli (kparajuli@vt.edu). Thank you very much for your time and support. Please start with the survey now by clicking on the Continue button below.

* If you would like to participate in this survey, and you are currently 18 years of age or older, click YES to begin or NO to exit

- ○ Yes
- ○ No

* What CS classes have you taken/are taking?

- [ ] CS 1014: Introduction to Computational Thinking
- [ ] CS 1044: Introduction to Programming in C
- [ ] CS 1054: Introduction to Programming in Java
- [ ] CS 1064: Introduction to Programming in Python
- [ ] CS 2064: Intermediate Programming in Python

*** Did you take any of the classes mentioned above during a virtual semester (Spring 2020, Fall 2020 or Spring 2021)?**

- ○ Yes
- ○ No

*** Have you taken any other CS classes?**

- ○ Yes
- ○ No

*** Do you agree/disagree with the following:**

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am comfortable with learning computer science concepts	○	○	○	○	○
I have little self-confidence when it comes to computer science classes	○	○	○	○	○
I do not think I can learn to understand computer science concepts	○	○	○	○	○
I can learn to understand computer science concepts	○	○	○	○	○
I can achieve good grade (C or better) in computer science classes	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am confident that I can solve problems by using computer science applications	◯	◯	◯	◯	◯
I am not comfortable with learning computer science problems	◯	◯	◯	◯	◯
I doubt that I can solve problems by using computer science applications	◯	◯	◯	◯	◯

* Do you agree/disagree with the following:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I would not take additional computer science courses if I were given the opportunity	◯	◯	◯	◯	◯
I think computer science is boring	◯	◯	◯	◯	◯
I hope that my future career will require the use of computer science concepts	◯	◯	◯	◯	◯
The challenge of solving problems using computer science does not appeal to me	◯	◯	◯	◯	◯
I like to use computer science to solve problems	◯	◯	◯	◯	◯
I do not like using computer science to solve problems	◯	◯	◯	◯	◯
The challenge of solving problems using computer science appeals to me	◯	◯	◯	◯	◯
I hope that I can find a career that does not require the use of computer science concepts	◯	◯	◯	◯	◯
I think computer science is interesting	◯	◯	◯	◯	◯
I would voluntarily take additional computer science courses if I were given the opportunity	◯	◯	◯	◯	◯

* Do you agree/disagree with the following:

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

I doubt that a woman could excel in computing courses	○	○	○	○	○
Men are more capable than women at solving computing problems	○	○	○	○	○
Computing is an appropriate subject for both men and women to study	○	○	○	○	○
Women and men can both excel in careers that involve computing	○	○	○	○	○
It is not appropriate for women to study computer science	○	○	○	○	○
Men produce higher quality work in computing than women	○	○	○	○	○
Men are more likely to excel in careers that involve computing than women are	○	○	○	○	○
Women produce the same quality work in computing as men	○	○	○	○	○
Men and women are equally capable of solving computing problems	○	○	○	○	○
Men and women can both excel in computer science courses	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Non-binary person can excel in careers that involve computing	○	○	○	○	○
It is not appropriate for a non-binary person to study computer science	○	○	○	○	○
Re	○	○	○	○	○

* Do you agree/disagree with the following:

The CS community:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Gives me the feeling that I belong	○	○	○	○	○
Gives me the feeling that I am part of this group	○	○	○	○	○

Gives me the feeling that I fit in.	○	○	○	○	○
Treats me as an insider.	○	○	○	○	○
Likes me.	○	○	○	○	○
Appreciates me.	○	○	○	○	○
Is pleased with me.	○	○	○	○	○
Cares about me.	○	○	○	○	○
Allows me to be authentic.	○	○	○	○	○
Allows me to be who I am	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Allows me to express my authentic self.	○	○	○	○	○
Allows me to present myself the way I am.	○	○	○	○	○
Encourages me to be authentic.	○	○	○	○	○
Encourages me to be who I am.	○	○	○	○	○
Encourages me to express my authentic self.	○	○	○	○	○
Encourages me to present myself the way I am	○	○	○	○	○

*** Your class standing:**

○ Freshman

○ Sophomore

○ Junior

○ Senior

○ Other

* What's your Major?

* Did you complete one or more computer science courses in high school?

- Yes
- No

* Are you/Do you plan on doing a CS minor?

- Yes
- No

* Gender: How do you identify?

- Male
- Female
- Non-binary
- Prefer not to say
- Other (please specify)

* Do you consider yourself a first generation college student?

- Yes
- No

* Which ethnicity best describes you?

- ◯ Hispanic or Latino
- ◯ Not Hispanic or Latino

* Which race/ethnicity best describes you? (Please choose only one.)

- ◯ Asian or Pacific Islander
- ◯ Black or African American
- ◯ Caucasian or White
- ◯ Hispanic or Latino
- ◯ Multiracial
- ◯ Native American
- ◯ Prefer not to say
- ◯ Other

* Would you like to enter for a chance to win a $20 Amazon Gift Card?

- ◯ Yes
- ◯ No

Email Address

* Would you be interested in participating in a one-hour group or individual interview? Selected participants for the group or individual interviews will receive a $20 Amazon gift card for their time and effort upon completion of the interview.

- ◯ Yes

No

Contact Information

First Name

Last Name

Email Address

Appendix B

Second Appendix

The questionnaire below are the questions used to interview the participants for the quantitative study.

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?
    - Was it just the computing requirements?
    - 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?
    - What did you like in the course? were you fascinated by any topics
    - Anything that turned off?
    - How engaged were you with the material?
    - 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
    - Class environment (tell us more)
    - Classmates
    - 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)
    - Role model
    - 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?