Sense of Community, Social Connections, and Collaborative Learning in Post-Secondary Computer-Science Education

by

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Abstract

In post-secondary education, sense of community supports student motivation, persistence, and well-being. However, students from underrepresented groups often have a lower sense of community than their peers. This issue is especially pronounced in the field of computer science, which, despite its rapid growth, still lacks balanced representation. Research has shown that computer science students experience a low sense of community in their departments and in their courses. This thesis explores the sense of community of computer science students from different demographic groups and in different years of their programs. We focus on two factors that influence sense of community: students' social connections and the use of collaborative learning in their courses. The thesis is composed of two studies.

The first study gathered data directly from undergraduate computer science students. We employed null hypothesis significance testing to investigate the sense of community and social connections of computer science students. We then used linear regression to determine how sense of community is affected by students' connections within their courses and by their supportive external connections. Finally, we used null hypothesis testing to determine how students' sense of community and the numbers of social connections they have differ across courses with different collaborative learning requirements. Our analysis indicated that students from underrepresented genders and students from underrepresented ethnic groups had a lower sense of community than majority students and that students from underrepresented genders had more external supportive connections than men. Similarly, students in the earlier years of their program had more external connections than students in later years. Connections with other students were a positive predictor of sense of community while external connections were a negative predictor. We did not find significant differences in sense of community across courses with varying collaborative learning requirements for most demographic groups. However, our analysis showed that men, domestic students, and students in their fourth year had more connections with their peers in courses with a collaborative learning component than in courses without such a component.

The second study used archival registration data of undergraduate computer science students and null hypothesis tests to investigate differences in students' course grades across courses with varying collaborative learning requirements. While domestic students performed better in courses that required collaboration than in courses that did not include collaborative learning, international students did not.

The findings of this thesis indicate that students in the first and second years of their programs require more opportunities to connect with their peers and to develop a sense of community in their courses. Moreover, the findings suggest that collaborative learning approaches employed in computer science need to be further developed to better support the academic achievement of international students. The findings of this thesis could be used to develop interventions to support the sense of community of computer science students from different demographic groups and in different years of their programs. However, as this study was conducted within a single computer science department at a single university, it is important to consider contextual differences when interpreting and applying these findings to other settings.

Preface

This thesis is an original work by Alaa Alajmy and was guided and reviewed by Alaa's supervisor, Carrie Demmans Epp.

The thesis comprises two research studies. Data collection for the first study, discussed in Chapter 3, was conducted by Alaa, Carrie, and their colleague, Emma McDonald, who at the time of writing this document was a Ph.D. student. Emma also advised on multiple aspects of this work.

The first study received research ethics approval from the University of Alberta Research Ethics Board, under the project title "Imposter Syndrome in Computer Science Education", No. Pro00112537, July 19, 2021. The approval letter is included in Appendix A.

The second study, discussed in Chapter 4, is part of a research project that received research ethics approval from the University of Alberta Research Ethics Board, under the project title "Program Improvement - Modelling Student Pathways", No. Pro00083059, August 28, 2018.

Dedication

To the students who stayed. To the students who left.

And to the students who were not given the chances I got.

Acknowledgements

I send my immense gratitude and appreciation to the people who made this milestone possible for me, to the people for whom I persisted:

To Carrie, whose kindness, guidance, and mentorship built me as a graduate student, as a researcher, and as a person. I am eternally thankful for Carrie's hundreds of comments on my documents, for her thoughts and answers to my questions, for all the times she guided my work, and for all the times she supported me when I couldn't work.

To Emma, who as my collaborator, my example, and my friend, taught me about research, about building communities, and about doing labors of love. I am deeply thankful to have got the opportunity to collaborate with Emma and I hope I continue to collaborate with her forever.

To the members of EdTeKLA, whose passionate care about research that makes a difference and about supporting one another taught me so much and was my motivation.

To the Turing Society, with whom I belonged.

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To my roommates and my friends, who surrounded me with noise and companionship that gave me light and warmth when it was dark and cold.

To the University of Science and Technology at Zewail City, for everything and for everyone.

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List of Abbreviations

CCS

Classroom Community Scale

CCS-SF

Classroom Community Scale - Short Form

SNA

Social Network Analysis

Glossary of Terms

Betweenness centrality is, in the context of social networks, a measure of how often a node lies on the shortest path between two other nodes. Betweenness centrality could be thought of as how often a node acts as a bridge between two other nodes and indicates how much control the node has on the flow of information and resources in the network.

Bonding social capital is the social capital that individuals could access through their strong connections. This type of social capital could reinforce existing similarities between individuals.

Bridging social capital is the social capital that individuals could access through their weak connections. This type of social capital enables individuals to access diverse resources and support.

Classroom Community Scale (CCS) is a scale composed of 20 Likert-type items developed by Rovai (2002) to measure sense of community in a learning environment.

Classroom Community Scale - Short Form (CCS-SF) is a short-form adaptation of Rovai's Classroom Community Scale (CCS). The CCS-SF was developed and validated by Cho and Demmans Epp (2022) and is composed of 8 Likert-type items.

Closeness centrality is, in the context of social networks, the total distance of a node from all other nodes in the network. Closeness centrality indicates how much influence a node has in the network.

Collaborative learning is an educational approach where learners work in a group to accomplish a common task. When collaborative learning is employed, learners are responsible for their own learning and for that of their peers.

Connectedness is, in the context of analysis related to students' sense of community, one of two components identified by Rovai (2002) that make up a students' sense of community. Connectedness refers to feeling a sense of belonging and acceptance and the establishment of meaningful relationships within the community.

Connectedness Score is a measure of connectedness as a component of sense of community. Connectedness scores are calculated using the responses to some items of the CCS or the CCS-SF. In the context of this thesis, Connectedness scores are calculated using responses to the 4 items of the CCS-SF measuring connectedness.

Degree centrality is, in the context of social networks, a simple count of the total number of connections a node has. Degree centrality is a basic indicator of popularity: a node with a high degree centrality is highly popular, while a node with a lower degree centrality is less popular.

Learning Support is, in the context of analysis related to students' sense of community, one of two components identified by Rovai (2002) that make up a students' sense of community. Learning support refers to students' ability to actively construct knowledge and understanding within the community and to feel supported by the community in meeting their learning needs.

Learning Support Score is a measure of learning support as a component of sense of community. Learning Support scores are calculated using the responses to some items of the CCS or the CCS-SF. In the context of this thesis, Learning Support scores are calculated using responses to the 4 items of the CCS-SF measuring learning support.

Legal status is, in the context of this thesis, the status of students in Canada, the country where this research was conducted, as international students, referring to students on a study permit or another temporary residence permit, or as domestic students, referring to students who are citizens or permanent residents.

Sense of community is a feeling of belonging and a feeling that members of a group matter to one another and to the group and that their needs will be met through commitment to be together. This definition is based on the work of McMillan and Chavis (1986) and Rovai (2002).

Social capital is the actual or potential resources associated with being part of a network of social connections. Social capital could be realized as economic, cultural, or symbolic resources that come from being connected to others.

Social network analysis (SNA), the study of social networks, is an approach to social analysis that prioritizes the relationships between actors.

Social networks are structures composed of a set of actors, or nodes, some of whom are connected to one another by one or more relations, also referred to as connections, links, or ties.

Strong connections, or strong ties, are, in the context of social networks, the connections between individuals who are close to one another. Granovetter (1973) postulates that such connections provide access to bonding social capital and tend to reinforce existing similarities between individuals and to provide redundant information.

Persistence is the quality that enables an individual to continue the pursuit of a goal even when challenges arise. In the context of post-secondary education, persistence is the continued pursuit of a degree. Tinto (2017) defines students' persistence as a manifestation of their motivation.

Weak connections, or weak ties, are in the context of social networks, the connections between individuals who are only acquaintances. Granovetter (1973) postulates that such connections provide access to bridging social capital.

Chapter 1

Introduction

"Only in community with others has each individual the means of cultivating his gifts in all directions; only in the community, therefore, is personal freedom possible." - Karl Marx and Friedrich Engels (1932)

Through community, students feel that they belong and that their learning expectations will be met (Rovai, 2002). Through community, students are motivated to persist (Tinto, 2017). But in computer science, students suffer a low sense of community (McDonald & Demmans Epp, 2023; Runa et al., 2023). Underrepresented students, in particular, often feel an even lower sense of community than their peers (Mooney et al., 2020; Rainey et al., 2018; Stout & Wright, 2016). In fact, a low sense of community is the main reason women choose to cease to persist and leave computer science (Biggers et al., 2018).

Students' sense of community is influenced by multiple personal and environmental factors (Strayhorn, 2018). These factors include students' social connections with their peers and with others who support them outside their classrooms (Dawson, 2006; Mishra, 2020; Royal & Rossi, 1996). These factors also include the learning approaches taken in their courses.

Motivated by the importance of a sense of community to students' well-being and persistence, the research discussed in this thesis investigated the sense of community of computer science students across different demographic groups and in different years of their undergraduate degree programs. We focused on social connections and on collaborative learning as environmental factors that influence students' sense of community. Collaborative learning is a learning approach found to influence the development of a sense of community (Frog, 2023; Laal & Ghodsi, 2012; Weaver et al., 2016) and to maximize persistence and learning (Johnson et al., 2007).

Conducted in the computer science department of a large Canadian university, this thesis comprises two studies. The first study (Chapter 3) gathered data directly from students through an optional questionnaire. The questionnaire measured their sense of community using the short form of the Classroom Community Scale (Cho & Demmans Epp, 2019) and measured the number of different types of connections they had with students in their courses and with supportive others outside their courses. We used this data to investigate the sense of community and the social connections of computer science students across different demographic groups and in different program years. The study then investigated the influence of the number of different social connections computer science students had on their sense of community and how their sense of community differed across courses with varying collaborative learning requirements, specifically courses with no collaborative component, courses with an optionally collaborative component, and courses with a required collaborative component. Finally, the study investigated how students' centrality in their social networks and how the formation of social connections among students vary across courses with different collaborative learning requirements.

Research has shown that sense of community, social connections, and collaborative learning approaches are all positively associated with academic achievement. Thus, the next step in our research was to study these influences. The second study (Chapter 4) investigated how the academic performance of computer science students in different demographic groups differs across courses with different collaborative learning requirements. This study used archival data and employed course grades as a measure of academic performance. Due to data and time limitations, this thesis did not investigate the association between sense of community or social connections and the academic performance of computer science students. However, we highlight this as an important area for future investigation.

The results of this work offer insights (Chapter 5) on the sense of community and supportive social connections of computer science students from different demographic backgrounds and in different program years. In particular, the findings underscore the importance of providing targeted support to students from underrepresented groups, international students, and students in the earlier years of their computer science programs. The results highlight the potential positive influences of social connections and collaborative learning on the sense of community and academic performance of computer science students.

Chapter 2

Background

This chapter reviews theory and literature related to sense of community, social connections, and collaborative learning in post-secondary education. In the first section, we discuss the context of this work: the field of computer science and its unprecedented growth. In the second section, we discuss representation in computer science post-secondary education and the persistence of underrepresented students in computer science.

As sense of community is a strong positive predictor of student persistence, we discuss sense of community, in the third section, highlighting previous work that studied the sense of community of computer science students and the sense of community of underrepresented students in computer science. We also discuss the factors that affect sense of community in post-secondary education.

Finally, in the fifth and sixth sections, respectively, we discuss social connections and collaborative learning, two environmental factors that predict students' sense of community. We also discuss the influence of social connections and collaborative learning on other aspects of students' academic experiences, mainly highlighting the positive association between these factors and academic achievement.

2.1 On Computer Science

Computer science is thriving at rates unmatched by any other field. Between 2022 and 2032, employment in computing occupations in the United States is projected to grow much faster than the average for all occupations (Bureau of Labor Statistics, 2023). In 2022, the median annual wage of computing workers was more than twice the median annual wage for all occupations (Bureau of Labor Statistics, 2023), illustrating the increased reliance of our society on computing. This surge in demand has made computer science programs highly sought after and increasingly attractive to students. In the United States, the number of computing bachelor degrees earned increased by 56.2% from 2013 to 2018 (National Center for Education Statistics, 2021).

However, this growth in computer science is not evenly distributed. In the United States, women constitute only around 21% of workers in computing (Fry et al., 2021), while 64.2% of workers are White and only 17% are neither White nor Asian (Zippia, 2023). These disparities are also reflected in computer science post-secondary education, where marginalized genders and non-White ethnicities are underrepresented (National Center for Education Statistics, 2021). These trends leave computer science lacking for diverse perspectives that could lead to better innovations (Hill et al., 2010). They also mean that only a small group of people have a say in and benefit from the growth of the field, which has been changing and will continue to change our lives and our world.

2.2 Persistence and Representation in Post-Secondary Computer-Science Education

"*Scary* and *afraid*" wrote Jane Margolis and Allan Fisher "are words that recur again and again in women's interviews when they describe qualities associated with being a computer science major" (2003, p. 70).

Much has changed in computing since Margolis and Fisher's interviews in 2003, yet women still struggle to identify with the computing community. Women are more likely to leave computing majors than their male peers (Tamer and Stout, 2016). Women make up only 20% of computing bachelor degree earners in the United States (National Center for Education Statistics, 2021) and 22% of students enrolled in computing or mathematics bachelor degrees in Canada (NSERC, 2017). At the graduate level and in the workplace, women's representation in computer science is lower (NSERC, 2017), leaving computer science lacking for diversified perspectives that could lead to better innovations (Hill et al., 2010).

A survey by Lehman et al. (2022) of students who completed introductory computing courses in the 2015-2016 academic year at 15 universities across the United States found that identifying as a female is a significant, negative predictor of persistence in computing fields. In fact, men were 2.72 times more likely to persist in computing than women. Beyer (2014) shows that although women exhibit less negative stereotypes about computing fields than men, negative stereotypes associated with computer science indirectly affect women's interest and persistence in computing.

Research exploring demographic representation in computer science has historically focused predominantly on gender diversity, inadvertently overlooking other aspects of demographic identity. In addition to being predominantly male, computer science is predominantly White and Asian (National Center for Education Statistics, 2021). Lehman et al (2022) report that like women, students from underrepresented ethnic groups are more likely to leave computer science than other students.

Throughout the remainder of this thesis, we use the term "underrepresented" to refer to students who are women, students identifying as other marginalized genders, LGBTQIA+ students, students from ethnicities underrepresented in computer science, and international students, who in the institution where this research is conducted are mostly from countries with non-White majorities.

Persistence in post-secondary education is inspired by motivation, and motivation is inspired by a sense of community (Tinto, 2017). In the following section, we discuss students' sense of community in post-secondary education.

2.3 Sense of Community

Sense of community is "a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through commitment to be together" (McMillan & Chavis, 1986, p. 9). In the context of students in classroom or a university, Rovai (2002, p. 198) expounds on sense of community as "a feeling that members have of belonging" and a feeling "that they have duties and obligations to each other and to the school, and that they possess shared expectations that members' educational needs will be met through their commitment to shared learning goals".

2.3.1 Sense of Community Predicts Persistence and Well-being

Sense of community is positively associated with adjustment to post-secondary education environments, well-being, and positive self-perceptions (Baumeister & Leary, 2017; Pittman & Richmond, 2008). Students with a higher sense of community are less likely to experience burnout (Royal & Rossi, 1996).

Along with self-efficacy and the perceived worth of the curriculum, a sense of community is a positive predictor of student motivation (Tinto, 2017). Motivation in turn gives rise to persistence, a student's continual pursuit of a degree (Tinto, 2012). Without motivation, a student is unlikely to persist (Tinto, 2012; Tinto, 2017). Indeed, students who remain in Science, Technology, Engineering, and Mathematics (STEM) majors report a greater sense of community than those who leave STEM (Rainey et al., 2018; Pittman & Richmond, 2008).

2.3.2 Computer Science Students Often Experience a Low Sense of Community

Biggers et al. (2008) demonstrated that the primary factor leading women to leave computer science was a low sense of community. In a study across departments at a large research-intensive European university, Runa et al. (2023) found that computer science students had a significantly lower sense of community than students from all other STEM fields. In fact, men in computer science, who had the highest sense of community among all genders, exhibited a statistically lower sense of community than all students in other STEM fields.

McDonald & Demmans Epp (2023) observed that computer science students, particularly women who are Black, Indigenous, or People of Color (BIPOC), reported feeling disconnected from their peers. Students mentioned having a peer group as being a good source of community in computer science, but expressed obstacles to finding such a group, including the "reserved" and "introverted" nature of the field. Women found it harder to belong to a community than men. Although most students did not feel connected to others in the department, most students expressed care for one another and felt that their peers do care about each other. The authors wrote:

> *"When asked if they had anything they wanted to share about their experiences with computer science, multiple participants framed their answer as advice to other students. […] In short, participants expressed care for one another. Moving forward, the challenge is not to get students to care for one another, but to channel this care into meaningful avenues and make this care apparent to one another."*

2.3.3 Computer Science Students from Underrepresented Groups Experience a Lower Sense of Community Than Their Majority Peers

In computer science, students from underrepresented groups often experience a lower sense of community than their peers (Mooney et al., 2020; Rainey et al., 2018). Women feel a weaker sense of community than men, and as courses progress, the gap between women and men's sense of community continues to grow (Sax et al., 2018). Mooney and Becker (2020) noted that said gap is especially large for women who identify with another underrepresented group. Similarly, Stout and Wright (2016) found that individuals who identify as both a woman and a part of the LGBTQIA+ community report the lowest sense of community in computer science programs. These findings suggest that belonging to two or more minority groups compounds the negative effect on students' sense of community.

Walton and Cohen (2007) explored the impact of sense of community on the academic outcomes of computer science students from different ethnic backgrounds. In one experiment using a pre-post design, students were induced to believe that they have few friends in the department. While White students were unaffected, underrepresented Black students displayed a drop in their sense of community and in their academic achievement. These results could suggest that members of underrepresented groups are uncertain about the quality of their social bonds in academic settings and are thus impacted disproportionately by even the most subtle events that confirm a lack of community. In a second experiment, the researchers normalized students' doubts about their belonging, presenting them as common across ethnic groups and portraying such doubts as temporary rather than permanent. While this intervention boosted Black students' sense of community and improved their academic engagement, it had no significant positive effect on White students and, on some measures, it may have had a negative effect. The authors hypothesized that the intervention might have challenged the belief of more prejudiced students in their racial superiority, reducing the effects of stereotype lift. Alternatively, they concluded, the intervention, in trying to assure people who did not need assurance, might have communicated to students that they should be concerned about their belongingness. In conclusion, the authors highlight that these results do not imply that a sense of community is more essential to underrepresented students' motivation than to majority students' motivation.

Rather, they suggest that majority students may benefit from an assumed belongingness in academic contexts.

2.3.4 Factors That Influence Sense of Community

Strayhorn's model (2018) identifies three factors that influence students' sense of community: (1) background characteristics, encompassing demographics and prior academic experiences, (2) incoming orientations, and (3) school environment and experiences. These factors often interact with one another, affecting, in particular, students from underrepresented groups in computer science. The remainder of this subsection discusses examples of the three factors identified by Strayhorn and how they act together to influence student's sense of community in computer science.

2.3.4.1 Background Characteristics

Students from underrepresented groups often experience a lower sense of community in computer science than their majority counterparts (Mooney et al., 2020; Rainey et al., 2018). Nguyen et al. (2020) show that competitive enrollment procedures have a detrimental effect on the sense of community and self-efficacy of computer science students lacking prior experience. Students from underrepresented groups are more likely to enter computer science with less computing experience than their majority peers (Margolis & Fischer, 2002), making their sense of community more likely to be negatively affected by competitive enrollment procedures.

2.3.4.2 Incoming Orientations

In a study of students who completed introductory computing courses in the 2015-2016 academic year at 15 universities across the United States, Sax et al. (2018) found that exhibiting communal orientations, such as placing high value on helping others and contributing to one's community, was associated with a lower sense of community in computing. This finding is corroborated by Lewis et al. (2019) in their study involving over 7,000 students from 104 American universities. Lewis et al. reason that while students from groups underrepresented in computer science, including women, non-White students, and first-generation college students, often hold strong communal values, computer science is mostly perceived as an individualistic rather than communal field. This dissonance between students' orientations and their perceptions of computer science might contribute to a lower sense of community.

Sax et al. also reported that women who exhibit artistic orientations experience a higher sense of community in computing classrooms than other women. This finding might be related to the connection Tinto (2017) draws between motivation, sense of community, and perceived curriculum worth, as students with artistic personalities might view technology as a tool with which they can achieve creative endeavors. Interestingly, artistic orientation did not have a similar positive association for men.

2.3.4.3 School Environment and Experiences

Cultural stereotypes and hostile learning environments can contribute to the perception that individuals from historically marginalized groups do not belong in STEM and computing (Hoffman et al., 2002). For example, social stereotypes about computer science and other math-related majors are associated with a lower sense of community for women in those fields. (Beyer, 2014). Cheryan et al. (2009) demonstrated that replacing stereotypical objects in computing classrooms, like video games and star trek posters, with objects not considered stereotypical of computer science, like nature posters, could have a positive effect on women's sense of community.

Sax et al. (2018) reported that feeling supported by instructors and feeling supported by peers are both positive predictors of sense of community. Alvarado et al. (2017) found that women are less likely to ask questions and to participate in computing classrooms. This might have a negative effect on women's ability to feel supported by their instructors and peers, affecting in turn their sense of community. At the same time, women's reluctance to participate in computer science might be partially caused by their lower sense of community in computing.

Rainey et al. (2018) demonstrated that perceived competence affects students' sense of community. Beyer (2014) shows that despite women and men performing equally well in computing courses, women in their first year often feel a significantly lower computing self-confidence than their male peers.

Mooney et al. (2020) reported that women who engaged in networking, outreach, and mentoring activities exhibited a higher sense of community than other women. Interestingly, engagement with such activities did not affect the sense of community of students from underrepresented ethnicities.

In a remarkable intervention at a private research university in the United States, Klawe (2013) showcased how altering the content of introductory computing courses and providing women with undergraduate research opportunities positively affects their sense of community in computer science. Klawe additionally implemented a mandate requiring all students in her institution to take at least one computing course, ensuring that all students gain an exposure to computer science. At the end of Klawe's intervention, women made up almost 50% of undergraduates in her department.

Students' sense of community is strongly determined by the number and type of social connections they have with one another (Rainey et al., 2018; Westwood & Barker, 1990). Students who engage in more frequent communication with their peers tend to experience a stronger sense of community than those who communicate less often (Dawson, 2006; Royal & Rossi, 1996). Laal and Ghodsi (2012) show that collaborative learning was found to encourage the formation of social connections among students. Through this and other mechanisms (Allen et al., 2021; Veilleux et al., 2013), collaborative learning positively influences students' sense of community (Laal and Ghodsi, 2012).

In the context of computer science, students' social connections and collaborative learning and their impact on sense of community are understudied and are thus the focus of this thesis. The remainder of this chapter delves into social connections and collaborative learning.

2.4 Social Connections

Social connections play a vital role in academic environments by enabling students to access various forms of "social capital" (Mishra, 2020). As defined by Bourdieu (1986), social capital is the actual or potential resources associated with being part of a lasting network of social connections. Social capital could be realized as economic, cultural, or symbolic resources that come from being connected to others.

An easy and intuitive method to analyze social connections is through conceptualizing groups of individuals and the connections among them as a "social network". A social network is a structure composed of a set of actors, or nodes, some of whom are connected by one or more relations (Mishra, 2020). Before discussing the effects of social connections on academic experiences later in this chapter, we will introduce Social Network Analysis (SNA), a method to analyze social connections in terms of social networks.

2.4.1 Social Network Analysis: A Method to Analyze Social Connections

Social network analysis (SNA) is an approach to social analysis that prioritizes the relationships between actors (Otte & Rousseau, 2002). While the focus in this approach is on relational data, social network analysis recognizes that understanding social phenomena requires consideration of both relational links and individual characteristics (Otte & Rousseau, 2002).

The amount of social capital a person can access is determined by the connections they have within their social network (Lin, 1999; Putnam, 2000). Figure 2.1 shows a diagram of a social network. Students' social networks, encompassing their family, friends, faculty members, and religious connections, play a crucial role in academic success (Mishra, 2020).

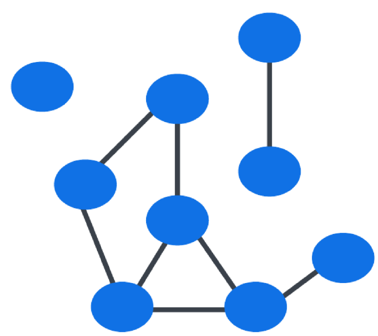

Figure 2.1: A diagram of a social network. Blue circles represent individuals. Some individuals are connected. Connections are represented by lines between individuals.

In their 2014 paper, Grunspan et al. introduce the concepts of social networks necessary for SNA in education research. The below introduction is based on their work.

Network analysis encompasses two primary categories of hypotheses: those that seek to identify the factors that influence the formation of a network and those that consider how networks shape outcomes at individual or population levels.

Networks can be unipartite, consisting of a single type of actor, for example, students, or bipartite, involving two distinct types. Unipartite networks are more common and easier to analyze. Ties within networks can be binary, denoting the presence or absence of a relation, or valued, incorporating quantitative information about the relation. For example, a valued tie between two students in a classroom could be the number of assignments they worked on together. While valued ties offer the advantage of incorporating detailed information into the network, information for tie values is challenging to gather and networks with valued ties are more complex to analyze.

Data collection and analysis in network studies can be categorized based on whether it considers a static network, a cross-sectional realization of an implicitly dynamic network, or an explicitly dynamic network.

When it comes to sampling a population, social networks are either ego-centric networks, census networks, or something in between. Ego-centric networks focus on a subset of individuals, called egos, and their immediate social surroundings, without being confined to any specific group such as a classroom. These networks gather information about the quantity and quality of relationships among egos and their relational counterparts, known as alters.

Census networks, also known as whole networks, collect data from an entire bounded population of actors. One issue with census networks is that they may lack information on potentially influential relations with actors outside the population of interest, like supportive faculty in a student network, leading to gaps in understanding important interactions.

At the level of whole networks, the density of a network is a metric that measures the number of links observed in the whole network divided by the total number of links that could exist if every actor were connected to every other actor, indicating the degree of interconnectedness among actors in the network.

2.4.1.1 Data for Social Network Analysis

Various methods are employed to gather data for social network analysis in educational settings. One such method is online communication networks where researchers use digital traces of student communication to reconstruct networks of students' online interactions (Saqr et al., 2022). Alternatively, Eckles et al. (2012) reconstructed a student social network using archival data related to student activities, course registrations, and roommate information extracted from their institution's student information system.

Along with digital traces of online communication and institutions' archival data, researchers often gather social network data directly from students. Surveys and interviews are popular techniques for gathering information on peer social relations and educational outcomes. Vörös et al. (2021) note that such methods are limited by cognitive constraints and recall biases. To address these challenges, the experience sampling method measures short-term dynamics by asking students every day about the important interactions they had the past day (Vörös et al., 2021). Such surveys, however, cannot be administered over long periods as answering the same questions over a long time may lead to response fatigue and high rates of non-response. Another approach uses social sensor techniques, like Bluetooth on smartphones, to collect fine-grained observational data on collocation and interactions between students (Vörös et al., 2021). This method aims to provide "objective" data while minimizing response fatigue and ensuring high temporal resolution. However, it it raises concerns about intrusiveness and poses potential risks to students' privacy

Vörös et al. (2021) argue that while each individual method has strengths, none alone provides a complete picture of social network processes in educational settings. Instead, they posit, a combination of methods seems more capable of uncovering the complexity of multidimensional networks occurring at various time scales. The authors successfully use such a mixed-method strategy in the Swiss StudentLife study, a longitudinal social network study of multiple engineering cohorts that underscored the effects of informal student communities on different student outcomes, including well-being and academic success.

2.4.1.2 Centrality in Social Networks

At the node level, the most widely used concept of social network analysis is centrality (Borgatti et al., 2009). Centrality describes a family of node properties relating to the structural prominence of a node (Borgatti et al., 2009). In other words, centrality illustrates how well an individual is positioned to receive and disseminate information and other resources that flow through social networks (Borgatti et al., 2009). Three main types of centrality are degree centrality, closeness centrality, and betweenness centrality. The discussion below is based on the introduction of centralities by Otte and Rousseau (2002) and addresses networks with binary, rather than valued, ties.

Degree centrality is a simple count of the total number of links a node has. Degree centrality serves as a basic indicator of popularity: an actor with a high degree centrality is highly popular, while an actor with a lower degree centrality is less popular. In mathematical terms degree centrality, $d(i)$, of a node i is defined as:

$$d(i) = \sum_{j} m_{ij}$$

where $m_{ij} = 1$ if there is a link between nodes i and j, and $m_{ij} = 0$ if there is no such link. The degree centrality in an N-node network can be standardized as:

$$d_s(i) = \frac{d(i)}{N-1}$$

Betweenness centrality is a measure of how often a given node lies on the shortest path between two other nodes. Betweenness centrality can be thought of as how often an individual acts as a “bridge” between other people in the network. Individuals exhibiting a high betweenness value are often referred to as brokers as a result of their controlling position in influencing the flow of information and resources in the network. Individuals exhibiting a high betweenness value also have access to diverse resources and information. In mathematical terms betweenness centrality, $b(i)$, of a node i, is defined as:

$$b(i) = \sum_{j,k} \frac{g_{jik}}{g_{jk}}$$

where g_{jk} is the number of shortest paths from node j to node k ($j,\ k \neq i$), and g_{jik} is the number of shortest paths from node j to node k passing through node i. It can be shown that for an N-node network the maximum value for $b(i)$ is $(N^2 - 3N + 2)/2$. Hence the standardized betweenness centrality is:

$$b_s(i) = \frac{2b(i)}{N^2-3N+2}$$

Closeness centrality measures the total distance of a node from all other nodes in the network. A low closeness centrality means that an actor is directly connected to most others in their network. This indicates that the actor could be highly influential in the network. Such actors are often referred to as “broadcasters”. In contrast, nodes in peripheral positions in a network may have high closeness centrality scores, indicating a high number of nodes between them and distant others in the network. In mathematical terms betweenness centrality, $c(i)$, of a node i, is defined as:

$$c(i) = \sum_{j} d_{ij}$$

where d_{ij} is the number of links in a shortest path from node i to node j. Closeness is an inverse measure of centrality since a larger value indicates a less central actor while a smaller value indicates a more central actor. The standardized closeness is defined as

$$c_s(i) = \frac{N-1}{c(i)}$$

making it again a direct measure of centrality.

2.4.1.3 Strong and Weak Ties

Burt (2004) observed that individuals who act as “links” or “bridges” across disparate groups that are otherwise disconnected, that is, individuals who bridge “structural holes” in their network, have enhanced access to information and resources compared to those with more insular networks. Figure 2.2 shows a network with a structural hole between two subgroups. The subgroups are later linked by a connection between two nodes, a bridge, in Figure 2.3. Such ties provide access to a type of social capital referred to as “bridging” social capital and are most often ‘weak’ ties, connecting individuals who are acquaintances (Granovetter, 1973). On the other hand, strong ties are connections between individuals who are closely connected, and provide a type of social capital called “bonding” (Granovetter, 1973).

Granovetter's Strength of Weak Ties (SWT) theory suggests that strong ties tend to reinforce existing similarities and provide redundant information, while weak ties often connect individuals who are dissimilar, providing access to novel information. Individuals who connect otherwise unconnected groups via weak ties occupy “brokerage positions". Those individuals, through occupying brokerage positions and acting as “bridges” across multiple groups, have a high betweenness centrality in their social networks. This provides them with access to diverse resources and information that would not otherwise be available and with the ability to relay and transport such information and resources across different groups in their network. Burt (2004) shows that employees who bridge structural holes within their organizations are promoted faster than others. In the context of post-secondary education, occupying such positions could provide students with knowledge about diverse courses offered by their departments and about faculty members and instructors who could offer them various types of support. A high betweenness centrality could also facilitate the process of finding members to form groups in various courses where group work is required.

Dawson (2008) found that social connections among post-secondary students are predominantly weak rather than strong ties. This implies that students mainly have access to “bridging” rather than “bonding” social capital through their connections with one another, likely because they form most of their connections with one another with the aim of completing required academic tasks rather than with the aim of “bonding” or forming a community.

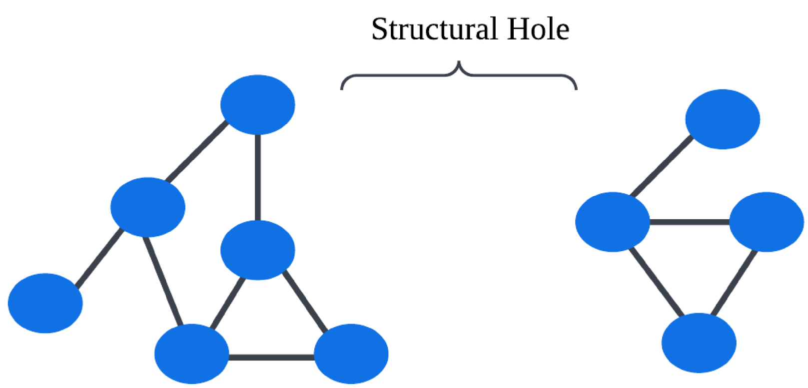

Figure 2.2: A structural hole between two subgroups of a social network.

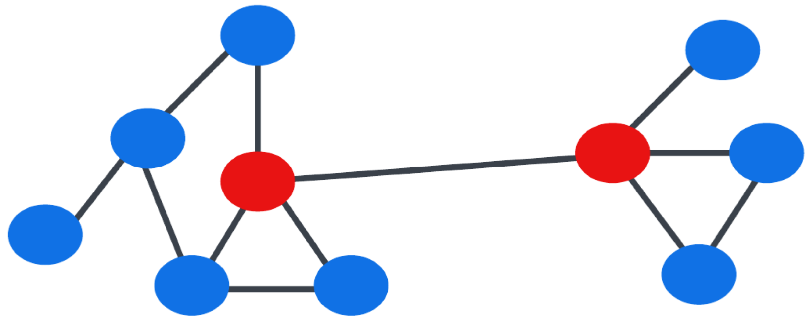

Figure 2.3: A connection between the nodes in red “bridges” the structural hole. The nodes in red are in a “brokerage position” in their respective subgroups.

2.4.1.4 Homophily

In their seminal work “Birds of a Feather: Homophily in Social Networks”, McPherson et al. (2001) define homophily as the tendency for contact among similar people to occur at a higher rate than among dissimilar people. Homophily implies that the separation based on social traits directly corresponds to network distance, representing the quantity of relationships through which information needs to traverse to link two individuals (McPherson et al., 2001).

The pervasive nature of homophily means that people’s social networks are often homogenous with regard to many social, demographic, and behavioral characteristics and that people’s social worlds are “limited” in a way that limits the information they receive, the attitudes they form, and the interactions they experience (McPherson et al., 2001). McPherson et al. additionally report that ties between dissimilar individuals tend to break at a higher rate than those between similar individuals.

Homophily can arise through various mechanisms, including social selection and social influence (McPherson et al., 2001). Social selection is the phenomenon where a relationship is more likely to form between two individuals if they share similar characteristics. Meanwhile, social influence is the phenomenon where individuals modify their own characteristics to match those of people they already have relationships with.

2.4.2 Social Connections Positively Influence Academic Achievement and Persistence

Through connections, students develop enhanced coping abilities and increased resilience in their university environments (Hoffman et al., 2002). Being central in social networks is a positive predictor of academic achievement (Ivan & Duduciuc, 2011; Rizzuto et al., 2009). Dawson et al. (2011) show that centrality can also be a positive indicator of a learner's creative capacity.

Binning et al. (2021) found that going to university with more of a student's high school peers was a positive predictor of grades in introductory STEM courses and a positive predictor of student retention, especially for first generation university students. However, Binning et al. note that it is students from privileged backgrounds, rather than underrepresented students, who are more likely to go to university with high school peers.

In a study of the connections among medical students, Vaughan et al. (2015) report that low-achieving students are more likely to be peripheral in their social networks. Similarly, Eckles & Stradley (2012) report that students who are least central to the networks seem to be at a high risk of attrition. Macfadyen & Dawson (2010) utilized social network analysis to develop an early warning system for educators to help them identify disconnected students and patterns of student-to-student communication.

Alongside simply "having" connections, “whom” students are connected affects their academic performance. For example, high-achieving peers in a student’s social network are a positive predictor of their academic achievement (Androushchak et al., 2013; Eckles & Stradley, 2012). In fact, the retention and attrition behaviors of a students’ connections have a greater impact on their retention than any background or performance variable (Eckles & Stradley, 2012). Eckles and Stradley (2012) further note that previous research at the institution where they conducted their study identified factors such as athletic participation, fraternity or sorority membership, religion, and ethnicity as crucial contributors to student retention. However, the findings of their current study imply that the significance of these factors in the past simply stems from their representation of strong social connections among students.

Vaughan et al. (2015) found no noteworthy correlation between ethnic homophily, or being connected to others identifying with the same ethnicity, and academic achievement.

Conversely, homophily based on age exhibited a negative association with achievement, suggesting that less interaction with more senior students was linked to lower academic performance.

2.4.3 Social Connections Positively Influence Sense of Community

Connections with others provide students with support and guidance, leaving them feeling cared for and sensing that they are a part of a network of mutual obligation, or, in other words, a community (Hoffman et al., 2002) Indeed, students who engage in more frequent communication with their peers tend to experience a stronger sense of community compared to those who communicate less often (Dawson, 2006; Royal & Rossi, 1996).

Dawson (2008) found that degree and closeness centralities are positive predictors of sense of community. Conversely, betweenness centrality emerged as a negative predictor of sense of community. Dawson observed that students with high betweenness centrality scores possessed effective external social networks, that is, their connections outside their classrooms already provided them with substantial social capital. Those students likely required only very specific supplements to their existing social capital from their classrooms' internal network, leading them to mainly form only weak connections with other students.

2.4.4 Social Connections of Underrepresented Students

Research across various studies emphasizes the importance of social connections for the academic success and well-being of underrepresented students. Those students often feel stuck between two cultures and struggle to balance between their "origin" and "host" environments (Lehmann, 2014). Adapting to their new academic environment is often marked by experiences of isolation, depression, diminished self-esteem, decreased mental and psychological well-being, and a decline in physical health (Dávid, 2023).

Underrepresented students find emotional support in their peers who share similar backgrounds, relying on fellow underrepresented students to cope with the challenges of social isolation (Putnam, 2000). In Canadian universities, underrepresented students benefit more than others when they have high school friends at university (Abada et al., 2009).

While formal peer relationships carry significance for all students, their importance is heightened for underrepresented students (Meeuwisse et al., 2010). Specifically, ethnic minority students tend to foster a more robust sense of community when they have positive formal relationships with their instructors and peers (Meeuwisse et al., 2010).

International students experience improved academic achievement and reduced dropout rates when connected to domestic students (Westwood & Baker, 1990). Dávid (2023) posits that the ideal social network for underrepresented students is a heterophilic, multicultural network that includes connections from both their origin and host environments. This kind of network ensures resources by both bonding and bridging ties, and therefore provides the emotional stability and the structural resources required to adjust to the host environment.

2.4.5 Social Connections Among Computer Science Students are Understudied

Very few studies have examined the social connections and social networks of students in computer science departments. Figl et al. (2008) analyzed social network drawings and detailed descriptions provided by 20 computer science students. On average, students depicted 12.45 relations to their peers. Notably, a comparable number of relations were categorized as weak, intermediate, and strong. Students expressed that they were more likely to feel supported when they had a greater number of connections and stronger ties to those connections.

The authors additionally conducted interviews with students to explore how course instructors could foster the formation of connections in their classrooms. Participants suggested that incorporating more collaborative learning into their coursework would help them develop connections with one another.

2.5 Collaborative Learning

Collaborative learning is an educational approach where groups of learners work together to solve problems, complete tasks, or create products (Laal & Ghodsi, 2012). Through emphasizing the responsibility of each learner for their own learning and for that of their peers (Gokhale, 1995), collaborative learning is rooted in positive social interdependence.

Social interdependence, as explained by Johnson et al. (2007), occurs when the achievement of individual goals is influenced by the actions of others. This interdependence can take two forms: positive interdependence, characterized by collaboration, and negative interdependence, characterized by competition. In positive interdependence, individuals believe that they can achieve their goals only if others with whom they are cooperatively linked also succeed. On the contrary, negative interdependence arises when individuals perceive that their goals hinge on the failure of others. According to the social interdependence theory (Deutsch, 1949), the type of interdependence among individuals plays a pivotal role in shaping how they interact, and this interaction pattern determines the outcomes of the situation. Positive interdependence fosters promotive interaction, where individuals encourage and facilitate each other's efforts to accomplish tasks and reach common goals. Conversely, negative interdependence results in oppositional interaction, where individuals discourage and obstruct each other's efforts, focusing on increasing their own productivity while impeding others. Positive interaction through positive interdependence supports the formation of community.

2.5.1 Collaborative Learning Positively Influences Learning and Persistence

According to the sociocultural theory of learning, knowledge acquisition occurs through the exchange of ideas and experiences among individuals (Sims, 2003). Social processes not only motivate students to learn but also lead to cognitive changes, fostering focus, active participation, and dedication to exchanging ideas with one another (Sims, 2003). Similarly, the constructivist theory of learning posits that people build their definitions of reality based on their perceptions and personal experiences (Vygotsky, 1978). The process of knowing is affected by social interaction with people, and cognitive growth happens first on a social level and then on individual level (Vygotsky, 1978).

Collaborative learning is supported by multiple mechanisms including the use of collective knowledge to cue other group members' prior knowledge (Congleton & Rajaram, 2011), complementary knowledge or expertise among group members (Johansson et al., 2005), and an increase in available working memory resources (Kirschner et al., 2009).

In their review of over 300 studies, Johnson et al. (2007) found that collaborative learning methods emerged as the preferred instructional approach for maximizing student learning and long-term persistence. In another expansive review of collaborative learning literature, Laal and Ghodsi (2012) found that collaborative learning was shown to promote critical thinking skills, actively involve students in the learning process, improve classroom results, and model appropriate student problem-solving techniques.

Nokes-Malach et al. (2012) propose that the effectiveness of collaborative learning depends on the complexity of the task, individual competence, and group competence. If individuals can handle the task alone, collaboration may not bring much benefit and could even lead to worse performance due to the challenges of coordinating different approaches. Collaborative learning could also fail when the task is too complex beyond the group's competence.

Shibley and Zimmaro (2002) also show that collaborative learning has a positive effect on student achievement and attitudes in introductory post-secondary courses. Courses employing collaborative learning approaches often have higher retention rates than other courses (Cámara-Zapata & Morales, 2020). In computer science courses, pair programming has a positive impact on students' grades and retention (Umapathy & Ritzhaupt, 2017).

Furthermore, collaborative learning is positively associated with student engagement, as it encourages information exchange, knowledge sharing, and discussions among group members (Qureshi et al., 2023). These interactions provide students with increased access to resources and information while fostering the development of meaningful connections.

2.5.2 Collaborative Learning Positively Influences Sense of Community

Allen et al. (2021) define community in terms of four components: (1) competencies for belonging to a community, such as possessing social skills to connect with others, (2) opportunities to belong to a community, (3) motivations to belong to a community, and (4) perceptions of belonging to a community. According to Allen et al.'s framework, collaborative learning fosters the development of competencies for belonging and offers opportunities to belong by allocating dedicated class time for students to collaborate. Collaborative environments may also boost students' motivations to belong. Furthermore, participating in diverse groups throughout undergraduate studies may shape students' perceptions of belonging.

In their analysis of collaborative learning literature, Laal and Ghodsi (2012) found that collaborative learning does indeed contribute to an increased sense of community. Laal and Ghodsi (2012) reported that other social effects of collaborative learning include contributing to the development of a social support system for students, fostering understanding of diversity among students and faculty, creating a positive atmosphere, and contributing to an increased self-esteem and reduced anxiety. Similarly, Johnson et al. (2007) found that collaborative learning was more successful than individual learning approaches at cultivating positive connections among students, providing students with social support, enhancing psychological well-being, and fostering positive attitudes towards the postsecondary experience. These social effects of collaborative learning likely contribute to its influence on sense of community.

Examining the sense of community of STEM students before and after courses, Fong (2023) and Weaver et al. (2016) observed a statistically significant rise in sense of community through collaborative courses, particularly among women.

Veilleux et al. (2013) propose that sense of community is more closely linked to a student's perception of their ability than to their actual ability. They suggest that collaborative learning relationships enable students to provide others with feedback, potentially offsetting the negative implications from other feedback, like a low grade, and enhancing their sense of community.

2.6 Summary and Following Chapters

This chapter discussed sense of community, social connections, and collaborative learning in post-secondary contexts. The discussion focused on the experiences of computer science students. The discussion underscored the positive impact of a sense of community on student persistence. It also emphasized the role of social connections in fostering a sense of community as well as the beneficial effects of collaborative learning on both the formation of social connections and the development of a sense of community.

While extensive research has been conducted to investigate sense of community, social connections, and collaborative learning in post-secondary education, there is a notable gap in the literature regarding these topics within the context of computer science, a field that is different from others in its remarkable growth rate and notably low levels of balanced demographic representation. The two studies that will follow address some of those gaps.

The first study examines the sense of community and social connections of computer science students across different demographic groups, and then explores the interactions among students' sense of community, students' social connections, and collaborative learning. The second study investigates how the academic performance of computer science students in different demographic groups differs across courses with different collaborative learning requirements.

Chapter 3

Exploring the Interactions Among Sense of Community, Social Connections, and Collaborative Learning in Computer Science

In computer science, students often experience a low sense of community (McDonald & Demmans Epp, 2023; Runa et al., 2023), especially when they identify with one or more of the groups underrepresented in the field (Mooney et al., 2020; Rainey et al., 2018; Stout & Wright, 2016). As persistence is tied to motivation and motivation to a sense of community (Tinto, 2012; Tinto, 2017), a low sense of community is the primary reason women leave computer science (Biggers et al., 2018). Alongside inspiring persistence, a sense of community is positively associated with students' well-being and positive self-perceptions (Baumeister & Leary, 2017; Pittman & Richmond, 2008).

Students' sense of community is influenced by their background characteristics, their orientations and values, and the environments of their academic institutions and classrooms (Strayhorn, 2018). Among the environmental influences on sense of community are students' social connections (Dawson, 2006; Mishra, 2020; Royal & Rossi, 1996) and the implementation of collaborative learning in their courses (Frog, 2023; Laal & Ghodsi, 2012; Weaver et al., 2016). Collaborative learning additionally encourages the formation of connections among students (Laal & Ghodsi, 2012).

This study examines the sense of community and social connections of computer science students across different genders, ethnic groups, and legal statuses in Canada, the country where the study is conducted, and in different years of their academic programs. The study then investigates the influence of computer science students' centrality in their social networks on their sense of community and how their sense of community differs across courses with varying collaborative learning requirements. Finally, the study investigates how the formation of social connections among students and with students' centrality in their social networks differs across courses with different collaborative learning requirements.

In computing, as in other STEM fields, classrooms are the main venue where students learn and interact with one another and with faculty members. Classrooms, therefore, play a crucial role in creating students' sense of community (Barker et al., 2014). Accordingly, this study will analyze the sense of community and the social connections of computer science students in classrooms with varying collaborative learning requirements.

We begin by examining the sense of community of computer science students in their courses. Specifically, we address the following questions:

RQ1: Is the sense of community of computer science students different across genders, ethnic groups, legal statuses, or year in program?

RQ2: What do computer science students have to say about their sense of community in their courses?

Subsequently, we investigate the social connections of computer science, addressing the following questions:

RQ3: Do computer science students have different numbers of strong and weak connections in their course support networks?

RQ4: Are the numbers of different types of social connections of computer science students different across genders, ethnic groups, legal statuses, or year in program?

RQ4: What do computer science students have to say about their social connections and how they support their academic success in their courses?

Following this, we explored the potential impacts of social connections on sense of community and how sense of community differs across courses with varying collaborative learning requirements, focusing on the following questions:

RQ6: Is the sense of community of computer science students influenced by their degree centrality in their courses' social networks?

RQ7: Is the sense of community of computer science students different across courses with varying collaborative learning requirements?

Finally, we investigated social connections across courses with different collaborative learning requirements, addressing the following questions:

> RQ8: Are the degree centralities of computer science students in their courses' social networks different across courses with varying collaborative learning requirements?
>
> RQ9: Do strong connections among computer science students form at different numbers across courses with varying collaborative learning requirements?

When addressing the above questions, we will examine groups of students who identify with different genders, different ethnicities, and different legal statuses as well as students in different years of their programs separately to determine whether the investigated effects and differences persist across student identities. Although we recognize the importance of examining the intersections of student identities to gain a comprehensive understanding of student experiences, our analysis will look at gender, ethnicity, and legal status divisions separately. This decision is due to the relatively small dataset that has low representation of students at each intersection of the three demographic factors in our analysis and due to the low representation of marginalized genders in the department where the study is conducted.

3.1 Methods

This study received research ethics approval from the University of Alberta's Research Ethics Board. The approval letter is included in Appendix A as Figure A.1.

In this section, we discuss the educational context where this study was conducted, the data collection approach, the instruments used, and the hypotheses and analysis methods for each research question.

3.1.1 Educational Context

This study was conducted at the computer science department of a large public research university in western Canada. The department under study offers multiple four-year bachelor's degree programs in computer science: a general bachelor's degree in computer science and a bachelor's degree in computer science with various specialization options.

To gather data to investigate the interplay among sense of community, social connections, and collaborative learning in computer science, we contacted instructors teaching courses offered by the department, except where there was a potential conflict of interest, requesting to include their courses in our study. Ultimately, our study included 26 courses offered by the computer science department.

We examined course syllabi and, when they were not readily available, contacted course instructors to determine whether courses incorporated any collaborative learning. At the end, we classified courses into one of three categories: courses with no graded collaborative component, courses with a graded optionally collaborative component, and courses with a graded required collaborative component. A graded required collaborative component refers to an assignment or a project where students are required to work in groups of two or more. A graded optionally collaborative component refers to an assignment or a project where students are free to either work individually or in groups of two or more. Table 3.1 shows the distribution of courses included in our study and their respective sizes across course categories with varying collaborative learning requirements.

Table 3.1: Distribution of courses and their respective sizes across course categories by the inclusion of a collaborative component.

	No Collaborative Component	**Optionally Collaborative Component**	**Required Collaborative Component**	**Total**
No. of Courses	15	2	9	26
No. of Students	2758	378	1027	4163
Students/ Course as *M(SD)*	183.8 (135.22)	189.0 (45.00)	114.0 (99.33)	160.1 (125.91)
Students/Course (Max)	559	234	379	559
Students/Course (Min)	19	114	36	19

Table 3.2 Shows the distribution of courses included in our study by course category and course level. A course level of “100” indicates that a course is introductory and often taken by students in the earlier years of their programs. Higher course levels indicate courses are taken by students in the later years of their program. In the department where the study is conducted, students in their final year mainly enroll in courses with levels of “300” and “400”. In our study, courses with a level of “100” are only represented in the category of courses without a collaborative component. This is representative of the department under study as introductory courses mainly rely on individual rather than collaborative work. Courses with a required collaborative component are mainly present at higher levels, both in this study and in the department where it is conducted.

Table 3.2: Distribution of courses across course categories and course levels.

Course Level	**No Collaborative Component**	**Optionally Collaborative Component**	**Required Collaborative Component**	**Total**
100	2	0	0	2
200	6	0	2	8
300	4	2	3	9
400	3	0	4	7

Among the courses without a collaborative component, one small course was conducted entirely in a virtual format. The remaining courses predominantly took place on-campus. While most of the included courses were offered mainly to students in an undergraduate computer science program, in one of the small courses containing a required collaborative component, half of the students enrolled were in a computer-science program, while the other half were from arts or engineering programs. In courses with a required collaborative component, students had varying degrees of autonomy in selecting their group members: they could either freely choose their partners, choose them under certain constraints, or be assigned to groups by their instructors. Some courses employed different techniques across different collaborative components.

3.1.2 Data Collection

We administered a voluntary questionnaire to all students enrolled in the courses described above. Data collection was conducted by the author of this thesis, a colleague who is a PhD student, and their supervisor. The gathered data will be used in this study as well as in other studies pertaining to students' experiences and sense of community.

In most of the courses studied, the researchers distributed the questionnaire by directly emailing students with an invitation to participate and an introduction to the studies that will be conducted using the questionnaire responses. A reminder to fill the questionnaire was sent to students one week after the questionnaire was initially shared, then once again five days later. In other cases, course instructors preferred that they relay the researchers' message and questionnaire to students, rather than allow the researchers to contact their students directly. These instructors shared the questionnaire through an announcement on their courses' online management system. Students enrolled in most of these courses did not receive a reminder. Table 3.3 shows the distribution of courses by type and how students enrolled in them were contacted.

Table 3.3: Number and percentage of courses across methods of questionnaire distribution.

Method of Questionnaire Distribution	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
By Researchers	10 (66.67%)	1 (50%)	7 (77.78 %)	18 (69.23%)
By Course Instructors	5 (33.33%)	1 (50%)	2 (22.22 %)	8 (30.77%)

Typically, in the department under study, computer science students enroll in one or more computer science courses each semester. Consequently, some students may have received multiple invitations to participate in the study through different courses they were enrolled in. Since the researchers directly contacted students in only certain courses and thus have access to only a limited subset of the names of all students enrolled in the courses under study, it's difficult to determine the exact number of students invited to participate and the number of invitations each student received. However, the number of students we directly contacted comprised approximately 63.53% of the total number of invitations we sent out. Among those, each student received, on average, 1.57 invitations (SD = 0.713).

The questionnaire was distributed to students six weeks after the start of the semester, by which time they had completed at least one course assignment and, if applicable, one midterm. Data collection through the questionnaire took place during the seventh and eighth weeks of the Winter semester of 2024. These weeks are notably busy times of the semester, which might have affected the response rate.

All students who completed the questionnaire were given the option to provide their emails separately for entry into a draw for a $20 gift card and to receive a summary of the results once the studies were concluded.

3.1.3 Instruments

The distributed questionnaire was composed of five main sections:

1. The first section assessed students' sense of community in the studied courses. It also included a free-response question where students could share additional thoughts about their course experience.
2. The second section gathered data on students' social connections. This section also included a free-response question where students could share additional thoughts about their social connections and how they support their academic success.
3. In the third section, students were given the option to respond to items related to their sense of community in the department where the study was conducted as a whole, rather than focusing solely on individual courses. Responses to this section will not be used in this study but will be used in future research.
4. The fourth section gathered information related to students' demographic backgrounds and to their current degree program at the university where the study was conducted. Students were given the choice to opt out of answering any of these demographic questions. Responses to some questions in this section will not be used in this study and will be used in future research.
5. The final section asked students for permission to obtain their final course grades when the course is over. Responses to this section and obtained course grades will not be used in this study but will be used in future research.

Appendix B shows all questionnaire items. The subsequent subsections discuss selected items in more detail.

3.1.3.1 Measuring Sense of Community

Community, as defined by Rovai (2002, p. 198), is “a feeling that members have of belonging, a feeling that members matter to one another and to the group, that they have duties and obligations to each other and to the school, and that they possess shared expectations that members' educational needs will be met through their commitment to shared learning goals”. According to Rovai (2002), community in educational contexts can be understood as made of two main elements: connectedness among its members and a shared expectation of learning support. Connectedness, the first component, refers to the sense of belonging, acceptance, and the establishment of meaningful relationships within the community. It involves acknowledging one's membership within the community and experiencing emotions such as friendship and unity. The second component, learning support, emphasizes the active construction of knowledge and understanding within the community. It represents the role that community plays in facilitating the acquisition of knowledge and meeting the learning needs of its members.

We measure sense of community in the courses under study using the short form of the Classroom Community Scale (CCS-SF) developed by Cho and Demmans Epp (2019) as a shorter version of the original scale by Rovai (2002). The CCS-SF is composed of 8 Likert-type items, four of which relate to feelings of connectedness, while the other four relate to learning support. Each item is rated using a five-point scale, from “strongly disagree” to “strongly agree”. Item ratings are then converted to numerical values from 4 to 0. Five of those items are worded positively, meaning that a rating of “strongly agree” corresponds to a value of 4, while the remaining three items are worded negatively. Section B.1 in Appendix B details the items of the CCS-SF and how the ratings of each item are converted to numerical values.

The numerical values of all eight items are summed to calculate the CCS-SF score for each participant. Scores range from 0 to 32 and higher scores indicate a stronger sense of community. Items related to connectedness can be used to calculate a Connectedness score, while items related to learning support can be used to calculate a Learning Support score.

Evaluating the CCS-SF’s reliability, we observed a Cronbach's alpha of 0.80, indicating that the scale is sufficiently reliable.

3.1.3.2 Measuring Social Connections

To measure social connections, we rely on social network analysis and the concept of centralities. SNA models social connections as a network comprising individuals, groups, or organizations as nodes, and the connections between them as edges (Mishra, 2020).

At the node level, centrality is a key concept in social network analysis (Borgatti et al., 2009). Centrality encompasses various node properties that indicate the structural importance of a node (Borgatti et al., 2009). Essentially, centrality indicates an individual's capacity to receive and disseminate information and resources within social networks (Borgatti et al., 2009). The three primary types of centrality are degree centrality, closeness centrality, and betweenness centrality.

Degree centrality is a straightforward count of the total number of links a node possesses and serves as a fundamental measure of popularity. It can be standardized by dividing the number of connections by the total number of nodes in the network minus one, the node being assessed. Betweenness centrality quantifies how frequently a node lies on the shortest path between any two other nodes. Closeness centrality measures a node's total distance from all other nodes in the network. Standardizing betweenness and closeness centralities involves more complex calculations than standardizing degree centrality. The Background chapter of this thesis provides the precise formulas for calculating centralities.

Due to low response rates, this study was not able to investigate whole class networks and thus focused solely on non-standardized degree centralities. However, we strongly recommend that future research on computer science students' social networks explore betweenness and closeness centralities and their associations with student experiences.

To limit privacy concerns, we solely relied on social network data provided directly by students via the questionnaire, rather than utilizing potentially intrusive methods such as digital traces of online communication (Saqr et al., 2022), archival data (Eckles et al., 2012), or social sensors (Vörös et al., 2021).

For each course, we collected social network data by asking enrolled students to list the names of their peers in the same course with whom they are connected and to identify individuals outside the course who support them in course-related activities. When listing connections within the course, students were instructed to report from 0 to 20 connections, specifying whether they are:

1. Students they consider friends.
2. Students they were friends with before the course began.
3. Students they interact with in academic activities related to the course.

Students could choose one or more of the above options to describe their relationship to others in the course. We presume that connections with individuals identified as friends would generally be strong, whereas connections with students with whom participants interact but do not consider friends represent weaker connections. Connections identified as friends and pre-course friends are likely the strongest connections. When listing supportive connections outside the course, students were prompted to report from 0 to 10 relationships.

Although limiting the number of connections students could report might induce them to enter data to fill up their perceived quota, we had to impose this restriction due to technical limitations. To mitigate this issue, we explicitly stated that students were not obliged to fill every box and could choose to enter no connections at all.

Using this data, we constructed unipartite course networks, where all nodes represented individuals: students and their external supportive connections. The connections between nodes were binary, indicating only the presence or absence of a relationship without further detailed information. The constructed networks were static, depicting the connections between nodes at a single point in time when the data was collected, rather than illustrating how the networks evolved over time.

As discussed in the Background chapter of this thesis, social networks could be categorized as ego-centric networks, census networks, or falling somewhere in between. Ego-centric networks focus on a subset of individuals and their social connections, gathering information on the number and nature of their relationships, as well as the attributes of those they are connected to. Census networks collect data from an entire bounded population of actors. However, one drawback of census networks is the potential lack of information on influential relationships with actors outside the population of interest.

The course networks we constructed lie somewhere between the extremes of census and ego-centric networks. While the networks focused on the bounded population of students enrolled in a course, students were also prompted to report their supportive connections outside the course. Additionally, participation was voluntary, resulting in the networks representing only a small subset of individuals and their social connections. However, to protect the privacy of students who opted not to participate, respondents were not required to report the attributes of individuals they were connected to. Each respondent described only their own sense of community and demographic background. This, combined with the optional nature of participation, limits the scope of analyses that can be conducted with this data.

3.1.3.3 Gathering Demographic Information

To gather gender information, the questionnaire gave students the option to describe themselves or to identify as either male, female, or non-binary. To gather ethnic group information, students were asked to select one or more of the population groups recognized by the Canada Statistics Census of Population. To determine students' legal status in Canada, where the study department is located, students were prompted to indicate whether they are citizens, permanent residents, students with a study permit, or students with another permit. Students were given the choice to opt out of answering any of these demographic questions. The questionnaire also included other demographic questions that will not be used in this study, but in future research. Appendix B outlines the demographic questions included in the questionnaire along with their corresponding response options.

3.1.4 Hypotheses and Analysis

The following subsections detail the hypotheses related to and the analysis methods used to address each research question. Where we indicate that a distribution is not normal, that was determined by applying the Shapiro-Wilk Test (Shapiro & Wilk, 1965) and achieving a p-value smaller than .001. This study employs a mix of both qualitative and quantitative methods. All analysis was conducted by the author of this thesis and reviewed by her supervisor, Carrie Demmans Epp.

We followed all null hypothesis significance tests by statistical power analysis. We performed both post-hoc analysis to determine the observed power of the tests we conducted on the sample we had and a priori analysis to determine the sample sizes that would be required by future work to enable the detection of moderate effects with a statistical power of 80%. Details of the power analysis results for each test are shown in Appendix C. Notable power analysis results are also highlighted in the results and discussion sections of this chapter.

3.1.4.1 RQ1: Sense of Community Differences Across Genders, Ethnic Groups, Legal Statuses, and Program Years

Computer science students from underrepresented groups often experience a lower sense of community than their majority peers (Rainey et al., 2018; Mooney et al., 2020). We thus hypothesized that students from underrepresented genders and ethnic groups as well as international students would experience a lower sense of community, represented by a lower CCS-SF score, lower Connectedness score, and lower Learning Support score, than their majority and domestic peers. We also hypothesized that there will be differences in the CCS-SF scores across different years in students' programs.

To evaluate these hypotheses, we employed null hypothesis significance tests to compare students' CCS-SF scores, connectedness scores, and learning support scores across different genders, ethnic groups, and legal statuses.

As the distribution of these scores is not normal and since we are performing comparisons across unpaired groups, we used Mann-Whitney U tests (Mann & Whitney, 1947) to perform comparisons across different genders and different legal statuses.

Since our final data includes more than two different ethnic groups and since students usually complete their programs in at least four years, we used Kruksal-Wallis tests (Kruskal & Wallis, 1952) to perform comparisons across different ethnic groups and across different program years. Where the Kruskal-Wallis tests revealed a significant difference across any of these categories, we conducted pairwise Mann-Whitney U tests to identify the specific differences between each pair of ethnic groups or program years. To rebalance the risk of false positives compounded by multiple comparisons, we applied Bonferroni Correction (Bonferroni, 1936) on the Mann-Whitney U test results, multiplying resultant p-values by 6, the number of pairwise comparisons performed when comparing sense of community scores across the four identified ethnic groups or across the four program years.

3.1.4.2 RQ2: Students' Responses to Free-response Question About Sense of Community

To better understand how computer science students perceive the community in their courses, our questionnaire included an optional free-response question where students could share anything they would like to share about their experience in the courses under study. The question's wording was intentionally broad, asking about course experiences generally rather than sense of community specifically, to avoid restricting students' responses. However, the question was placed directly after the CCS-SF items to ensure that students were still primed to consider community aspects.

To analyze the responses, we condensed each response into a brief list of the topics it covered. We then identified the topics that recurred across multiple responses.

3.1.4.3 RQ3: Differences Between the Numbers of Strong and Weak Connections

Our questionnaire gathered information about three different types of supportive connections students could have with others enrolled in their courses :

1. Students they consider friends.
2. Students they were friends with before the course began.
3. Students they interact with in academic activities related to the course.

As discussed above, we presumed that connections with other students identified as friends would generally be strong, whereas connections with students with whom participants interact but do not consider friends represent weaker connections.

Dawson (2008) observed that the social connections among students are predominantly weak connections. Based on this finding and the relative ease of forming weak connections compared to strong ones in classroom contexts, we hypothesized that computer science students will have more weak connections - connections with people they work with but do not consider friends - than strong connections - connections with people they consider friends.

To evaluate these hypotheses, we employed null hypothesis significance tests to compare the numbers of students' weak and strong connections. As the distribution of the number of connections students have is not normal and since we are comparing the numbers of weak and strong connections of the same students, we used the Wilcoxon Signed-rank test (Wilcoxon, 1992).

3.1.4.4 RQ4: Differences in the Numbers of Different Types of Social Connections Across Genders, Ethnic Groups, Legal Statuses, and Program Years

Students from underrepresented groups often experience isolation as they adapt to their new post-secondary environments (Dávid, 2023). Therefore, we hypothesized that students from underrepresented genders and ethnic groups and international students will generally have fewer connections within their courses compared to their majority and domestic peers. We hypothesized that the number of supportive connections outside the course will be different across genders, ethnic groups, and legal statuses. We also hypothesized that there will be differences in the numbers of the different types of connections students have across the different years of their programs.

To evaluate these hypotheses, we employed null hypothesis significance tests. Since the distribution of the number of connections students have is not normal and since we are performing comparisons across unpaired groups, we used Mann-Whitney U tests (Mann & Whitney, 1947) to compare the number of connections of different types across different genders and different legal statuses. We similarly used Kruksal-Wallis tests (Kruskal & Wallis, 1952) to perform comparisons across different ethnic groups and across different program years, followed by pairwise Mann-Whitney U tests when needed. We applied the Bonferroni Correction (Bonferroni, 1936) on the Mann-Whitney U test results, multiplying resultant p-values by 6.

3.1.4.5 RQ5: Students' Responses to Free-response Question About their Supportive Connections

To better understand how computer science students perceive their supportive connections, our questionnaire included an optional free-response question where students could share anything they would like to share about their connections and how they support their academic success. To analyze the responses, we condensed each response into a brief list of the topics it covered. We then identified the topics that recurred across multiple responses.

3.1.4.6 RQ6: The Influence of Degree Centrality on Sense of Community

Building on the findings of Dawson (2006; 2008) and Royal & Rossi (1996), we hypothesized that degree centrality inside course social networks positively influences the sense of community of computer science students, particularly their Connectedness scores and, subsequently, their CCS-SF scores. However, we hypothesized that connections with supportive individuals outside the course would negatively influence students' sense of community, since students with effective external networks might be less likely to form strong connections with others in their courses (Dawson, 2008). Learning Support scores measure students' feelings that their classroom community supports their knowledge acquisition. Since the support students receive from their connections towards knowledge acquisition likely depends on features of whom they are connected to rather than the number of connections they have, we did not expect degree centrality in courses or the number of external connections to strongly influence Learning Support scores.

Given the size of our data (n = 235), we used linear regression to assess these influences. To calculate students' degree centralities, we counted the number of people they were connected to in their course, excluding connections with individuals not enrolled in the course. We treated those degree centralities as a predictor and entered the number of connections outside the course separately as another predictor. We treated CCS-SF scores, Connectedness Scores, and Learning Support scores as target variables in separate regression models. We normalized the predictors and target variables using min-max normalization before entering them into the models.

3.1.4.7 RQ7: Sense of Community Differences Across Collaborative Requirements

Following the findings of Laal and Ghodsi (2012) and Fong (2023) and Weaver et al. (2016), we hypothesized that students experience a higher sense of community in courses with an optionally collaborative component compared to courses without any collaborative component and in courses with a required collaborative component compared to both other course categories: courses with an optionally collaborative component and courses without a collaborative component. We expect to see this effect in all of the overall CCS-SF score, the Connectedness score, and the Learning Support score.

To evaluate these hypotheses, we first employed Kruskal-Wallis tests (Kruskal & Wallis, 1952) to determine if there is any difference in CCS-SF scores across the three different course categories, followed by pairwise Mann-Whitney U tests (Mann & Whitney, 1947) to identify the specific differences between each pair of course categories where needed. We applied the Bonferroni Correction (Bonferroni, 1936) on the Mann-Whitney U test results, multiplying resultant p-values by 3, the number of pairwise comparisons performed when comparing sense of community scores across the three identified course categories.

3.1.4.8 RQ8: Degree Centrality Differences Across Collaborative Requirements

We hypothesized that students have higher degree centralities in courses with an optionally collaborative component compared to those without any collaborative component, and in courses with a required collaborative component compared to both other course categories. When addressing this question, we excluded connections with individuals not enrolled in the course from degree centrality calculations.

To evaluate these hypotheses, we employed null hypothesis significance tests. Since the distribution of students' degree centralities in their course networks is not normal and since we are performing comparisons across unpaired groups, we employed Kruskal-Wallis tests (Kruskal & Wallis, 1952) to first determine if there is any difference in centralities across the three different course categories, followed by Mann-Whitney U tests (Mann & Whitney, 1947) to pinpoint differences between each two course categories where needed. We again applied the Bonferroni Correction (Bonferroni, 1936) on the Mann-Whitney U test results, multiplying resultant p-values by 3.

3.1.4.9 RQ9: Differences in the Number of Strong Connections Formed Across Collaborative Requirements

To determine whether strong connections among computer science students form at different numbers across courses with varying collaborative learning requirements, we compared the number of friends who were not friends before the course began across the identified course categories.

Although we gathered data from courses in three different categories, the number of responses we received from courses with an optionally collaborative component was especially small. Additionally, participants from these courses reported fewer connections with their peers compared to students in the other two categories. This led to an especially small number of reported friends who were not friends before the course began for participants from courses with an optionally collaborative component. Accordingly, we excluded that course category from this analysis.

Comparing the remaining two course categories, we hypothesized that students have more friends who were not friends before the course began in courses with a required collaborative component compared to courses without a collaborative component. To evaluate these hypotheses, we employed Mann-Whitney U tests (Mann & Whitney, 1947) .

3.2 Results

In this section, we look at the demographic distribution of students who participated in this study. Subsequently, we discuss the distribution of participants' sense of community scores and the distribution of the numbers of different types of social connections they reported. Finally, we report the results of the analysis conducted to address each research question.

3.2.1 Participants

Our questionnaire has an overall response rate of 5.64%. Notably, higher response rates were observed when students were contacted directly by the researchers than when they were contacted by course instructors. Response rates across different course categories and methods of questionnaire distribution are presented in Table 3.4.

More than 63% of the responses came from courses without a collaborative learning component. This outcome is expected, considering that 15 out of the 26 courses where students were invited to participate in our study did not incorporate collaborative learning. Only 9.4% of the responses were from courses with an optionally collaborative component.

Table 3.4: Number of participants and participation rates across course categories and methods of questionnaire distribution.

Contacted by	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
Researchers	111 (6.89%)	19 (8.12%)	57 (6.65 %)	187 (6.92 %)
Course Instructors	38 (3.32%)	3 (2.08%)	7 (4.12%)	48 (3.29%)
Total	149 (5.40%)	22 (5.82%)	64 (6.23%)	235 (5.64%)

Table 3.5 presents the distribution of participants across course categories and years in their program. Students in their first and second years responded predominantly in courses without a collaborative component. This again is expected, since most introductory courses in the department where the study was conducted rely solely on individual rather than collaborative learning. In contrast, responses from students in their third and fourth were almost evenly distributed between courses without collaborative learning and courses with a required collaborative component.

Table 3.5: Distribution of participants across course categories and program years.

	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
1st Year	18	-	1	19
2nd Year	67	2	13	82
3rd Year	34	9	29	72
4th Year or Beyond	30	11	21	62

Table 3.6 shows the distribution of participants by gender. Due to the limited number of participants who selected "Non-binary/Other" genders, we merged those with participants who

identified as women into a category labeled "Underrepresented Gender". The final distribution of participant genders is shown in Table 3.7.

Table 3.6: Distribution of participants across course categories and genders.

	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
Women	67	10	36	99
Men	77	11	22	124
Non-binary/Other	3	0	2	5
I prefer not to share this information	2	1	4	7

Table 3.7: Distribution of participants across course categories and genders after combining “Women” and “Non-binary/Other” into one category, “Underrepresented Genders”.

	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
Underrepresented Genders	70	10	38	104
Men	77	11	22	124
Total	147	21	60	228

Table 3.8 illustrates the distribution of participants' legal statuses. "International Students" refers to students who indicated that they are on a study permit. Domestic students are those who are identified as Canadian citizens or as permanent residents. Most participants (68%) were domestic students.

Table 3.8: Distribution of participants across course categories and legal statuses.

	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
International Students	47	9	19	75
Domestic Students	102	13	45	160
Total	149	22	64	235

Table 3.9 shows the distribution of ethnic groups selected by students. Due to the limited number of responses in each group, we aggregated student ethnic groups into four categories: "East Asian," "South Asian or South-East Asian," "White," and "Underrepresented ethnic groups". "East Asian" includes students who identified as either Chinese, Korean, or both. "South Asian or South-East Asian" includes students who identified as Filipino, South Asian, South-East Asian, or a combination of those groups. "Underrepresented ethnic groups" encompass students who did not select East Asian or South Asian or South-East Asian options, nor selected White alone. This category includes students who are identified as "Arab or Middle Eastern", "Indigenous: First Nations, Metis, Inuk (Inuit)", "Latin American", "West Asian (e.g., Iranian, Lebanese)", or a combination of multiple groups that do not all fall under either the "East Asian" or the "South or South-East Asian" categories. Table 3.10 presents the final distribution of participants across the aggregated ethnic groups.

Table 3.9: Distribution of participants' ethnic groups.

Ethnic groups	Response Counts
Arab or Middle Eastern	5
Black	18
Chinese	36
Filipino	8
Indigenous: First Nations, Metis, Inuk (Inuit)	2
Korean	8
Latin American	3
South Asian	47
South-East Asian	17
South Asian and South-East Asian	2
West Asian (e.g., Iranian, Lebanese)	3
White	65
Other two or more groups	15
I prefer not to share this information	6

Table 3.10: Distribution of participants across course categories and merged ethnic groups.

Ethnic group	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
East Asian	19	8	17	44
South Asian or South-East Asian	46	5	23	74
White	49	4	12	65
Underrepresented Ethnic Groups	31	3	12	46
I prefer not to share this information	145	20	64	229

Tables 3.11, 3.12, and 3.13 display the distribution of students' legal statuses and ethnic groups across course categories for students who identified as one of the underrepresented genders, students who identified as men, and students who preferred not to share their gender information, respectively. Due to the low representation of participants at each intersection of gender, legal status, and ethnic group, analyses will address gender, ethnicity, and legal status divisions separately.

Table 3.11: Demographic information of participants. The number of participants at the intersections of demographic variables is small.

Ethnic group	Legal Status	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
Gender: Woman or Non-binary/Other					
East Asian	International	6	3	4	13
East Asian	Domestic	5	0	7	12
South Asian or South-East Asian	International	7	2	3	12

South Asian or South-East Asian	Domestic	10	2	2	14
White	International	0	0	0	0
White	Domestic	21	1	3	25
Underrepresented Ethnic Groups	International	9	0	1	10
Underrepresented Ethnic Groups	Domestic	11	0	4	15
Preferred not to answer	Domestic	1	1	0	2
Preferred not to answer	International	0	1	0	1
		Gender: Man			
East Asian	International	4	3	2	9
East Asian	Domestic	4	2	4	10
South Asian or South-East Asian	International	16	0	8	24
South Asian or South-East Asian	Domestic	13	1	8	22
White	International	1	0	0	1
White	Domestic	25	3	8	36
Underrepresented Ethnic Groups	International	2	0	0	2
Underrepresented Ethnic Groups	Domestic	9	2	6	17
Preferred not to answer	International	2	0	0	2
Preferred not to answer	Domestic	1	0	0	1

Gender: Preferred not to disclose gender identity					
South Asian or South-East Asian	International	0	0	1	1
South Asian or South-East Asian	Domestic	0	0	1	1
White	Domestic	2	0	1	3
Underrepresented Ethnic Groups	Domestic	0	1	1	2

3.2.1.1 Participants' Sense of Community

Figure 3.1 illustrates the distribution of participants' CCS-SF scores, Connectedness scores, and Learning Support scores. Table 3.12 presents the mean and standard deviation of those scores for participants in each demographic group.

The table shows that the subset of East Asian students has the highest mean CCS-SF scores and the highest mean Connectedness scores. Meanwhile, fourth year students have the highest mean Learning Support scores. Students from underrepresented genders or underrepresented ethnic groups have the lowest mean scores in all three categories.

Figures 3.2 and 3.3 show the distribution of the CCS-SF scores, Connectedness scores, and Learning Support scores of participants from underrepresented genders and participants who are men, respectively. Figures 3.4 and 3.5 show the distribution of the CCS-SF scores, Connectedness scores, and Learning Support scores of participants from underrepresented ethnic groups and other participants, respectively. Figures 3.6 to 3.9 show the distribution of the CCS-SF scores, Connectedness scores, and Learning Support scores of participants in different years of their programs.

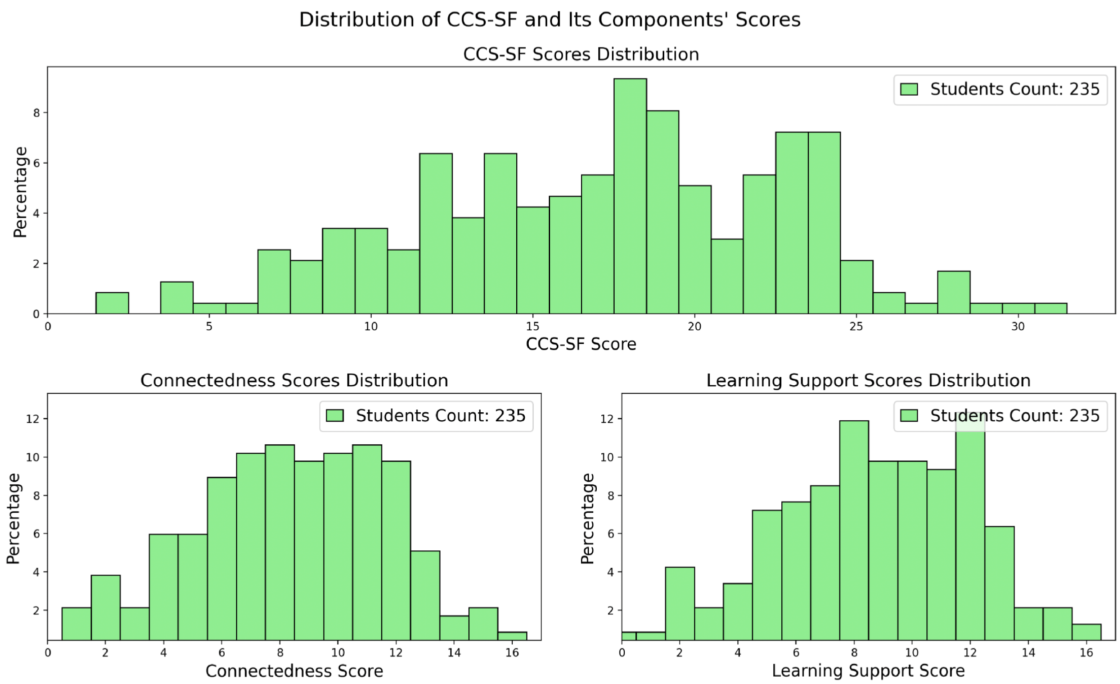

Figure 3.1: Distribution of all participants' CCS-SF scores, Connectedness scores, and Learning Support scores.

Table 3.12: Mean and standard deviation of CCS-SF scores, Connectedness scores, and Learning Support scores for participants in each subset.

Subset	**n**	**CCS-SF Score**	**Connectedness Score**	**Learning Support Score**
		M(SD)	***M(SD)***	***M(SD)***
Underrepresented Genders	104	15.74 (5.74)	7.86 (3.313)	7.88 (3.272)
Men	124	18.22 (5.485)	8.83 (3.354)	9.39 (3.397)
International	75	17.2 (5.932)	8.52 (3.256)	8.68 (3.735)
Domestic	160	17.04 (5.668)	8.35 (3.417)	8.69 (3.28)
East Asian	44	18.39 (6.303)	9.82 (3.157)	8.57 (3.806)
South Asian or South-East Asian	74	17.16 (5.286)	8.57 (3.193)	8.59 (3.448)
White	65	17.55 (5.377)	8.15 (3.241)	9.4 (3.244)
Underrepresented Ethnic Groups	46	15.37 (5.851)	7.41 (3.512)	7.96 (3.091)
1st Year	19	16.05 (4.428)	7.47 (2.951)	8.58 (2.567)
2nd Year	82	16.35 (6.125)	8.02 (3.492)	8.33 (3.45)
3rd Year	72	17.18 (5.868)	8.72 (3.32)	8.46 (3.685)
4th Year	62	18.27 (5.317)	8.82 (3.312)	9.45 (3.253)

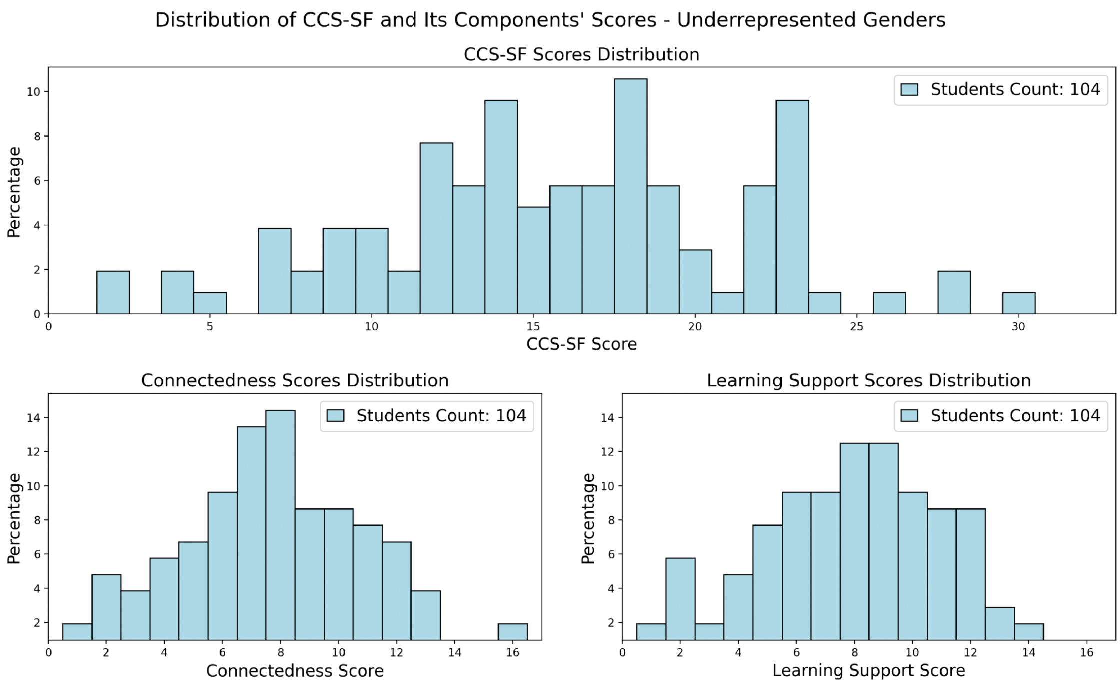

Figure 3.2: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants from underrepresented genders.

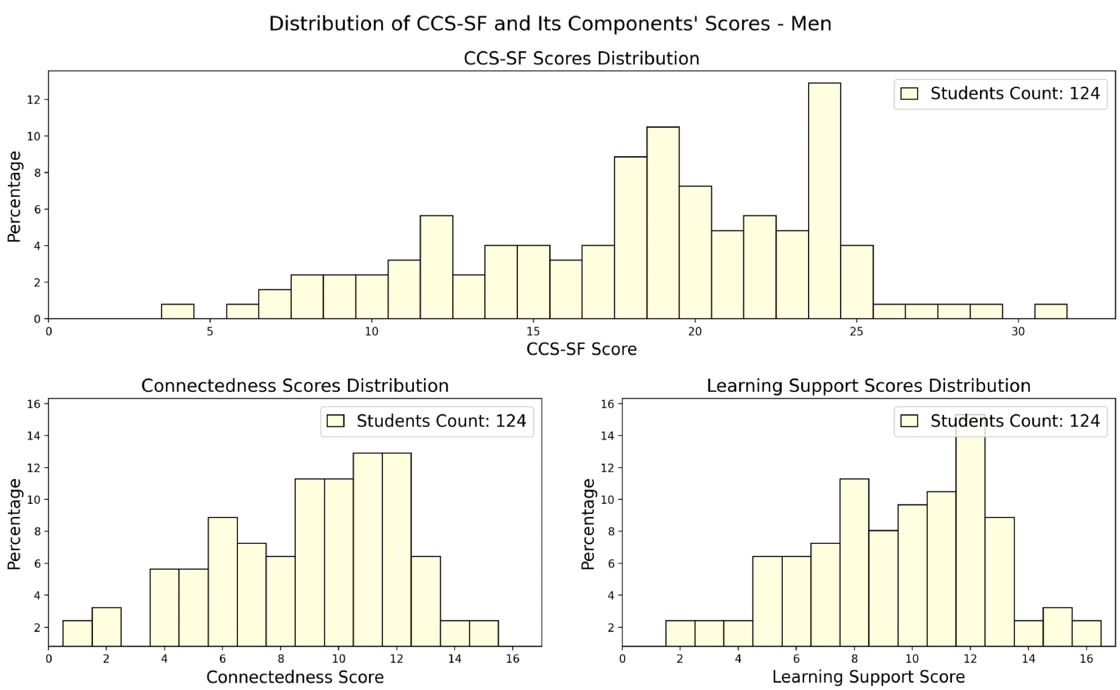

Figure 3.3: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of men.

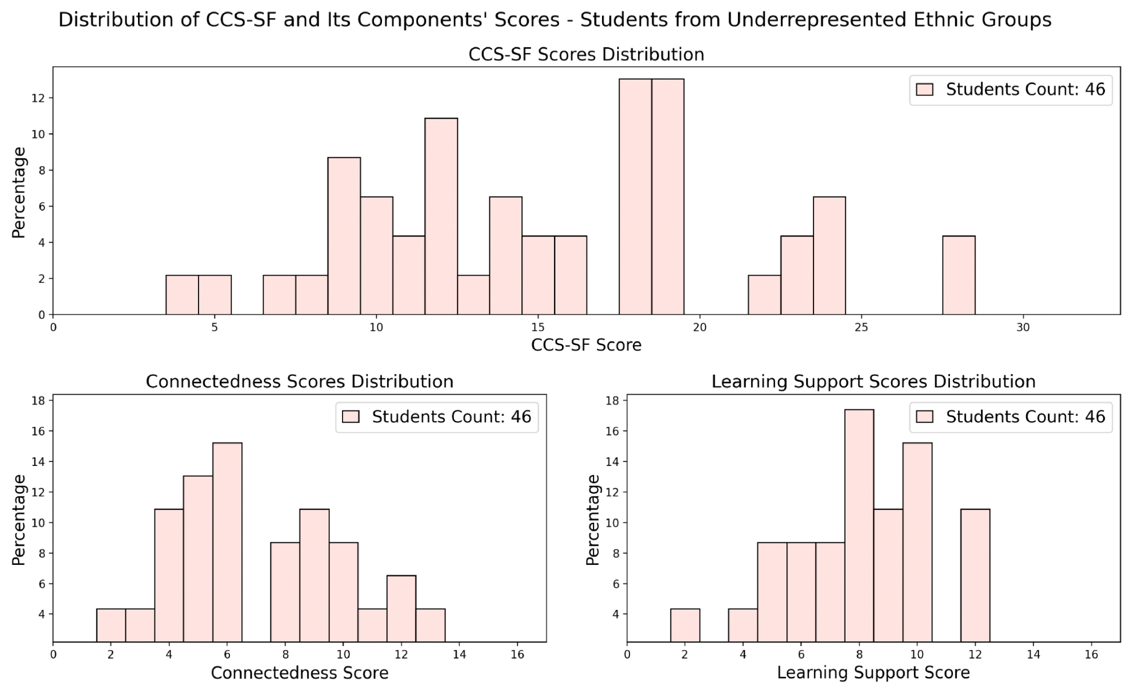

Figure 3.4: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants from underrepresented ethnic groups.

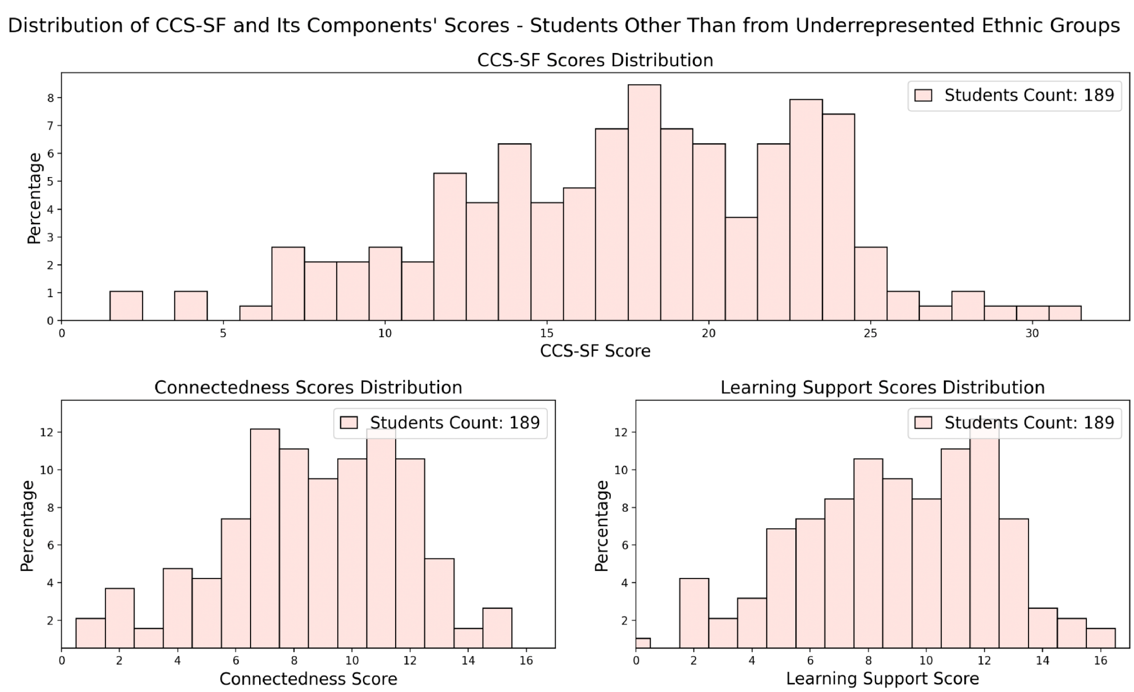

Figure 3.5: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants other than those from underrepresented ethnic groups.

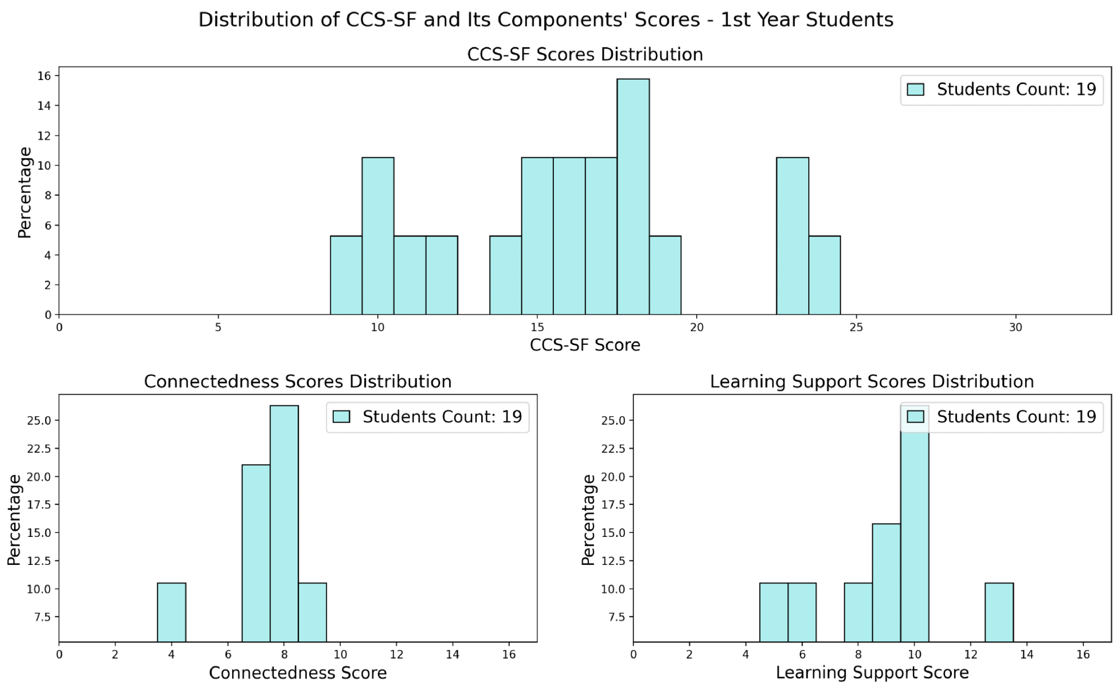

Figure 3.6: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants in the first year of their program.

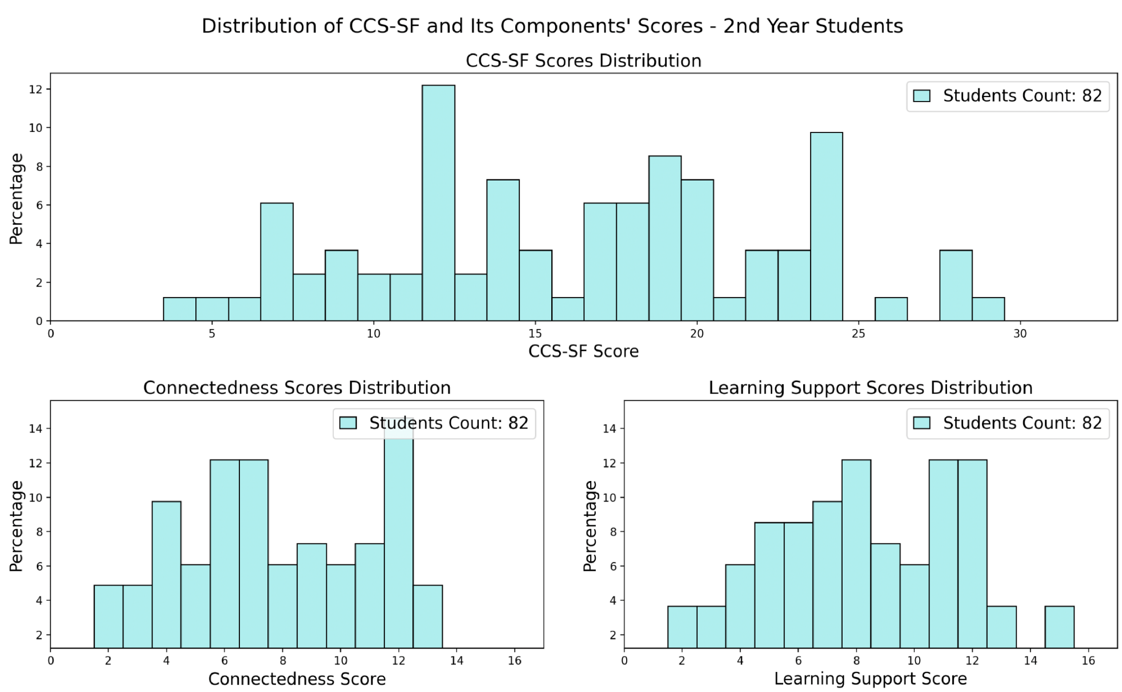

Figure 3.7: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants in the second year of their program.

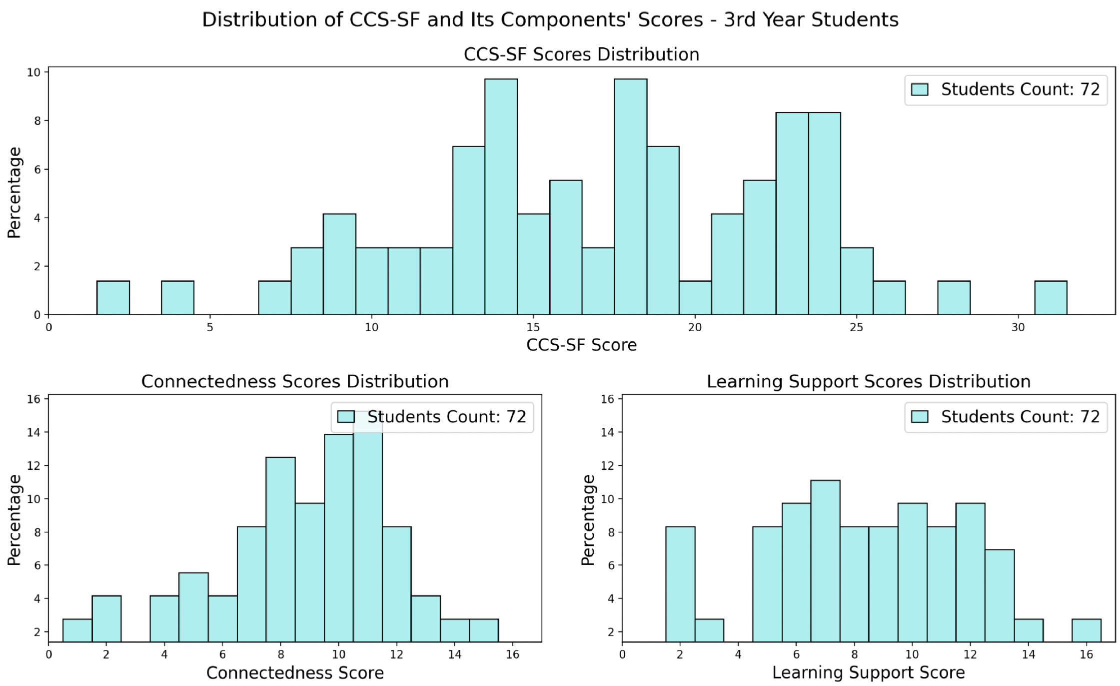

Figure 3.8: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants in the third year of their program.

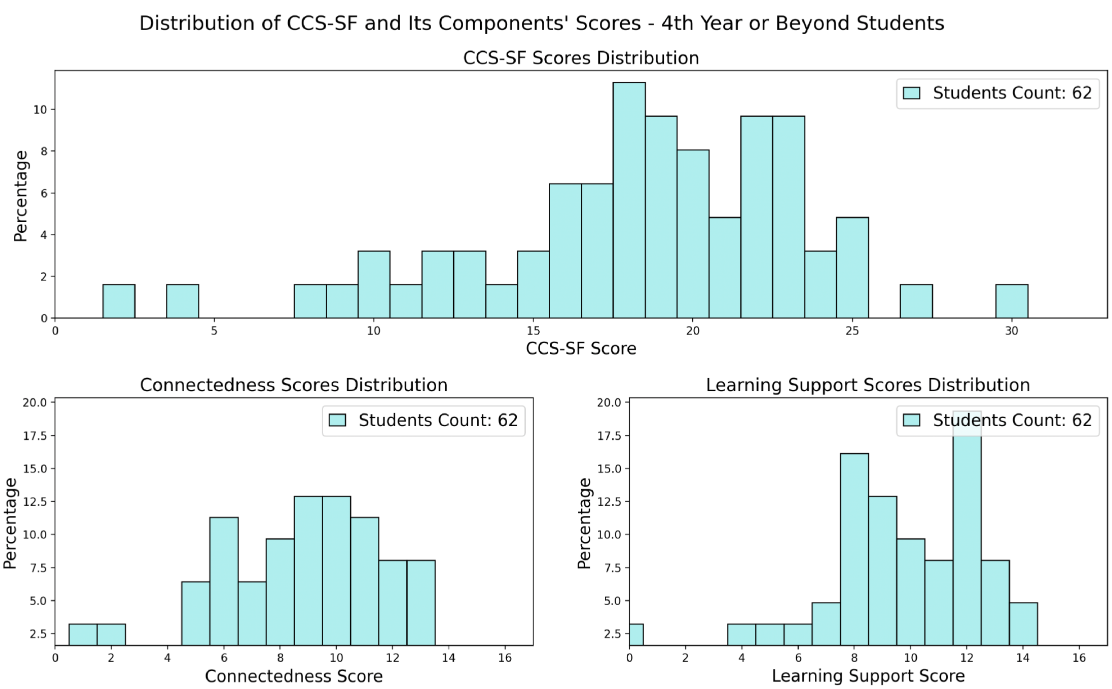

Figure 3.9: Distribution of CCS-SF scores, Connectedness scores, and Learning Support scores of participants in the fourth year of their program.

3.2.1.2 Participants' Social Connections

Figure 3.10 shows the distribution of participants' degree centralities in their courses' support networks, once excluding their external connections, that is, their connections with supportive individuals not enrolled in the course, and another time including those connections. Figure 3.11 shows the distribution of the numbers of different types of connections participants have in their courses' support networks. Table 3.13 shows the means and standard deviations of the numbers of different types of connections participants have in their courses' support network for participants in each demographic group.

The subset of first year students has the highest mean number of external connections, whereas the subset of fourth year students has the lowest number of external connections. The subset of South Asian or South-East Asian students has the highest mean number of different types of connections within their courses, while first year students have the lowest mean number of those connections. The table shows that among subsets of students in different program years, students in their second year have the highest number of connections in their courses. These numbers decrease slightly as students enter their third and fourth years. Second year students, however, also have the highest variability in the number of connections they have in their courses. The mean number of external connections students have decreases consistently as their program years increase.

It is worth noting that a large portion of participants (31.06%) did not list any connections inside their courses or outside them, likely because they do not have connections to list or because they might have been uncomfortable sharing such information. Only 53.6% of participants mentioned any connections with other students in their course. Only 37.45% of participants mentioned any external connections, predominantly mentioning family members, significant others, classmates from previous courses, and friends in the department who were not enrolled in the same course. Three students mentioned their pets and five students mentioned their course instructors or teaching assistants.

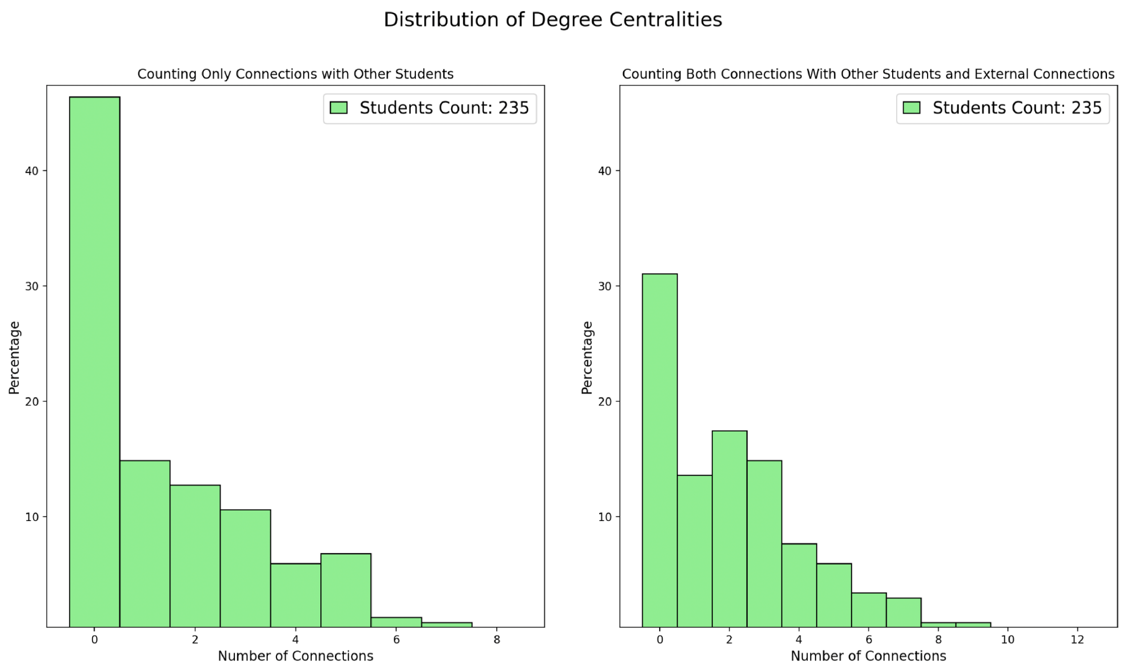

Figure 3.10.: Distribution of participants' degree centralities in their course support networks.

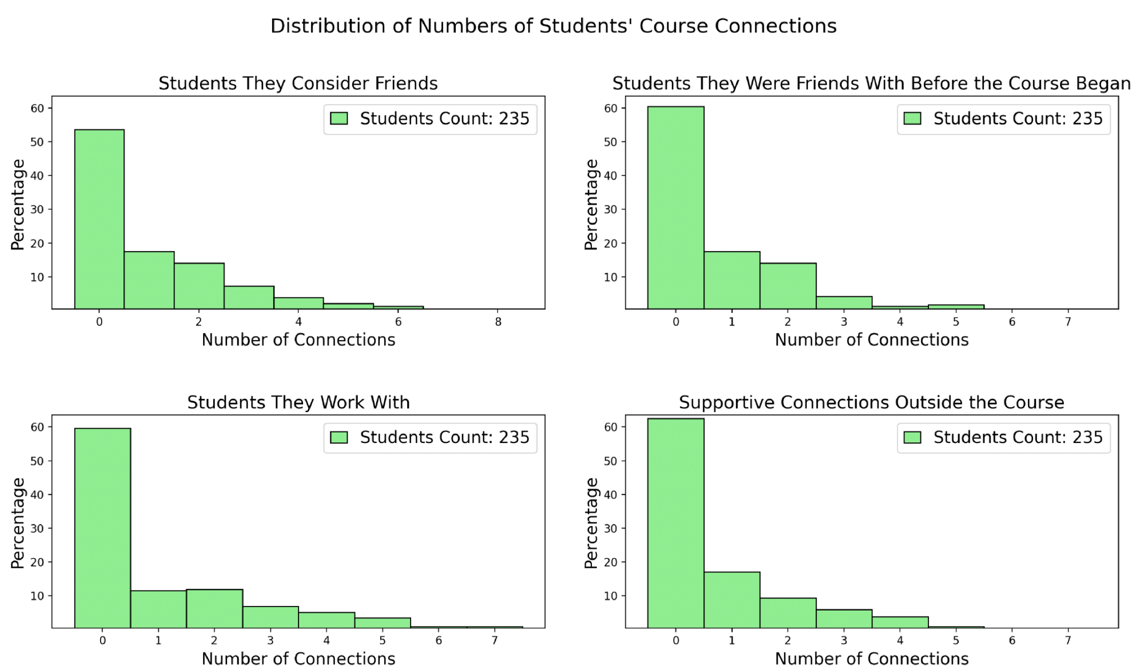

Figure 3.11: Distribution of the numbers of different types of connections participants have in their course support networks.

Table 3.13: Mean and standard deviation of the numbers of different types of connections participants have in their course support networks for participants in each subset.

Subset	**n**	**No. of Friends**	**No. of Friends Before Course**	**No. of Students they Work With**	**No. of Connections Outside Course**
		M(SD)	***M(SD)***	***M(SD)***	***M(SD)***
Underrepresented Genders	104	1.00 (1.533)	0.78 (1.322)	1.07 (1.742)	1.04 (1.513)
Men	124	1.11 (1.466)	0.81 (1.18)	1.04 (1.462)	0.57 (0.939)
International	75	1.37 (1.894)	1.00 (1.568)	1.11 (1.76)	0.79 (1.266)
Domestic	160	0.89 (1.213)	0.67 (1.026)	1.01 (1.505)	0.75 (1.234)
East Asian	44	0.80 (1.153)	0.57 (0.818)	0.98 (1.502)	0.48 (0.976)
South Asian or South-East Asian	74	1.39 (1.595)	1.04 (1.318)	1.41 (1.735)	0.68 (1.206)
White	65	0.89 (1.348)	0.66 (1.108)	0.85 (1.471)	0.88 (1.364)
Underrepresented Ethnic Groups	46	0.87 (1.641)	0.65 (1.509)	0.83 (1.596)	1.02 (1.325)
1st Year	19	0.37 (0.761)	0.21 (0.535)	0.32 (0.671)	1.47 (1.349)
2nd Year	82	1.27 (1.693)	0.96 (1.494)	1.16 (1.781)	1.07 (1.377)
3rd Year	72	1.00 (1.492)	0.72 (1.178)	1.08 (1.726)	0.60 (1.274)
4th Year	62	1.00 (1.268)	0.76 (1.003)	1.06 (1.291)	0.32 (0.672)

3.2.2 RQ1: Sense of Community Differences Across Genders, Ethnic Groups, Legal Statuses, and Program Years

We conducted null hypothesis significance tests to compare computer science students' CCS-SF scores, connectedness scores, and learning support scores across different genders, ethnic groups, legal statuses and program years. Our hypothesis was that students from underrepresented genders and ethnic groups and international students will have lower CCS-SF scores, Connectedness Scores, and Learning Support scores than their majority and domestic peers and that there will be differences in those scores across different program years.

Table 3.14 shows the results of the Kruskal-Wallis tests comparing participants' CCS-SF scores, Connectedness scores, and Learning Support scores across ethnic groups and participants' years in their programs. The results indicate a significant difference only in the Connectedness scores of students from different ethnic groups. However, power analysis, presented in Table C.1 in Appendix C indicates that all other tests lacked sufficient statistical power, with observed power values ranging between 18% and 33%. This indicates that the sample was inadequate for detecting small differences.

Given the relatively small, despite being larger than the significant thresholds, p-values and the low observed power of the Kruskal-Wallis tests, it is likely that with a bigger sample size we would observe significant differences in the CCS-SF and learning Support scores across different ethnic groups and in all three sense of community scores across students' different years in their programs.

Table 3.14: Comparing participants' CCS-SF scores, Connectedness scores, and Learning Support scores across ethnic groups and across program years using Kruskal–Wallis tests.

Subsets	**Kruskal-Wallis Tests**		
	CCS-SF Score	**Connectedness Score**	**Learning Support Score**
East Asian South Asian or South-East Asian White Underrepresented Ethnic Groups	$H = 6.84$ $p = .077$	$H = 12.68$ $p = .005$*	$H = 5.34$ $p = .148$
1st Year 2nd Year 3rd Year 4th Year	$H = 5.61$ $p = .132$	$H = 5.16$ $p = .160$	$H = 5.75$ $p = .124$

Note: * indicates $p < 0.05$.

Table 3.15 shows the results of Mann-Whitney tests comparing the Connectedness scores across each pair of ethnic groups. When conducting those tests, we hypothesized that White students will have higher scores than all other groups and that all groups will have higher scores than students from underrepresented ethnic groups. We hypothesized that the groups of East Asian and South Asian or South-Esat Asian students will have different scores. The results only support our hypothesis that students from underrepresented ethnic groups have lower scores than East Asian students.

Table 3.15 also shows the results of the Mann-Whitney U tests comparing participants' scores across genders and legal statuses. Students from underrepresented genders have significantly lower CCS-SF scores, Connectedness Scores, and Learning Support Scores than men.

Power analysis, presented in Table C.2 in Appendix C, indicates that where Mann-Whitney U tests failed to find significant differences, observed power was low. In all tests comparing the scores of international and domestic students, observed power was consistently at or below 5%.

Table 3.15: Comparing participants' CCS-SF scores, Connectedness scores, and Learning Support scores across genders, legal statuses, and ethnic groups using Mann-Whitney U tests.

Subset 1	**Subset 2**	**Mann-Whitney U Tests**		
		CCS-SF Score	**Connectedness Score**	**Learning Support Score**
Underrepresented Genders	Men	U = 4,740.0 p < .001* ***r* = .23**	U = 5,246.5 p = .008* ***r* = .16**	U = 4,820.5 p < .001* ***r* = .22**
International	Domestic	U = 6,088.0 p = .572 r = .01	U = 6,082.5 p = .568 r = .01	U = 6,167.0 p = .635 r = .02
East Asian	South Asian or South-East Asian	-	U = 1,971.5 p = 1.000 r = .18	-
East Asian	White	-	U = 1,836.5 p = 1.000 r = .24	-
Underrepresented Ethnic Groups	East Asian	-	U = 609.0 p < .001* ***r* = .34**	-
South Asian or South-East Asian	White	-	U = 2,607.0 p = 1.000 r = .07	-
Underrepresented Ethnic Groups	White	-	U = 1,314.0 p = .108 r = .19	-
Underrepresented Ethnic Groups	South Asian or South-East Asian	-	U = 1,287.0 p = .636 r = .12	-

Note: * indicates $p < 0.05$; bold indicates a medium or large effect size; a dash indicates this test was not performed due to insignificant Kruskall-Wallis results. P-values for tests across ethnic groups are Bonferroni corrected.

3.2.3 RQ2: Students' Responses to Free-response Question on Sense of Community

To better understand how computer science students perceive the community in their courses, we analyzed the responses to an optional free-response question where students could share anything they would like to share about their experience in the courses under study. We summarized each response into a brief list of the topics it covered and then identified the topics that recurred across multiple responses.

Of all participants, 110 (46.8%) had something to say in the free-response question. Of those responses, 47 (42.72%) were from students from underrepresented genders, 40 (36.36%) were from international students, 21 (19.09%) were from students from underrepresented ethnic groups, 35 (31.82%) were from White students, 35 (31.82%) were from students who identified with one of the South asian or South-East Asian ethnic groups, and 19 (17.27%) were from students who identified with one of the East Asian groups.

The most discussed topic related to the courses being challenging and that participants felt that they were struggling to succeed (n = 21). Eight students mentioned feeling that they do not have opportunities to connect with others in their courses.

> *"Since the class is so large, there is not really much opportunity for group bonding."*

> *"Not a lot of people go to class or lab so it's hard to find a study group or people to talk to about the course besides the discord chat."*

Nine students mentioned online communication, four of them referring to it as a way to connect with others and find support, while three mentioned that it limits their ability to feel connected to others in their courses.

> *"We were assigned groups for a presentation given during class; however, the presentations were held online with everyone leaving their camera turned off. This made it feel like I wasn't presenting to anyone (eased my anxiety, but it made me feel less connected to my peers)."*

“Unfortunately the format and time slot of this class means most students attend online via zoom, so there is not much opportunity for camaraderie.”

Three students mentioned that their classrooms are often too quiet.

“The classroom feels empty sometimes, and very quiet. It doesn't get loud before the lecture begins and it's very off putting.”

Thirteen students highlighted feeling supported by their course instructors.

“I like how the professors are understanding that we might be shy in admitting we got something wrong but they [...][they] encourage us that it is a good thing.”

“[The course instructor] creates a welcoming community in his classes.”

Five students mentioned that their course instructors do not foster the formation of community in their courses for example because their “rules are too harsh” or because students feel that their questions are not welcome.

Three students mentioned feeling unconfident in their abilities compared to their peers.

“There are a couple of people who are quite vocal (asking questions, etc.) and seem to have a lot of knowledge about all sorts of AI fields. At times, I get a bit of an imposter syndrome feeling when I compare my own knowledge to theirs.”

Two students mentioned perceiving competition among students in their courses.

“Like [...] other math related and cs related courses, I feel like there is constant competition going on behind the curtains, and feel like students are all (myself included) desperately trying to not look stupid by not being up to date with the recent trends and/or being a little different than most of the students.”

3.2.4 RQ3: Differences Between the Numbers of Strong and Weak Connections

We conducted Wilcoxon Signed-rank tests to compare the number of students' strong and weak. We hypothesized that all student subsets will have more weak than strong connections. Table 3.16 however shows that contrary to our hypothesis, all student subsets have more strong than weak connections with others in their courses. Power analysis, presented in Table C.3 in Appendix C, shows that the observed power for these tests ranged from moderate to high.

Table 3.16: Comparing number of strong connections and number of weak connections participants have in their courses for each subset using Mann-Whitney U tests.

Subset	**n**	**No. of Strong Connections**	**No. of Weak Connections**	**Wilcoxon Signed-rank Tests**		
		M(SD)	***M(SD)***	***U***	***p***	***r***
Underrepresented Genders	104	1.00 (1.533)	0.22 (0.668)	953	<.001*	**.71**
Men	124	1.11 (1.466)	0.19 (0.561)	1,902	<.001*	**.65**
International	75	1.37 (1.894)	0.17 (0.554)	604	<.001*	**.68**
Domestic	160	0.89 (1.213)	0.22 (0.641)	2,706.5	<.001*	**.68**
East Asian	44	0.80 (1.153)	0.27 (0.758)	155	.007*	**.72**
South Asian or South-East Asian	74	1.39 (1.595)	0.34 (0.781)	850	<.001*	**.60**
White	65	0.89 (1.348)	0.12 (0.451)	491	<.001*	**.66**
Underrepresented Ethnic Groups	46	0.87 (1.641)	0.07 (0.250)	136	<.001*	**.75**
1st Year	19	0.37 (0.761)	0.00 (0.000)	15	.017*	**.78**
2nd Year	82	1.27 (1.693)	0.21 (0.680)	803	<.001*	**.66**
3rd Year	72	1.00 (1.492)	0.25 (0.645)	494	<.001*	**.70**
4th Year	62	1.00 (1.268)	0.21 (0.577)	531	<.001*	**.62**

Note: *indicates $p < 0.05$; bold indicates a medium or large effect size.

3.2.5 RQ4: Differences in the Numbers of Different Types of Social Connections Across Genders, Ethnic Groups, Legal Statuses, and Program Years

We conducted null hypothesis significance tests to compare the numbers of different types of social connections computer science students have in their course support networks across different genders, ethnic groups, legal statuses, and students' years in their programs. Our hypothesis was that students from underrepresented genders and ethnic groups and international students will have fewer connections in their courses than their majority and domestic peers, while the number of supportive external connections will be different across genders, ethnic groups, and legal statuses. We hypothesized that there will be differences in the numbers of all types of connections across different years in students' programs.

Table 3.17 shows the results of the Kruskal-Wallis tests comparing the numbers of connections across ethnic groups and participants' years in their programs. The table shows a significant difference in the number of friends before the course began across ethnic groups. Power analysis, presented in Table C.4 in Appendix C indicates that all other tests across ethnic groups lacked statistical power, ranging from 43% to 54%. Across program years, Table 3.17 shows a significant difference in the number of external connections and an almost significant difference in the numbers of all types of connections with other students.

Table 3.18 shows the results of using Mann-Whitney tests to pinpoint the differences in the numbers of friends before the course between each pair of ethnic groups. When conducting those tests, we hypothesized that White students will have more friends before the course than all other groups and that all groups will have more friends before the course than students from underrepresented ethnic groups. We hypothesized that the groups of East Asian and South Asian or South-Esat Asian students will have a different number of friends before the course. The results only support our hypothesis that students from underrepresented ethnic groups have less friends before the course than White students. Table 3.13, showing the mean number of different types of connections students have, suggests that East Asian students have more friends before the course began than their South Asian or South-East Asian counterparts.

Table 3.17: Comparing numbers of different types of connections participants have across ethnic groups and across program years using Kruskal–Wallis tests.

Subsets	**Kruskal-Wallis Tests**			
	No. of Friends	**No. of Friends Before Course**	**No. of Students they Work With**	**No. of External Connections**
East Asian South Asian or South-East Asian White Underrepresented Ethnic Groups	$H = 6.79$ $p = .079$	$H = 8.3$ $p = .040$*	$H = 5.77$ $p = .124$	$H = 6.39$ $p = .094$
1st Year 2nd Year 3rd Year 4th Year	$H = 5.86$ $p = .119$	$H = 6.14$ $p = .105$	$H = 5.12$ $p = .163$	*$H = 23.86$* *$p < .001$**

Note: * indicates $p < 0.05$; bold indicates a medium or large effect size.

Table 3.18 also shows the results of using Mann-Whitney tests to pinpoint the differences in the numbers of external connections between each pair of program years. When conducting those tests, we hypothesized that students in each year will have a different number of connections than students in all other years. The results support our hypothesis except when comparing the number of external connections of students in their first and second years. Table 3.13 shows that the mean number of external connections students have decreases as their years in their program increase.

Finally, Table 3.18 shows the results of the Mann-Whitney U tests comparing the number of connections participants have across genders and legal statuses. Students from underrepresented genders have a significantly different number of external connections than men. Table 3.13 suggests that students from underrepresented genders (M = 1.04) have more external connections than men (M = 0.57).

Power analysis, presented in Table C.5 in Appendix C, indicates that where Mann-Whitney U tests failed to find significant differences, observed power was consistently low, ranging from 0% in the test comparing the scores of White to South Asian or South-East Asian students to 33% in the test comparing the scores of third and fourth year students.

Table 3.18: Comparing numbers of different types of connections participants have across genders, legal statuses, ethnic groups, and program years using Mann-Whitney U tests.

Subset 1	**Subset 2**	**Mann-Whitney U Tests**			
		No. of Friends	**No. of Friends Before Course**	**No. of Students they Work With**	**No. of External Connections**
Underrepresented Genders	Men	U = 6,118.0 p = .234 r = .04	U = 6,244.5 p = .321 r = .03	U = 6,180.5 p = .272 r = .04	U = 7,296.0 p = .050* r = .11
International	Domestic	U = 6,490.0 p = .865 r = .07	U = 6,452.0 p = .856 r = .06	U = 6,004.5 p = .505 r = .00	U = 5,976.0 p = .955 r = .00
East Asian	South Asian or South-East Asian	-	U = 1,342.5 p = .246 r = .15	-	-
East Asian	White	-	U = 1,429.0 p = 1.000 r = .00	-	-
Underrepresented Ethnic Groups	East Asian	-	U = 903.5 p = .858 r = .09	-	-
South Asian or South-East Asian	White	-	U= 2,802.5 p = 1.000 r = .14	-	-
Underrepresented Ethnic Groups	White	-	U= 1,290.5 p = .036* **r = .20**	-	-
Underrepresented Ethnic Groups	South Asian or South-East Asian	-	U = 1,328.0 p = .684 r = .09	-	-
1st Year	2nd Year	-	-	-	U = 932.0 p = .948 r = .13

1st Year	3rd Year	-	-	-	U = 977.5 p = .006* **r = .30**
1st Year	4th Year	-	-	-	U = 896.0 p <.001* **r = .38**
2nd Year	3rd Year	-	-	-	U = 3,598.5 p = .048* **r = .19**
2nd Year	4th Year	-	-	-	U = 3,311.5 p < .001* **r = .26**
3rd Year	4th Year	-	-	-	U = 2,401.5 p = 1.000 r = .07

Note: *indicates $p < 0.05$; bold indicates a medium or large effect size; a dash indicates this test was not performed due to insignificant Kruskall-Wallis results. P-values for tests across ethnic groups or across program years are Bonferroni corrected.

3.2.6 RQ5: Students' Responses to Free-response Question About their Supportive Connections

To better understand how computer science students perceive their supportive connections, we analyzed the responses to an optional free-response question where students could share anything they would like to share about their connections and how they support their academic success. We summarized each response into a brief list of the topics it covered and then identified the topics that recurred across multiple responses.

Of all participants, 73 (31.1%) had something to say about their supportive connections. Of those responses, 35 (47.94%) were from students from underrepresented genders, 22 (30.14%) were from international students, 17 (23.29%) were from students from underrepresented ethnic groups, 22 (30.14%) were from White students, 22 (30.14%) were from students who identified with one of the South asian or South-East Asian ethnic groups, and 12 (16.44 %) were from students who identified with one of the East Asian groups.

Twenty students mentioned that their connections support academic success.

> *"I usually ask my connections when there is something I don't understand in the lecture before asking the professor or a [teaching assistant]."*

> *"People are trying to teach each other in discord, giving links to material that helped them, etc. Never experienced this sort of community in other courses."*

> *"Without my friends, I would be suffering a whole lot more in this course and doubt my skills and knowledge all the time."*

> *"My one friend that I have had prior to this class encourages me to attend [...] lectures."*

> *"I would have quit school without my friends."*

Three said that their interactions with people they are connected to help them gauge their level of understanding of their course material. However, twenty-three students talked about having no strong connections in their course.

> *"I would just like to clarify that I did not list any names [...] despite interacting with various students often during class. Not only do I not know most of their names, the frequency of our interaction depends mostly on where we choose to sit when we arrive, so I do not have any specific students in mind when I consider frequent interactions with classmates."*

> *"I honestly do not really have any friends in my program. I guess I know some people by face but not enough to consider them friends."*

> *"I am not a social person to begin with, but after starting my studies in CS, I feel like my socialization deteriorated even more. There are times I feel I don't fit in and feel detached from other students in the lectures."*

> *"I don't actively make friends in-class in many of my classes, especially in [computer science] classes. As a first year [student], I especially do not have many friends in this class as most people cannot relate to me."*

> *"I have zero social connections (although I do want to [have connections])"*

Five students said their courses do not provide them with an opportunity to connect to their peers.

> *"What social connections? I mean, where is the opportunity to develop social connection in this class?"*

Six students said they do not have connections or that they feel lonely in the university as a whole.

> *"[The university] is an extremely lonely place for undergraduate science students."*

Seven students mentioned online communication as a way to connect with and be supported by their peers, and two mentioned that they would prefer if they could interact with their peers in real life too.

3.2.7 RQ6: The Influence of Degree Centrality on Sense of Community

We used linear regression to assess the influence of students' degree centrality in their courses' social networks and the number of external supportive connections they have on their CCS-SF scores, Connectedness scores, and Learning Support scores. We hypothesized that degree centrality in course social networks positively influences the Connectedness and CCS-SF scores of computer-science students. Meanwhile, we hypothesized that connections with supportive individuals outside the course would negatively influence computer-science students' sense of community. We also hypothesized that Learning Support scores will not be strongly influenced by students' degree centrality in their courses or by the number of external connections they have.

Table 3.19 shows the linear regression models predicting participants' CCS-SF scores for each demographic group. Although not always statistically significant, our analysis revealed that degree centrality is a weak positive predictor of CCS-SF scores except for students in their first year, while the number of external connections is a weak negative predictor except for students in their fourth year. This finding supports our hypothesis across most demographic groups. However, the variance explained by these models is below 10%.

Table 3.20 shows the models predicting Connectedness and Learning Support scores. Again, for most demographic groups, degree centrality is a positive predictor of both scores, while the number of external connections is a negative predictor. Notably models predicting Connectedness scores have larger adjusted beta values and explain a larger proportion of the variance in scores than both other types of models. The explained variance is particularly high for the subsets of students from underrepresented genders, students from underrepresented ethnic groups, domestic students, White students, and students in their second year. As we anticipated, the variance explained by models predicting Learning Support is low, consistently below 5%, and the variance explained by models predicting CCS-SF scores, calculated as the sum of Connectedness and Learning Support scores, is higher than that of Learning Support models but lower than that of Connectedness models.

Table 3.19: Linear regression predicting participants' CCS-SF scores using their degree centrality in their course social networks and the number of their external connections for each student subset.

Subset	CCS-SF Score		
	Adj. R^2	**Degree Centrality in Course**	**No. of External Connections**
Underrepresented Genders	0.045	Adj. β = 0.224 *p* = .01*	Adj. β = -0.058 *p* = .532
Men	0.038	Adj. β = 0.121 *p* = .093	Adj. β = -0.158 *p* = .041*
International	0.016	Adj. β = 0.169 *p* = .082	Adj. β = -0.017 *p* = .834
Domestic	0.061	Adj. β = 0.165 *p* = .012*	Adj. β = -0.211 *p* = .014*
East Asian	0.045	Adj. β = 0.039 *p* = .706	Adj. β = -0.02 *p* = .888
South Asian or South-East Asian	0.091	Adj. β = 0.237 *p* = .005*	Adj. β = -0.153 *p* = .107
White	0.034	Adj. β = 0.114 *p* = .346	Adj. β = -0.255 *p* = .076
Underrepresented Ethnic Groups	0.019	Adj. β = 0.272 *p* = .105	Adj. β = -0.05 *p* = .647
1st Year	0.052	Adj. β = -0.224 *p* = .383	Adj. β = -0.345 *p* = .116
2nd Year	0.082	Adj. β = 0.337 *p* = .003*	Adj. β = -0.092 *p* = .348
3rd Year	0.007	Adj. β = 0.056 *p* = .535	Adj. β = -0.201 *p* = .134
4th Year	0.045	Adj. β = 0.194 *p* = .055*	Adj. β = 0.079 *p* = .464

Note: * indicates $p < 0.05$.

Table 3.20: Linear regression predicting participants' Connectedness scores and Learning Support scores using their degree centrality in their course social networks and the number of their external connections for each student subset.

Subset	Connectedness Score			Learning Support Score		
	Adj. R^2	Degree Centrality in Course	No. of External Connections	Adj. R^2	Degree Centrality in Course	No. of External Connections
Underrepresented Genders	0.145	Adj. β = 0.379 p < .001*	Adj. β = -0.151 p = .116	0.016	Adj. β = 0.039 p = .679	Adj. β = 0.042 p = .685
Men	0.038	Adj. β = 0.167 p = .049*	Adj. β = -0.163 p = .073	0.006	Adj. β = 0.057 p = .451	Adj. β = -0.124 p = .131
International	0.04	Adj. β = 0.216 p = .029*	Adj. β = -0.031 p = .703	0.016	Adj. β = 0.093 p = .391	Adj. β = -0.0 p = .997
Domestic	0.103	Adj. β = 0.29 p <.001*	Adj. β = -0.282 p = .007*	0.003	Adj. β = 0.048 p = .522	Adj. β = -0.145 p = .141
East Asian	0.012	Adj. β = 0.116 p = .277	Adj. β = 0.036 p = .806	0.04	Adj. β = -0.031 p = .787	Adj. β = -0.069 p = .663
South Asian or South-East Asian	0.052	Adj. β = 0.226 p = .022*	Adj. β = -0.143 p = .204	0.044	Adj. β = 0.201 p = .031*	Adj. β = -0.133 p = .213
White	0.100	Adj. β = 0.231 p = .059	Adj. β = -0.318 p = .027*	0.021	Adj. β = -0.038 p = .784	Adj. β = -0.127 p = .435
Underrepresented Ethnic Groups	0.121	Adj. β = 0.421 p = .007*	Adj. β = -0.066 p = .506	0.046	Adj. β = 0.015 p = .924	Adj. β = -0.015 p = .883
1st Year	0.021	Adj. β = -0.145 p = .446	Adj. β = -0.182 p = .255*	0.004	Adj. β = -0.149 p = .557	Adj. β = -0.293 p = .175
2nd Year	0.116	Adj. β = 0.392 p = .001*	Adj. β = -0.122 p = .212*	0.016	Adj. β = 0.196 p = .074	Adj. β = -0.039 p = .682
3rd Year	0.084	Adj. β = 0.214 p = .038*	Adj. β = -0.338 p = .027*	0.014	Adj. β = -0.092 p = .408	Adj. β = -0.073 p = .653
4th Year	0.045	Adj. β = 0.212 p = .07	Adj. β = 0.118 p = .345	0.003	Adj. β = 0.149 p = .203	Adj. β = 0.029 p = .818

Note: * indicates $p < 0.05$.

3.2.8 RQ7: Sense of Community Differences Across Collaborative Requirements

We conducted null hypothesis significance tests comparing the CCS-SF, Connectedness, and Learning Support scores of students in different demographic groups across courses with varying degrees of collaborative learning: none, optional, and required. We hypothesized that students will have higher scores in courses with an optionally collaborative component compared to courses without a collaborative component and in courses with a required collaborative component compared to both other course categories: courses with an optionally collaborative component and courses without a collaborative component. Table 3.21 shows the mean and standard deviation of participants' CCS-SF score, Connectedness scores, and Learning Support scores across the three course categories.

Table 3.21: Mean and standard deviation of participants' CCS-SF score, Connectedness scores, and Learning Support scores across course categories.

Subset	**Score**	**No Collaborative Component**		**Optional Collaborative Component**		**Required Collaborative Component**	
		n	***M(SD)***	***n***	***M(SD)***	***n***	***M(SD)***
Underrepresented Genders	CCS-SF	70	15.66 (5.988)	10	13.8 (3.882)	24	16.79 (5.595)
	Connectedness	70	7.67 (3.300)	10	7.5 (3.100)	24	8.54 (3.476)
	Learning Support	70	7.99 (3.420)	10	6.3 (2.163)	24	8.25 (3.124)
Men	CCS-SF	77	17.88 (5.492)	11	19.0 (5.02)	36	18.69 (5.691)
	Connectedness	77	8.39 (3.121)	11	9.91 (3.081)	36	9.44 (3.806)
	Learning Support	77	9.49 (3.575)	11	9.09 (3.78)	36	9.25 (2.941)
International	CCS-SF	47	17.43 (6.230)	9	13.67 (4.000)	19	18.32 (5.538)
	Connectedness	47	8.26 (3.326)	9	8.0 (2.828)	19	9.42 (3.254)
	Learning Support	47	9.17 (3.886)	9	5.67 (2.55)	19	8.89 (3.264)

Domestic	CCS-SF	102	16.47 (5.623)	13	18.46 (4.824)	45	17.91 (5.919)
	Connectedness	102	7.93 (3.176)	13	9.23 (3.419)	45	9.04 (3.837)
	Learning Support	102	8.54 (3.406)	13	9.23 (2.976)	45	8.87 (3.109)
East Asian	CCS-SF	19	17.84 (7.057)	8	16.75 (4.921)	17	19.76 (6.037)
	Connectedness	19	9.05 (3.358)	8	10.0 (2.928)	17	10.59 (3.001)
	Learning Support	19	8.79 (4.077)	8	6.75 (3.454)	17	9.18 (3.592)
South Asian or South-East Asian	CCS-SF	46	16.65 (5.458)	5	17.0 (4.743)	23	18.22 (5.099)
	Connectedness	46	8.24 (3.308)	5	10.0 (2.236)	23	8.91 (3.118)
	Learning Support	46	8.41 (3.606)	5	7.0 (3.082)	23	9.3 (3.154)
White	CCS-SF	49	17.24 (5.456)	4	17.25 (4.992)	12	18.92 (5.384)
	Connectedness	49	7.88 (2.913)	4	6.5 (3.0)	12	9.83 (4.152)
	Learning Support	49	9.37 (3.444)	4	10.75 (2.062)	12	9.08 (2.746)
Underrepresented Ethnic Groups	CCS-SF	31	15.45 (5.999)	3	18.67 (3.055)	12	14.33 (6.005)
	Connectedness	31	7.42 (3.364)	3	9.33 (2.309)	12	6.92 (4.166)
	Learning Support	31	8.03 (3.371)	3	9.33 (1.155)	12	7.42 (2.644)
3rd Year	CCS-SF	34	18.09 (5.921)	9	17.33 (4.822)	29	16.07 (6.088)
	Connectedness	34	8.79 (2.993)	9	9.67 (2.55)	29	8.34 (3.885)
	Learning Support	34	9.29 (3.842)	9	7.67 (3.606)	29	7.72 (3.422)
4th Year	CCS-SF	30	17.73 (5.813)	11	16.45 (5.574)	21	20.0 (4.037)
	Connectedness	30	8.03 (3.124)	11	8.64 (3.414)	21	10.05 (3.309)
	Learning Support	30	9.7 (3.761)	11	7.82 (3.459)	21	9.95 (1.987)

Table 3.22 shows the results of Kruskal-Wallis tests comparing students CCS-SF, Connectedness, and Learning Support scores across the three course categories. The table only indicates significant differences in the Learning Support scores of international students across the three course categories. Again, power analysis, presented in Table C.6 in Appendix C

indicates that all other tests had low to moderate statistical power, ranging from 7% to 66% when comparing the CCS-SF scores of international students across course categories.

Table 3.22: Comparing participants' CCS-SF scores, Connectedness scores, and Learning Support scores across course categories for each subset using Kruskal–Wallis tests.

Subset	Kruskal-Wallis Tests					
	CCS-SF Score		**Connectedness Score**		**Learning Support Score**	
	H	***p***	***H***	***p***	***H***	***p***
Underrepresented Genders	1.89	.389	1.66	.437	3.64	.162
Men	0.31	.856	4.05	.132	0.57	.753
International	4.85	.088	2.71	.258	8.10	.017*
Domestic	1.79	.409	4.51	.105	0.81	.669
East Asian	1.70	.427	1.69	.430	2.63	.269
South Asian or South-East Asian	1.19	.552	1.97	.373	2.75	.253
White	0.67	.717	3.91	.141	0.90	.638
Underrepresented Ethnic Groups	1.29	.526	1.21	.545	1.34	.512
3rd Year	3.23	.199	0.46	.794	3.50	.174
4th Year	3.50	.174	4.53	.104	3.38	.184

Note: * indicates $p < 0.05$.

Table 3.23 shows the results of using Mann-Whitney tests to pinpoint those differences between each pair of course categories. The table shows that international students have higher Learning Support scores in courses with a required collaborative component than in courses where collaborative work is optional. However, contrary to our hypothesis, mean Learning Support scores, shown in the same table, suggest that international students in this department have higher Learning Support scores in courses without a collaborative component than in both other course categories. Power analysis, presented in Table C.7 in Appendix C, shows that all three Mann-Whitney U tests had an observed statistical power below 40%.

Table 3.23: Comparing Learning Support scores of participants who identified as international students across course categories by collaboration requirement using Mann-Whitney U tests.

Group 1			**Group 2**			**Mann-Whitney U Tests**		
Collaboration Requirement	***n***	***M(SD)***	**Collaboration Requirement**	***n***	***M(SD)***	***U***	***p***	***r***
None	47	9.17 (3.886)	Optional	9	5.67 (2.550)	331.0	1.000	**.36**
None	47	9.17 (3.886)	Required	19	8.89 (3.264)	481.5	1.000	.06
Optional	9	5.67 (2.550)	Required	19	8.89 (3.264)	33.5	.015*	**.48**

Note: * indicates $p < 0.05$; bold indicates a medium or large effect size. All p-values are Bonferroni corrected.

3.2.9 RQ8: Degree Centrality Differences Across Collaborative Requirements

We conducted null hypothesis significance tests comparing the degree centralities of students in different demographic groups across courses with varying degrees of collaborative learning: none, optional, and required. We hypothesized that students will have higher degree centralities in courses with an optionally collaborative component compared to courses without any collaborative component and in courses with a required collaborative component compared to both other course categories: courses with an optionally collaborative component and courses without a collaborative component.

Table 3.24 shows the results of Kruskal-Wallis tests comparing students' degree centralities across the three course categories. The table indicates significant differences in the degree centralities of men, domestic students, and students in their fourth year. The table additionally shows almost significant differences in the degree centralities of most other groups. Power analysis of these tests is presented in Table C.8 in Appendix C and indicates that in most cases where the tests failed to find significant results, observed power was low or moderate, ranging from 32% in the test comparing the degree centralities of White students across course categories to 71% in the test comparing the degree centralities of students from underrepresented genders.

Table 3.24: Comparing participants' degree centralities in their course social networks across course categories for each subset using Kruskal–Wallis tests.

Subset	**No Collaborative Component**		**Optional Collaborative Component**		**Required Collaborative Component**		**Kruskal–Wallis Tests**	
	n	***M(SD)***	***n***	***M(SD)***	***n***	***M(SD)***	***H***	***p***
Underrepresented Genders	70	1.26 (1.831)	10	0.70 (1.059)	24	2.25 (2.111)	5.06	.08
Men	77	1.31 (1.558)	11	0.64 (1.027)	36	2.25 (2.116)	7.25	.027*
International	47	1.74 (1.994)	9	0.33 (0.707)	19	2.37 (2.65)	4.74	.093
Domestic	102	1.06 (1.475)	13	0.92 (1.115)	45	2.13 (1.817)	12.17	.002*
East Asian	19	1.0 (1.202)	8	0.25 (0.707)	17	2.06 (2.135)	5.41	.067
South Asian or South-East Asian	46	1.63 (1.717)	5	1.8 (1.304)	23	2.87 (2.282)	4.76	.093
White	49	1.12 (1.576)	4	0.75 (0.5)	12	1.75 (1.913)	1.03	.596
Underrepresented Ethnic Groups	31	0.97 (1.888)	3	0.33 (0.577)	12	1.58 (1.564)	2.91	.234
3rd Year	34	1.35 (1.756)	9	0.33 (0.707)	29	1.93 (2.137)	4.36	.113
4th Year	30	1.03 (1.189)	11	0.91 (1.221)	21	2.43 (2.135)	6.26	.044*

Note: * indicates $p < 0.05$.

Table 3.25 uses Mann-Whitney tests to pinpoint differences between each pair of course categories. The table shows that men have higher degree centralities in courses with a required collaborative component than in both other course categories and that domestic students and students in their fourth year have higher degree centralities in courses with a required collaborative component than in courses without a collaborative component. Power analysis, presented in Table C.9 in Appendix C, shows that where our tests failed to find significant differences, observed power was below 5%, except in the test comparing men's degree centralities in courses without a collaborative component to their degree centralities in courses with a required collaborative component, where power was high (84%) and the p-value was almost significant (.08).

Table 3.25: Comparing degree centralities in course social networks of participants who identified as men, domestic students, or students in their 4th year across course categories by collaboration requirement using Mann-Whitney tests.

Subset	**Group 1**			**Group 2**			**Mann-Whitney U Tests**		
	Collaboration Requirement	***n***	***M(SD)***	**Collaboration Requirement**	***n***	***M(SD)***	***U***	***p***	***r***
Men	None	77	1.31 (1.558)	Optional	11	0.64 (1.027)	524.0	1.000	.14
	None	77	1.31 (1.558)	Required	36	2.25 (2.116)	1,057.0	.051	.19
	Optional	11	0.64 (1.027)	Required	36	2.25 (2.116)	115.5	.045*	**.30**
Domestic	None	102	1.06 (1.475)	Optional	13	0.92 (1.115)	657.0	1.000	.00
	None	102	1.06 (1.475)	Required	45	2.13 (1.817)	1,530.5	<.001*	**.27**
	Optional	13	0.92 (1.115)	Required	45	2.13 (1.817)	187.0	.066	**.26**
4th Year	None	30	1.03 (1.189)	Optional	11	0.91 (1.221)	180.5	1.000	.07
	None	30	1.03 (1.189)	Required	21	2.43 (2.135)	202.0	.039*	**.30**
	Optional	11	0.91 (1.221)	Required	21	2.43 (2.135)	69.0	.087	**.33**

Note: * indicates $p < 0.05$; bold indicates a medium or large effect size. All p-values are Bonferroni corrected.

3.2.10 RQ9: Differences in the Number of Strong Connections Formed Across Collaborative Requirements

Figure 3.8 and Table 3.26 show the distribution of the number of students who participants identified as their friends who were not friends before the course began, that is, the number of strong connections they formed during the course, across course categories. The table shows that the subsets of students from underrepresented genders, East Asian students, international students, and students in their fourth year have particularly high standard deviations in the number of connections they formed in courses with a required collaborative component.

Since over 90% of students enrolled in courses with an optional collaborative component did not identify any strong connections formed through these courses, we excluded such courses when addressing this question. We employed Mann-Whitney U tests to compare the number of strong connections students formed in courses without a collaborative component to the number of strong connections they formed in courses with a required collaborative component.

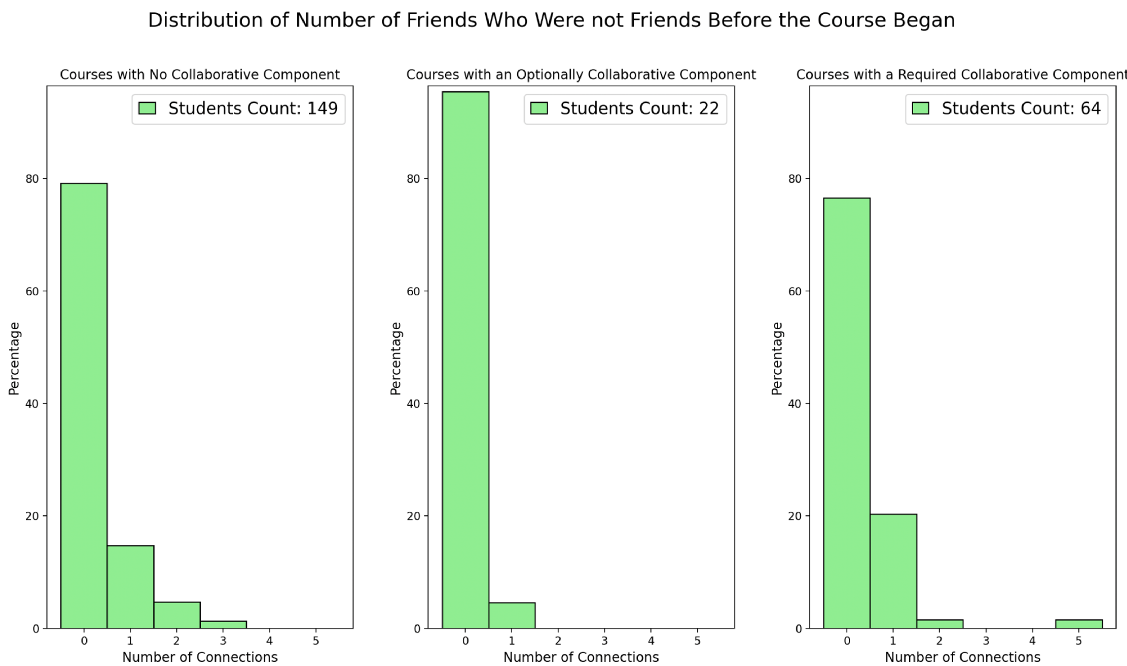

Figure 3.12: Distribution of participants' number of friends who were not friends before the course began across course categories.

Table 3.26: Mean and standard deviation of the number of students participants identified as their friends but not their friends before the course began across course categories.

Subset	No Collaborative Component		Optional Collaborative Component		Required Collaborative Component	
	n	***M(SD)***	***n***	***M(SD)***	***n***	***M(SD)***
Underrepresented Genders	70	0.17 (0.45)	10	0.00 (0.000)	24	0.46 (1.062)
Men	77	0.39 (0.728)	11	0.00 (0.000)	36	0.22 (0.485)
International	47	0.36 (0.705)	9	0.00 (0.000)	19	0.58 (1.216)
Domestic	102	0.25 (0.571)	13	0.08 (0.277)	45	0.2 (0.405)
East Asian	19	0.21 (0.419)	8	0.00 (0.000)	17	0.35 (1.222)
South Asian or South-East Asian	46	0.41 (0.748)	5	0.00 (0.000)	23	0.3 (0.559)
White	49	0.24 (0.522)	4	0.00 (0.000)	12	0.25 (0.452)
Underrepresented Ethnic Groups	31	0.16 (0.583)	3	0.33 (0.577)	12	0.33 (0.492)
3rd Year	34	0.41 (0.783)	9	0.0 (0.0)	29	0.21 (0.412)
4th Year	30	0.10 (0.305)	11	0.09 (0.302)	21	0.52 (1.167)

Our hypothesis was that students formed more strong connections in courses with a required collaborative component compared to courses without a collaborative component. Table 3.27 shows that our hypothesis was only supported for the subsets of students from underrepresented ethnic groups and students in their fourth year. Power analyses, presented in Table C.10 in Appendix C, show that where our tests failed to find significant results, the observed power was consistently below 25%, except in the test conducted on the responses of students from underrepresented genders where observed power was 57%. Table 3.27 also shows that this test has an almost significant p-value, suggesting that larger and more balanced sample sizes would likely show a significant difference.

Table 3.27: Comparing the number of students participants identified as their friends but not their friends before the course began across courses without a collaborative component and courses with a required collaborative component using Mann-Whitney U tests.

Subset	No Collaborative Component		Required Collaborative Component		Mann-Whitney U Tests		
	n	*M(SD)*	*n*	*M(SD)*	*U*	*p*	*r*
Underrepresented Genders	70	0.17 (0.45)	24	0.46 (1.062)	716.0	.055	.11
Men	77	0.39 (0.728)	36	0.22 (0.485)	1,509.5	.845	.07
International	47	0.36 (0.705)	19	0.58 (1.216)	418.0	.306	.05
Domestic	102	0.25 (0.571)	45	0.2 (0.405)	2,286.0	.479	.00
East Asian	19	0.21 (0.419)	17	0.35 (1.222)	174.5	.746	.07
South Asian or South-East Asian	46	0.41 (0.748)	23	0.3 (0.559)	549.5	.634	.03
White	49	0.24 (0.522)	12	0.25 (0.452)	283.5	.399	.02
Underrepresented Ethnic Groups	31	0.16 (0.583)	12	0.33 (0.492)	144.0	.040*	.17
3rd Year	34	0.41 (0.783)	29	0.21 (0.412)	533.5	.777	.07
4th Year	30	0.10 (0.305)	21	0.52 (1.167)	253.5	.039*	.16

Note: * indicates $p < 0.05$; bold indicates a medium or large effect size.

3.3 Discussion

This study examined interactions among the sense of community of computer-science students, the numbers of supportive social connections they have, and the employment of collaborative learning in their courses.

Our analysis did not find any significant differences between the sense of community of international and domestic students. This, however, might be due to the small representation of international students in our sample and the low observed statistical power, which was consistently at or below 5% for tests comparing the sense of community scores of international and domestic students.

Aligning with the recent findings of Mooney et al. (2020), Rainey et al. (2018), and Sax et al. (2018), our analysis showed that students from underrepresented genders experienced a lower sense of community in computer-science courses than men. Similarly, students from underrepresented ethnic groups had the lowest mean sense of community scores across ethnic groups. Our analysis also suggests that students in the earlier years of their programs experience a lower sense of community than students in later years. Sense of community, measured by CCS-SF scores and both of its components, tended to increase as program years increased.

As highlighted in the Background chapter of this thesis, sense of community is an important component of student motivation, which in turn is essential for persistence (Tinto, 2012). Students from underrepresented genders (Tamer and Stout, 2016) and underrepresented ethnic groups (Lehman et al., 2022) are more likely to leave computing majors than their majority peers. Similarly, students in their first year are more likely to leave post-secondary programs than students in any other year (Hanson, 2023; Tinto, 1975). The low sense of community experienced by these groups of students suggests that students from underrepresented genders, underrepresented ethnic groups, and students in their first year in the department where the study was conducted are at high risk of attrition.

Sense of community is affected by students' social connections (Rainey et al., 2018; Westwood & Barker, 1990). When responding to free-response questions, students expressed a belief that having connections in their courses would support their success in their programs. However, many students wrote that they feel disconnected from their peers. When listing their social connections with other students in their course or with individuals not enrolled in the course who support their academic success, more than 31% of participants listed no connections at all. Only 53.6% of participants had any connections with other students in their course and only 37.45% had supportive external connections.

Students from underrepresented genders had more external connections than men, and students in the earlier years of their programs had more external connections than students in their later years. As students' years in their programs increased, the number of connections they had within their courses increased and the number of their external supportive connections decreased. Our analysis did not indicate differences between the numbers of connections of international and domestic students. However, this again might be due to the low observed power (between 0% and 6%) of the related tests.

Generally, our analysis showed that the number of external connections a student has was a weak negative predictor of sense of community. This aligns with the interpretation by Dawson (2008) that students with strong external networks are less likely to look for community in their courses. It could also suggest that students who are unable to find community in their courses are more likely to rely on their external connections for support. Meanwhile, degree centrality in course social networks was a weak positive predictor of sense of community. A single exception for this pattern was found among first year students, for whom degree centrality was a negative predictor of sense of community. This exception could be attributed to the transitional nature of the first year. First year students may not yet be able to develop a sense of community through their newly formed social connections as they are still adapting to the new post-secondary environment.

Linear regression models predicting sense of community scores using students' degree centralities explained higher percentages of the variance in scores for students from underrepresented genders, students from underrepresented ethnic groups, domestic students, White students, and students in their second year than for other student subsets. This suggests that social connections have an especially large influence on the sense of community of students in these groups.

Among all subsets of students in different program years, students in their second year had the highest mean number of connections in their courses. This suggests that as courses became more demanding after the first year, some second year students actively sought to establish more connections with their peers to bolster their academic success. Interestingly, these numbers decreased as students entered their third and fourth years. Concurrently, the mean number of students' external connections decreased consistently as program years increased. This trend may imply that as students became more engaged with their university communities, they gradually disengaged from their external social networks. Alternatively, it could suggest that the stronger a university community students have, the less they rely on their external connections to support their academic success.

Contrary to the findings of previous research, students in this study generally had more strong than weak connections in their courses. A limited number of weak connections may indicate a low betweenness centrality (Otte and Rousseau, 2002), resulting in reduced access to bridging social capital. When available, bridging social capital increases the diversity of resources and support students could access (Burt, 2004). The scarcity of weak connections among students likely limits the flow of diverse information through students' social networks, limiting their knowledge of and access to the different supports they could receive and paths they could take in their post-secondary journeys. A low number of weak connections also means that any negative attitudes that students hold towards their courses or their department based on the experiences of a small number of their strong connections are less likely to be changed. This scarcity of weak connections might stem from the limited opportunities for collaborative work in most courses, as highlighted in multiple responses to the free-response questions. However, further analysis by future work is needed to validate this interpretation.

We investigated students' sense of community across courses with different collaborative requirements. In many cases, our analysis would have required a larger sample size, ranging from 101 students to more than 5,000 students, to detect moderate effects (see Table C.6 in Appendix C). Where our sample size was sufficient, our analysis showed that international students had higher Learning Support scores in courses with a required collaborative component than in courses where collaboration was optional. However, international students did not have higher Learning Support scores in courses with an optional or required collaborative component than in courses without any collaborative learning. The mean Learning Support score of international students was highest in courses that required no collaboration. This implies that the heightened interactions with other students encouraged by collaborative learning (Qureshi et al., 2023) did not aid international students in feeling that they have a course community to support them in meeting their learning needs.

For some student subsets, collaborative learning requirements were associated with a higher number of social connections. Men had higher degree centralities in their courses with a required collaborative component than in both other course categories. Domestic students and students in their fourth year had higher degree centralities in courses with a required collaborative component than in courses without a collaborative component. For other student groups, a larger sample size, ranging from 77 to 204 students, was required to detect differences in degree centrality across different collaborative learning requirements. Our analysis does not ascertain whether courses with a collaborative component led to an increase in students' degree centralities or if students avoided courses with collaborative components unless they could collaborate with pre-existing connections.

Finally, we examined the number of new strong connections formed by students across different course categories. Our analysis showed that students from underrepresented ethnic groups and students in their fourth year formed more strong connections in courses where collaboration was required than in courses without a collaborative component. These findings suggest that, by fostering the formation of connections, collaborative learning requirements may provide students with access to more social capital than courses without collaborative requirements, potentially supporting students' persistence and success.

3.3.1 Limitations

This study used relatively small sample sizes from a large research university in western Canada. The limited sample sizes hindered our ability to analyze the different intersections of student identities. This unfortunately reflects the unbalanced distribution of students in computer science (National Center for Education Statistics, 2021). A more nuanced understanding of identity would necessitate data collected from a much larger pool of students.

Our questionnaire had higher response rates from students from underrepresented genders and underrepresented ethnic groups than from their majority counterparts. This trend likely stemmed from the voluntary nature of participation in our study, with students from groups most impacted by the study's topics, such as the documented low sense of community among computer-science students, being more willing to participate. The voluntary nature of participation also means that the social networks constructed represent only a subset of individuals enrolled in each course, limiting the analysis we could perform. Despite the limited sample sizes, the statistical power was sufficient to detect important effects. In most cases where statistical power was not sufficient, data from between 77 to several hundred students would be needed to detect moderate effects.

To form a more comprehensive understanding of the experiences of computer-science students, we invited students enrolled in a significant portion of the department's courses to participate in the study. Consequently, some students received multiple invitations to participate. This approach, while ensuring more generalizable results, may have led to survey fatigue among those students, potentially contributing to the small response rate observed within individual courses. Nonetheless, this approach to gathering data enabled our sample to have a higher representation of students from underrepresented genders and from underrepresented ethnic groups, enabling our analysis in turn to provide more nuanced insights into the experiences of underrepresented students than in most previous work addressing the experiences of computer science students.

When responding to the study's questionnaire, many participants did not list any social connections they have in their courses or with others who support them. While it is likely that many of those participants did not have connections to list, this might also indicate that some participants were reluctant to disclose personal information to researchers they did not personally know. This may have limited the completeness of the data gathered on participants' social connections.

Although our data included responses from students enrolled in courses with different collaborative learning approaches, such as varying degrees of autonomy in selecting group members or subdivision of labor, the limited sample size did not enable us to explore the differences in student experiences across those various approaches.

This study highlighted important effects related to students' sense of community, their social connections, and collaborative learning in post-secondary computer-science education. The specific contexts of this department and the backgrounds of its students need to be considered when generalizing the findings of this work to other contexts.

3.3.2 Future Work

This study serves as an initial exploration, conducted with constrained resources and in a limited timeframe. Further work is needed to formulate a comprehensive understanding of the sense of community of computer-science students and how it is affected by their social connections and by collaborative learning.

Our analysis showed that computer-science students from underrepresented genders or from underrepresented ethnic groups had a lower sense of community than their majority peers. Mooney and Becker (2020) and Stout and Wright (2016) showed that belonging to two or more minority groups compounds the negative effect on students' sense of community. We could not investigate whether this applies to our population because this study had a relatively small size (n = 235) which hindered us from investigating the intersections of student identities.

Future work should prioritize methods to achieve higher response rates and to gather data from a larger pool of students in order to enable a more nuanced investigation of the experiences of students at the intersections of different identity variables and to enhance statistical power. Attempts to increase sample sizes should involve exploring alternative approaches to encouraging participation, preferably without resorting to methods such as assigning grades to study participation which may induce stress among students. Building on this work could also involve incorporating data gathered through other approaches than a student questionnaire, such as interviews with students or archival registration data.

Research conducted with such bigger samples and more varied data sources will be able explore other aspects of computer-science students' social connections. This could involve examining homophily trends across various factors such as gender, legal status, ethnicity, year in students' programs, and grades, or exploring different centrality measures beyond degree centrality, such as betweenness and closeness centralities.

In addition to gathering data from a larger pool of students and from different sources, future work could attempt to gather data across multiple points in time to track the evolution of the social networks and the sense of community of computer-science students. Such analysis would address the question posed earlier in this discussion of whether courses with a collaborative component led to an increase in students' degree centralities or if students avoided courses with a collaborative component unless they could take them with pre-existing connections.

When listing their connections in their courses, students generally listed more strong than weak connections. As discussed above, this suggests that students in this department had low betweenness centralities in their course networks, possibly due to limited collaborative work in their courses. Future work should attempt to validate this interpretation by comparing the number of student's weak connections across courses with different collaborative requirements.

On average, students in their second year listed more connections in their courses than students in any other year. This suggests that students lose some of the connections they form during the demanding second year courses as they progress through their academic programs. Given the positive influence of degree centrality on students' sense of community and on their access to social capital that could support their success, maintaining these formed connections could be beneficial as students advance in their studies. Developing interventions to assist computer-science students in maintaining connections they form with their peers could be an avenue of useful future research.

Meanwhile, when listing their supportive connections outside their courses, students listed fewer connections as their program years increased. This implies that as students became more engaged with their university communities, they gradually disengaged from their external social networks or they relied less on their external connections to support their academic success. Future work could investigate if students indeed disengage from their external social networks and what changes would support them in maintaining their external networks as they build a sense of community in their universities. Additionally, since the external networks of international students might look different from those of domestic students, future work should investigate how this trend differs between students with different legal statuses.

When listing their supportive connections outside their courses, many students listed friends who took the course in a previous semester and friends they met in other courses. This suggests that a portion of the external supportive networks of the study's participants were also members of the department where the study was conducted. To formulate a better understanding of computer-science students' social connections and their influence on sense of community, future work could investigate social networks across whole computer science departments, rather than only within specific courses.

Finally, future work should explore how the sense of community and social connections of computer science students vary across courses with different modes of instruction, for example courses where instruction is fully online, hybrid, or fully in-person, and courses with a collaborative learning component where students work in self-selected groups compared to those where groups are assigned by instructors.

Chapter 4

Collaborative Learning and Academic Performance in Computer Science

Collaborative learning is an educational approach where learners work together in groups to achieve a common goal (Laal & Ghodsi, 2012). By allowing students to leverage combined knowledge (Johansson et al., 2005) and combined working-memory resources (Kirschner et al., 2009), collaborative learning maximizes learning and persistence (Johnson et al., 2007), and positively influences students' attitudes towards their learning (Laal & Ghodsi, 2012; Shibley & Zimmaro, 2002).

By motivating positive interactions among students (Johnson et al., 2007), collaborative learning encourages the formation of connections (Laal & Ghodsi, 2012). Connections, in turn, positively influence the formation of a sense of community (Dawson, 2006; Royal & Rossi, 1996) and academic achievement (Ivan & Duduciuc, 2011; Rizzuto et al., 2009). A sense of community, inspired by both collaboration and connections, gives rise to motivation and persistence (Tinto, 2012; Tinto, 2017).

In this study, we will analyze archival data to explore the potential effect of collaborative learning on the academic performance of computer science students. We will focus on underrepresented students by looking at the demographic factors of gender and legal status in Canada, the country where the study is conducted. In more concrete terms, this study aims to investigate the following questions:

> RQ1: Do the course grades of computer science students differ across courses with varying collaborative learning requirements for students of each gender or for students of each legal status?
>
> RQ2: Are the course grades of computer science students different across genders or across legal statuses in courses with varying collaborative learning requirements?

While we recognize that course grades alone are an imperfect reflection of academic achievement, we rely on grades in this analysis as they are a readily available gauge of performance. However, we recommend that future work, whenever possible, leverages other measures of achievement than or in conjunction with course grades.

4.1 Methods

In the paragraphs that follow, we discuss the educational context where this study was conducted, the data used, the course categories investigated, and the hypotheses and analysis methods for each research question.

4.1.1 Educational context

This study uses anonymized archival data from a large public research university in western Canada. While the dataset includes archival information related to the university's faculty of science as a whole, this analysis specifically focuses on data related to the faculty's computer science department, its undergraduate students, and its undergraduate courses.

The department under study offers multiple four-year bachelor's degree programs in computer science: a general bachelor's degree in computer science and a bachelor's degree in computer science with various specialization options.

Like many computer science departments across the country and across the world, the department benefits from a flexible curriculum structure: students are required to fulfill course requirements from their department and to fulfill, in conjunction, requirements from other faculty of science departments or other faculties. Students are relatively free to take courses in any sequence, as long as they fulfill a course's prerequisite requirements and complete enough prerequisites to register in courses later in their programs. In light of this flexibility, second year students are often in computer science classrooms with third years, and third years are more often than not in classrooms with fourth years.

While this flexibility affords students the relative freedom to design their own academic paths and the opportunity to explore and master interdisciplinary topics of their choice, it also means that students may not consistently interact with the same peers across their courses. This lack of continuity in peer groups may hinder the formation of a strong sense of community within the department (Dawson, 2006; Royal & Rossi, 1996).

4.1.2 Data

We used anonymized archival data, provided to us through a larger project investigating student pathways at the university's faculty of science. The dataset documents students' admissions, registration, enrollment, and convocation information in the faculty of science from the Fall semester of 2015, starting in September, 2015, till the Winter semester of 2021, ending in April, 2021.

Students are identified by anonymized ID numbers. The registration table documents each semester a student has registered in the faculty of science, their program, their academic year, their gender, their legal status in Canada, and their country of citizenship. The enrollments table documents each course a student has enrolled in, the semester of their enrollment, their class section, their final course grade, the course's academic department, and the student's academic department.

While the full dataset contains information related to seven different departments in the faculty of science, this study will focus solely on data from the computer science department. To explore the effect of collaborative learning on academic performance in computer science, we used anonymized student IDs to merge students' gender and legal status data from the registrations archive with their course enrollments from the enrollments archive. We then conducted the following preprocessing steps:

1. We removed enrollments in courses not offered by the computer science department and ungraded enrollments in computer science. Ungraded enrollments include enrollments in course lab and seminar components which are offered alongside the graded "lecture" component. These lab and seminar components are not graded individually but rather contribute to the final grade of their course's "lecture" component.
2. We removed enrollments by students not registered in a computer science program.

3. We removed enrollments where the final grade is not in the ‘A+’ to ‘F’ range or a ‘W’, indicating that a student had withdrawn with permission from the department. Removed enrollments included ones where the final grade is “aegrotat standing”, “completed requirements”, “course in progress”, “incomplete”, “exempt”, “registered as an auditor”, “registered as an auditor and withdrew”, or “withdrew from or failed course in progress”. “Completed requirements" and “incomplete” grades include all grades from the Winter semester of 2020, the semester when the mandatory COVID-19 quarantine was in place and the university switched the grading system in all of its courses from a letter-grade based system to a “completed requirements” / “incomplete” one. Enrollments where a student withdrew with permission and received a grade of W were kept in this step to be used in further descriptive analysis of the data and then removed in a future step, step number 5.

4. We removed enrollments where a students’ gender, legal status, or academic year was missing.

5. Finally, we removed enrollments where the final grade is ‘W’, as they do not correspond to a grade point value.

Table 4.1 shows the number of enrollments and the number of students across data preprocessing steps. As shown in the table, the final dataset included a total of 2,951 students and 20,380 enrollments. Table 4.2 shows the distribution of students by gender and legal status across academic years in the final dataset. While we recognize the intricate nature of gender identity, we reported gender solely within the binary categories of 'woman' and 'man' to safeguard the identities of the few students whose gender was not reported within this binary during the final semesters documented in our dataset. Table 4.2 shows that students in the department are mostly men and domestic students. While the numbers of international and domestic women are consistently similar, the number of domestic men is much higher than that of international men.

Table 4.1: Number of enrollments and number of students across data preprocessing steps.

Step	Data Preprocessing Step	Enrollments Count	Students Count
0	Initial dataset	930,913	57,000
1	Removing enrollments in courses not offered by the computer science department and ungraded enrollments in computer science classrooms	49,448	10,853
2	Removing enrollments by students not registered in a computer science program	43,422	8,151
3	Removing enrollments where the final grade is not in the 'A+' to 'F' range or a 'W'	31,560	6,843
4	Removing enrollments with missing data	22,814	3,038
5	Removing enrollments where a student has withdrawn (Final dataset)	20,380	2,951

Table 4.2: Description of students in the final dataset. Most students in the department are men and domestic students.

	1st Year	2nd Year	3rd Year	4th Year
International Women	266	193	175	138
Domestic Women	285	139	168	134
International Men	934	644	550	432
Domestic Men	1,464	784	845	706
Women	551	332	343	272
Men	2,400	1,450	1,395	1,139
International	1,200	857	1,013	570
Domestic	1,749	923	725	841
All	2,951	1,782	1,738	1,412

Figures 4.1 and 4.2 show the percentages of women and men and international and domestic students, respectively, across semesters. These plots include Fall and Winter semesters which run September through April and exclude Spring and Summer semesters where enrollment numbers in computer science courses are extremely low or nonexistent. The department under study usually offers two or no courses in Spring semesters and no courses in Summer semesters. The figures show that while the ratio of international to domestic students was generally increasing, the ratio of women to men remained almost constant. Moreover, the plots show that the representation of international students in the department decreased during the Winter semester of 2020, the semester when mandatory COVID-19 quarantines and measures were imposed, indicating that international students were more severely impacted by the pandemic than domestic students.

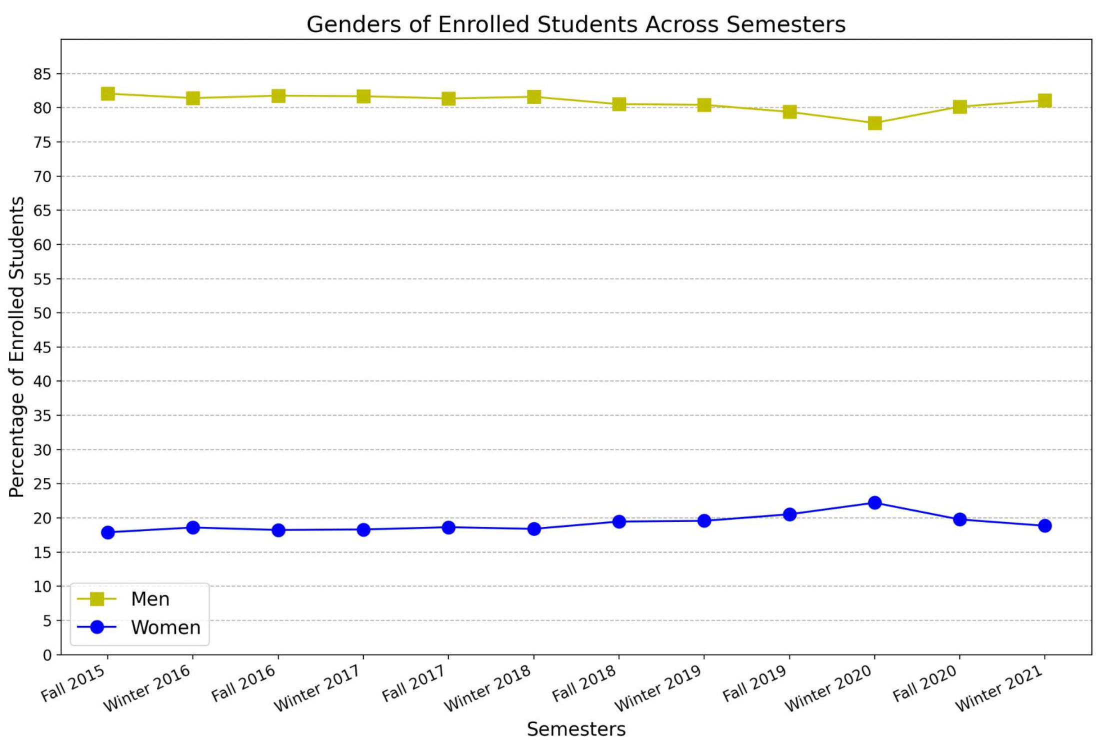

Figure 4.1: Genders of enrolled students across semesters. The ratio of women to men remains almost constant across semesters.

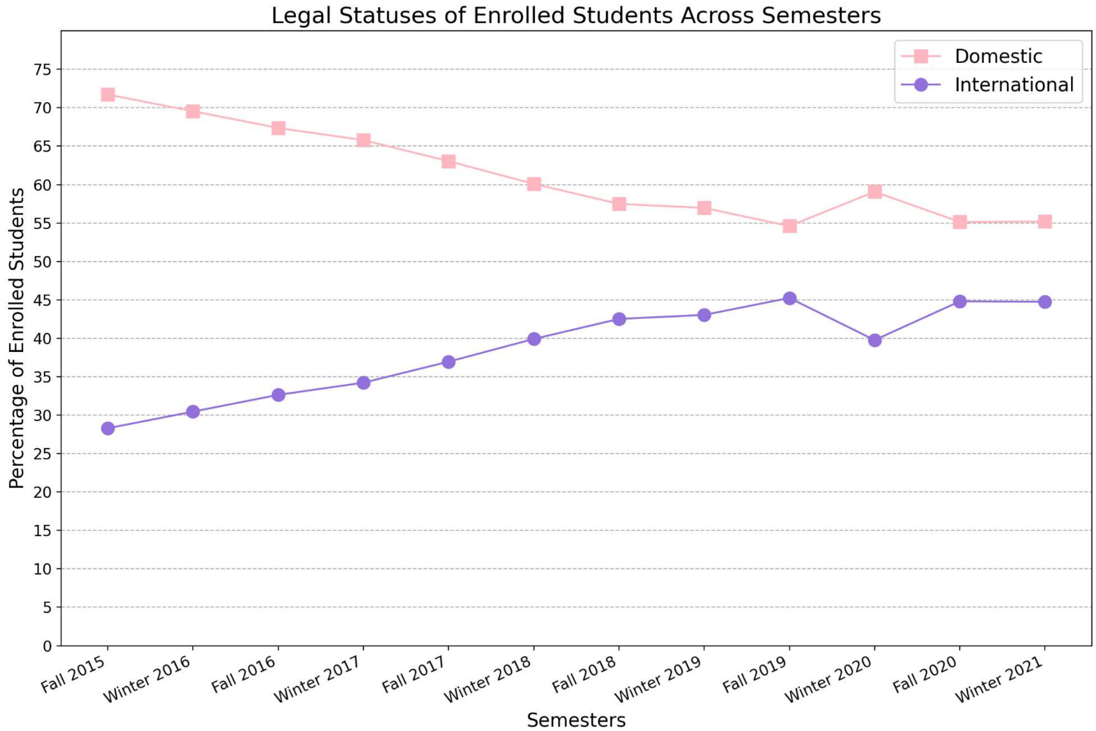

Figure 4.2: Legal statuses of enrolled students across semesters. The ratio of international to domestic students generally increases across semesters.

Table 4.3 shows the mean and standard deviation of students' mean course grades in the final dataset. To calculate mean course grades, we converted students' letter grades to their corresponding grade point value, shown in Table 4.4, and averaged each student's grades in the final dataset. Table 4.3 shows that mean grades are lowest when students are in their second year.

Table 4.3: Mean and standard deviation of students' mean course grades in the final dataset.

	1st Year	2nd Year	3rd Year	4th Year
International Women	2.89 (1.040)	2.81 (0.864)	2.89 (0.726)	3.20 (0.581)
Domestic Women	3.04 (0.960)	2.75 (0.970)	2.82 (0.830)	3.20 (0.570)
International Men	2.79 (1.040)	2.70 (0.864)	2.82 (0.726)	3.13 (0.581)
Domestic Men	3.07 (0.942)	2.75 (0.968)	2.92 (0.789)	3.15 (0.663)
Women	2.95 (1.010)	2.78 (0.919)	2.86 (0.778)	3.20 (0.573)
Men	2.94 (1.001)	2.73 (0.950)	2.89 (0.789)	3.15 (0.661)
International	2.81 (1.045)	2.73 (0.908)	2.84 (0.771)	3.15 (0.640)
Domestic	3.07 (0.945)	2.75 (0.968)	2.91 (0.796)	3.16 (0.649)
All	2.94 (1.002)	2.74 (0.944)	2.88 (0.786)	3.16 (0.645)

Table 4.4: Letter grade to grade point value conversion.

Letter Grade	Grade Point Value
A+	4.0
A	4.0
A-	3.7
B+	3.3
B	3.0
B-	2.7
C+	2.3
C	2.0
C-	1.7
D+	1.3
D	1.0
F	0.0

Figures 4.3 to 4.7 show the distribution of course grades by student years for all enrollments, enrollments by women, by men, by international students, and by domestic students respectively. In these plots, 'W1' refers to a grade of 'W' for a course withdrawal within the first month of the semester. 'W2' refers to a grade of 'W' for a withdrawal within the second month. 'W3' refers to a grade of 'W' for a withdrawal after the second month. The plots consistently show that the number of withdrawals increases from students' first year to their second year and then decreases each following year. This is likely because after the first year, when students complete their first computing courses, the department's highly flexible curriculum structures provide second year students with a wide array of course options. However, at this stage, second year students may still lack the readiness to discern which courses best align with their skills and interests. This might also be partially due to second year courses often requiring significantly more knowledge and work than courses students take in their first year.

The plots additionally show that most withdrawals occur closer to the end of the semester.

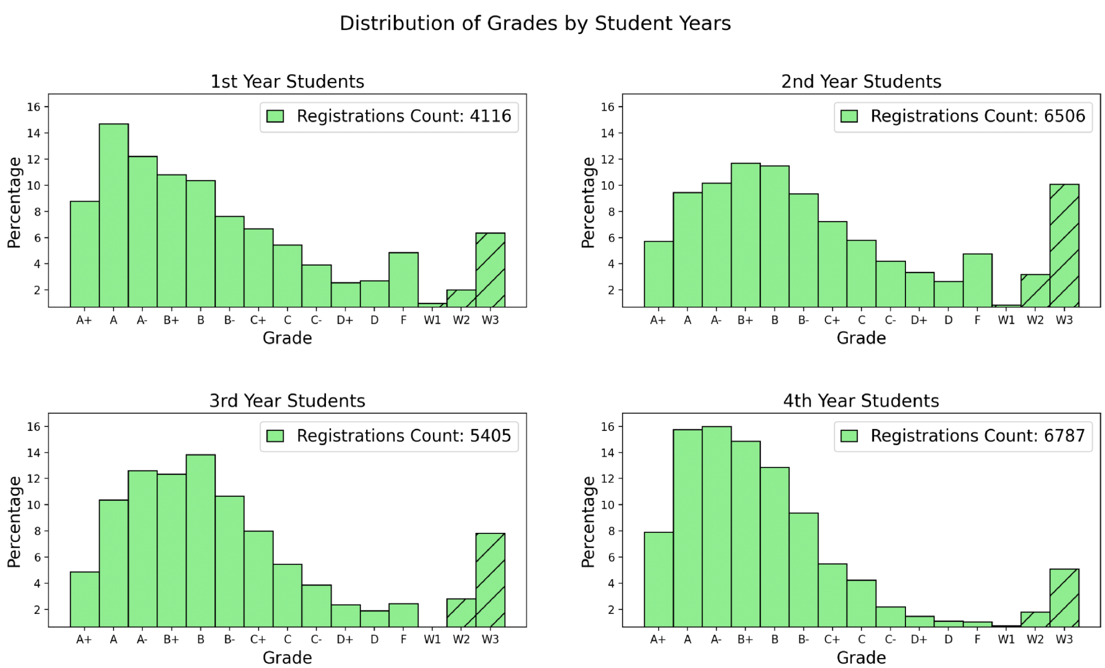

Figure 4.3: Distribution of all students' grades in different program years.

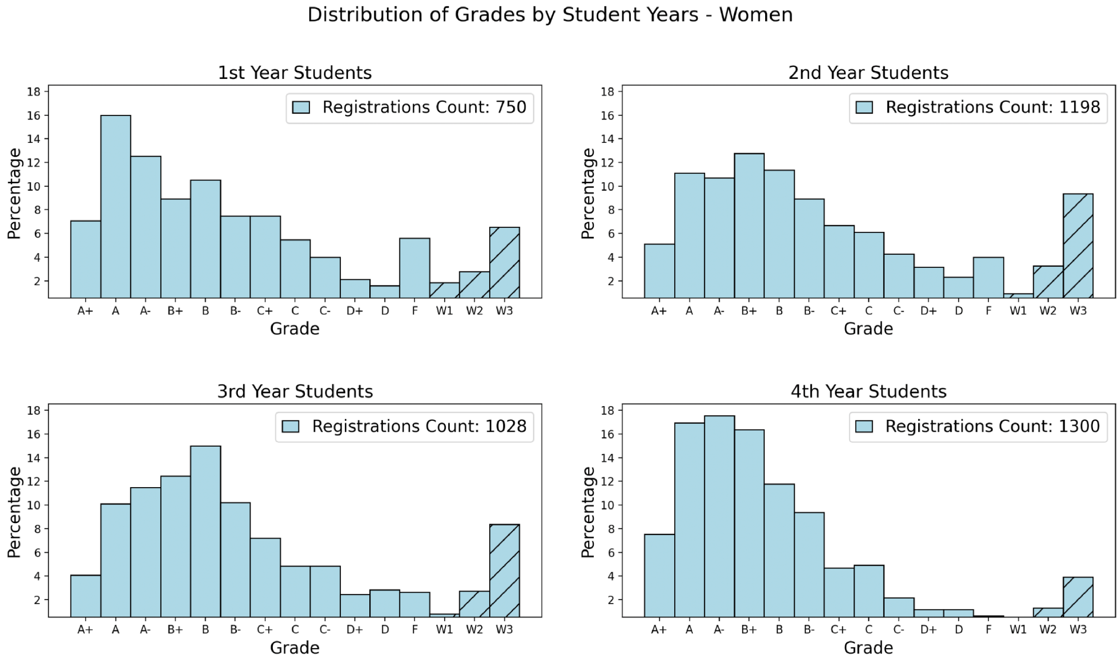

Figure 4.4: Distribution of women's grades in different program years.

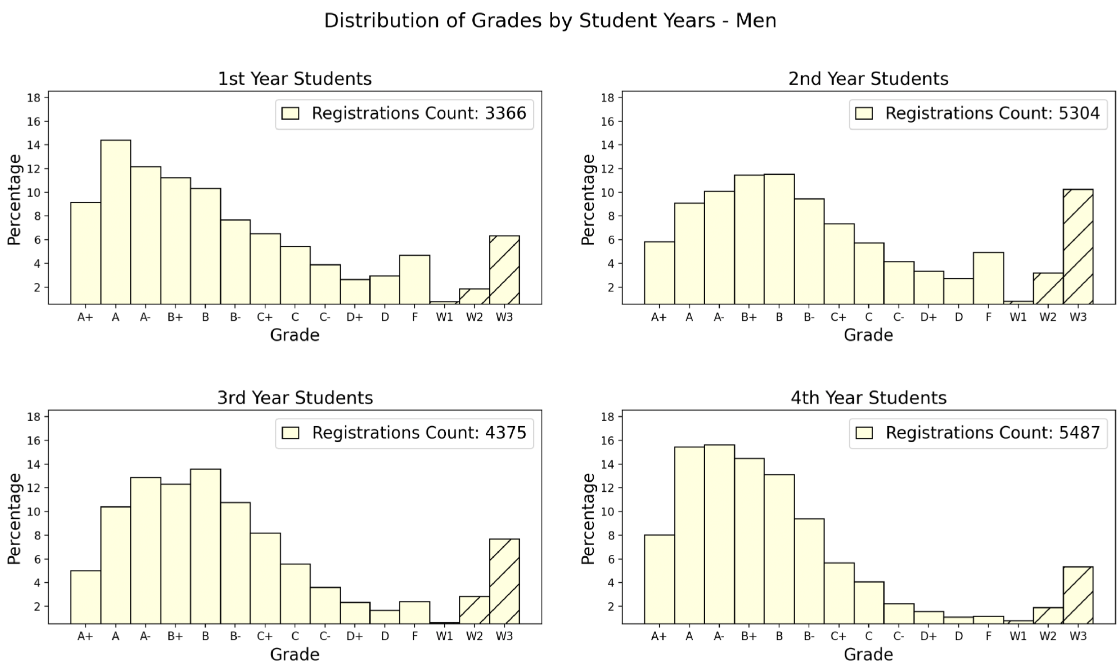

Figure 4.5: Distribution of men's grades in different program years.

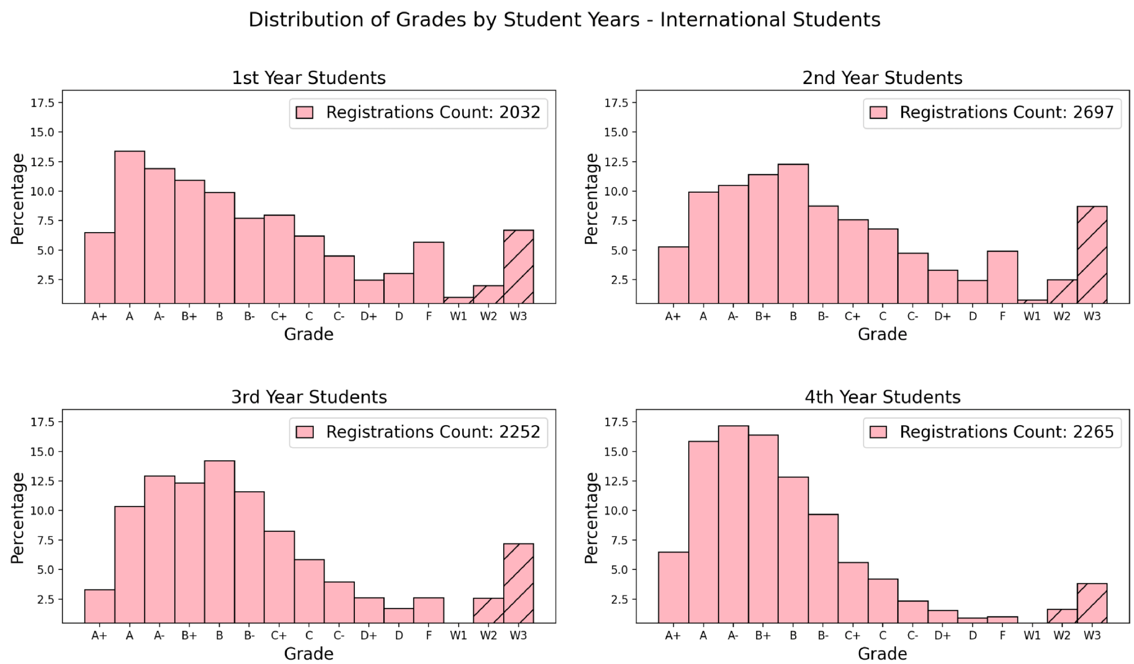

Figure 4.6: Distribution of international students' grades in different program years.

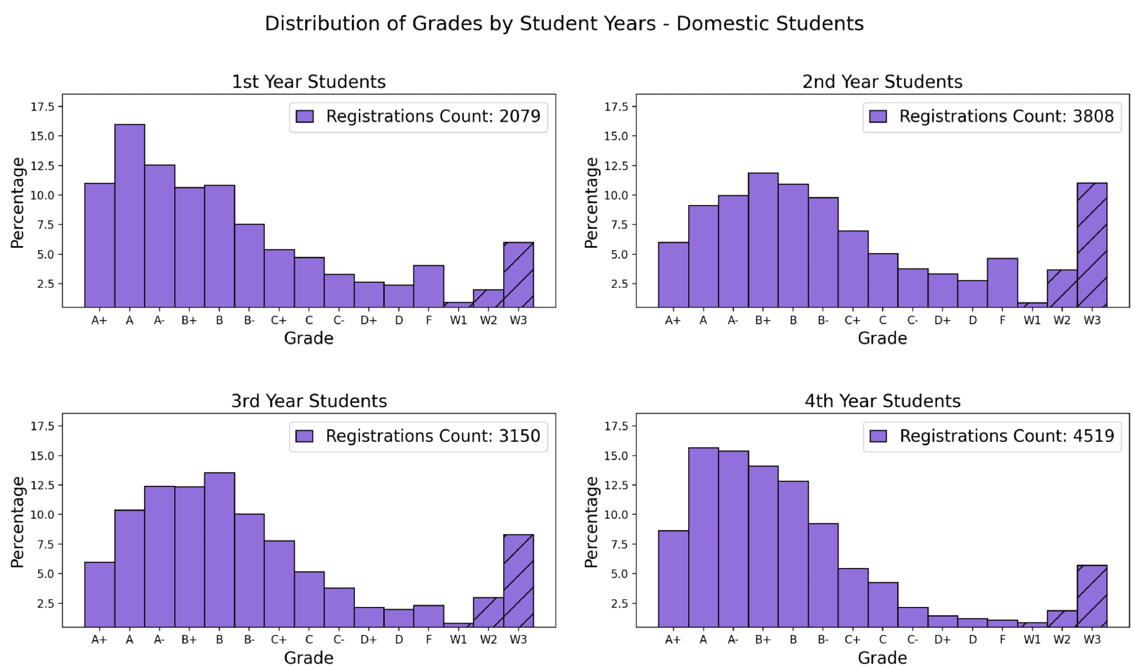

Figure 4.7: Distribution of domestic students' grades in different program years.

Figures 4.8 and 4.9 show the percentages of women and men and the percentages of international and domestic students, respectively, who persisted in their programs across semesters. These percentages take into account and exclude students who graduated. The figures show that while men and women persisted at similar rates, with men persisting at higher rates in some semesters and women in others, international students persisted at higher rates than domestic students in most semesters. This is likely because international students lose their status in the country when they are not enrolled in at least a specified minimum number of courses at the university during any Fall or Winter semester and are thus less able to take academic breaks when they require them. International students, however, persist at lower rates than domestic students in the Winter semester of 2020, showing again that they were more negatively impacted by the pandemic than their domestic counterparts.

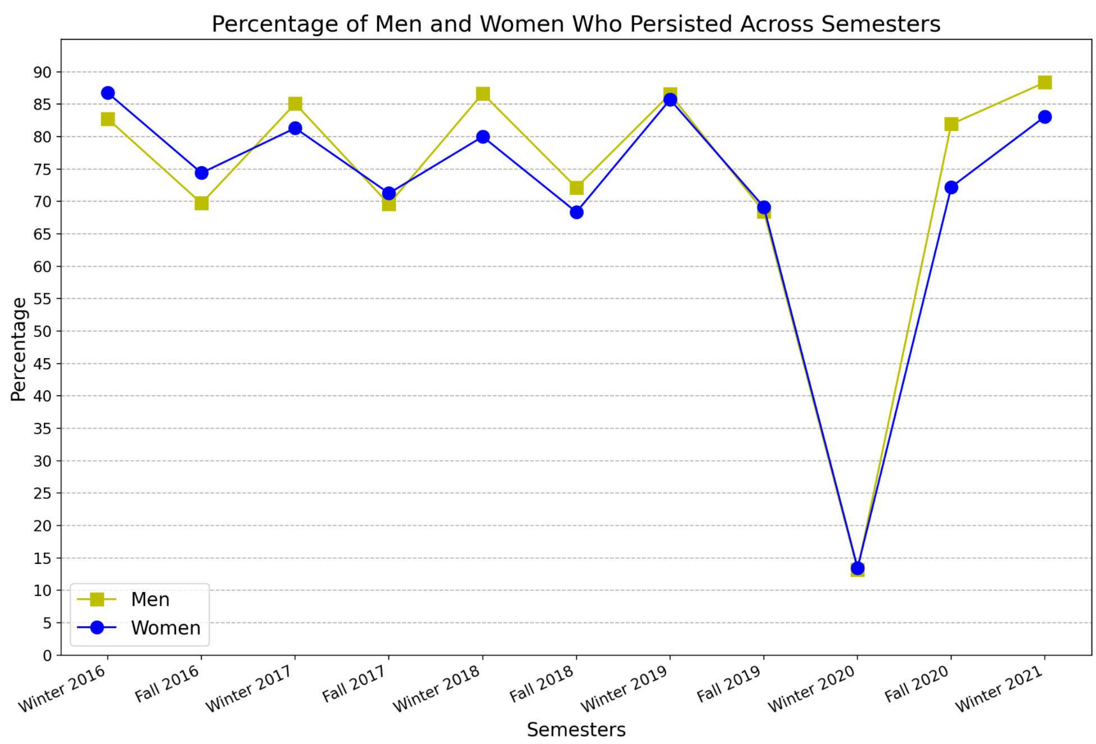

Figure 4.8: Percentages of men and women who persisted across semesters. Men and women show, on average, similar rates of persistence.

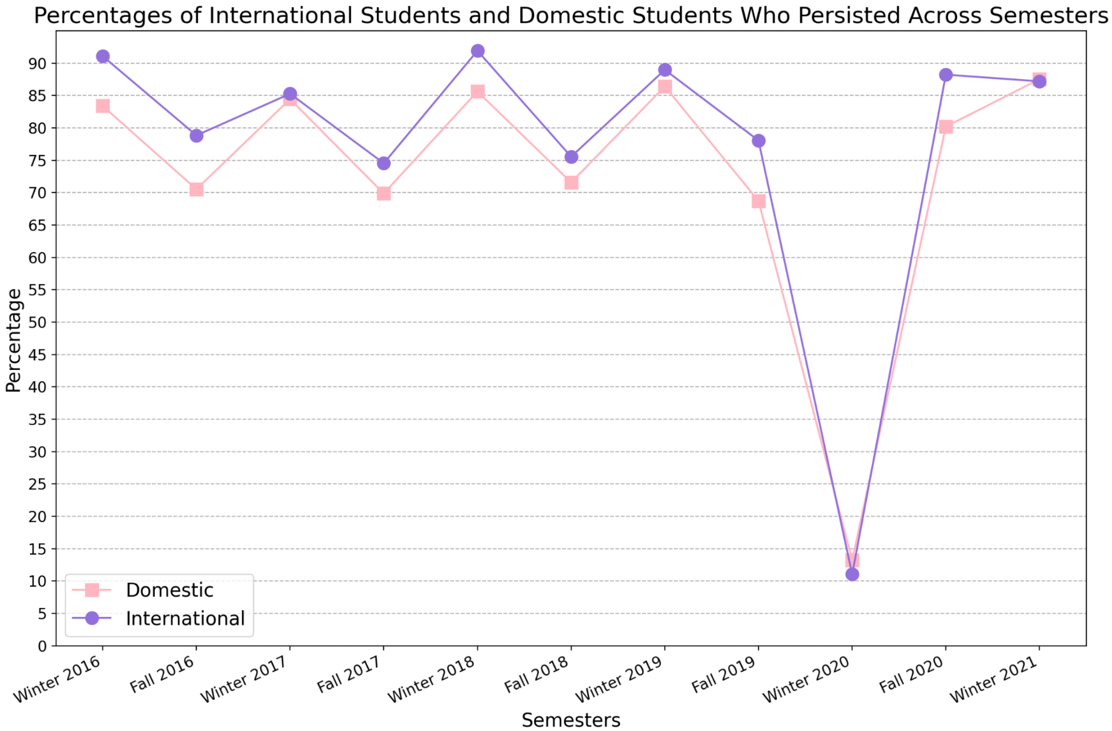

Figure 4.9: Percentages of international students and domestic students who persisted across semesters. International students persisted at higher rates than domestic students in all semesters, except the semester when pandemic measures were first taken.

4.1.3 Course Categories

The dataset used in this study does not specify whether courses in which students were enrolled included a collaborative learning requirement. Accordingly, to explore the effect of collaborative learning on academic performance in computer science, we studied course syllabi and, when they were not readily available, contacted course instructors to determine whether each course in our final dataset incorporated any collaborative learning.

In some cases, students were enrolled in courses under the title “Special Topics in Computer Science Courses”. Courses under that title are advanced courses whose topics and instructors vary by semester and are usually enrolled in by students in their third and fourth years. Our dataset did not document the titles and instructors of those courses, so we were unable to determine whether they incorporated collaborative learning and excluded them from further analysis. Removing these enrollments from our dataset did not affect the total number of students but decreased the number of enrollments to 18,713.

At the end, the remaining courses fell into one of three categories: courses with no graded collaborative component, courses with a graded optionally collaborative component, and courses with a graded required collaborative component. A graded required collaborative component refers to an assignment or a project where students were required to work in groups of two or more. A graded optionally collaborative component refers to an assignment or a project where students were free to either work individually or in groups of two or more. Table 4.5 shows the number of courses under each category enrolled in by students across different student years. Table 4.6 shows the number of enrollments across different student years in courses under each category. The majority of courses and enrollments fall under the no collaborative component category. A minority of courses and a small minority of enrollments fall under the optionally collaborative component category. The ratio of enrollments in courses with a required collaborative component to enrollments in courses without a required collaborative component was around 0.03 for first year students, 0.26 for second year students, 0.58 for third year students, and 0.92 for fourth year students.

Table 4.5: Number of courses by course category across program years. Most courses fall under the no collaborative component category.

Enrollments By	No Collaborative Component	Optionally Collaborative Component	Required Collaborative Component	Total
1st Year Students	19	2	8	29
2nd Year Students	24	5	11	40
3rd Year Students	26	6	17	49
4th Year Students	25	6	16	47

Table 4.6: Number of enrollments by course category across program years. Most enrollments were in courses without a collaborative component, especially enrollments by first and second year students.

Enrollments By	No Collaborative Component	Optional Collaborative Component	Required Collaborative Component	Total
1st Year Students	3,601	7	106	3,714
2nd Year Students	4,163	98	1,124	5,385
3rd Year Students	2,518	393	1,454	4,365
4th Year Students	2,426	597	2,226	5,249
Total	12,708	1,095	4,910	18,713

Tables 4.7, 4.8, and 4.9 show the distribution of students by gender and legal status across academic years in courses without a collaborative component, courses with an optionally collaborative component, and courses with a required collaborative component, respectively. Again, the tables show that students in their first and second years mainly enroll in courses without a collaborative component.

Due to the relatively low presence of collaborative learning in courses taken by first and second year students, all following analysis will focus on students in their third and fourth years. Moreover, although we recognize the importance of examining the intersections of student identities to gain a comprehensive understanding of student experiences, the low representation of both international and domestic women in our dataset and the department from which it came necessitates that our subsequent analysis investigates gender and legal status divisions separately.

Table 4.7: Description of students enrolled in courses with no collaborative component in the final dataset.

	1st Year	2nd Year	3rd Year	4th Year	All Students
International Women	193	170	118	102	265
Domestic Women	138	158	117	117	279
International Men	664	533	381	297	925
Domestic Men	781	819	594	570	1,434
Women	331	328	235	219	544
Men	1,447	1,352	976	868	2,361
International	857	703	499	399	1,190
Domestic	919	977	711	687	1,713
All	1,778	1,680	1,211	1,087	2,905

Table 4.8: Description of students enrolled in courses with an optionally collaborative component in the final dataset. Less students enrolled in courses with an optionally collaborative component than in any other course category.

	1st Year	2nd Year	3rd Year	4th Year	All Students
International Women	1	10	43	47	89
Domestic Women	0	4	29	57	85
International Men	2	46	126	132	280
Domestic Men	3	33	159	270	424
Women	1	14	72	104	174
Men	5	79	286	402	705
International	3	56	169	179	369
Domestic	3	37	188	327	509
All	6	93	358	506	879

Table 4.9: Description of students enrolled in courses with a required collaborative component in the final dataset.The number of enrollments increased as program years increased.

	1st Year	2nd Year	3rd Year	4th Year	All Students
International Women	11	87	96	85	172
Domestic Women	9	65	96	112	182
International Men	30	312	303	282	570
Domestic Men	47	424	501	592	971
Women	20	152	192	197	354
Men	78	736	805	875	1,542
International	41	399	399	367	742
Domestic	56	489	598	704	1,154
All	98	888	998	1,072	1,897

Figure 4.10 shows the distribution of course grades across course categories. Here again, ‘W1’ refers to a grade of ‘W’ for a course withdrawal within the first month of the semester. ‘W2’ refers to a grade of ‘W’ for a withdrawal within the second month. ‘W3’ refers to a grade of ‘W’ for a withdrawal after the second month. The figure shows that courses with an optionally collaborative component have the highest frequency of late withdrawals, while courses with a required collaborative component have a lower frequency of late withdrawals than the other two categories.

To the best of this author’s knowledge, while some degree programs offered by the computer science department under study require students to complete courses in the required collaborative component or optional collaborative component categories, other degree programs do not. However, since many of the courses students could choose to take in their third and fourth years to fulfill their degree requirements are courses with an optionally collaborative component or courses with a required collaborative component (refer to Table 4.5), most students do enroll in courses in one or both of these categories before they graduate.

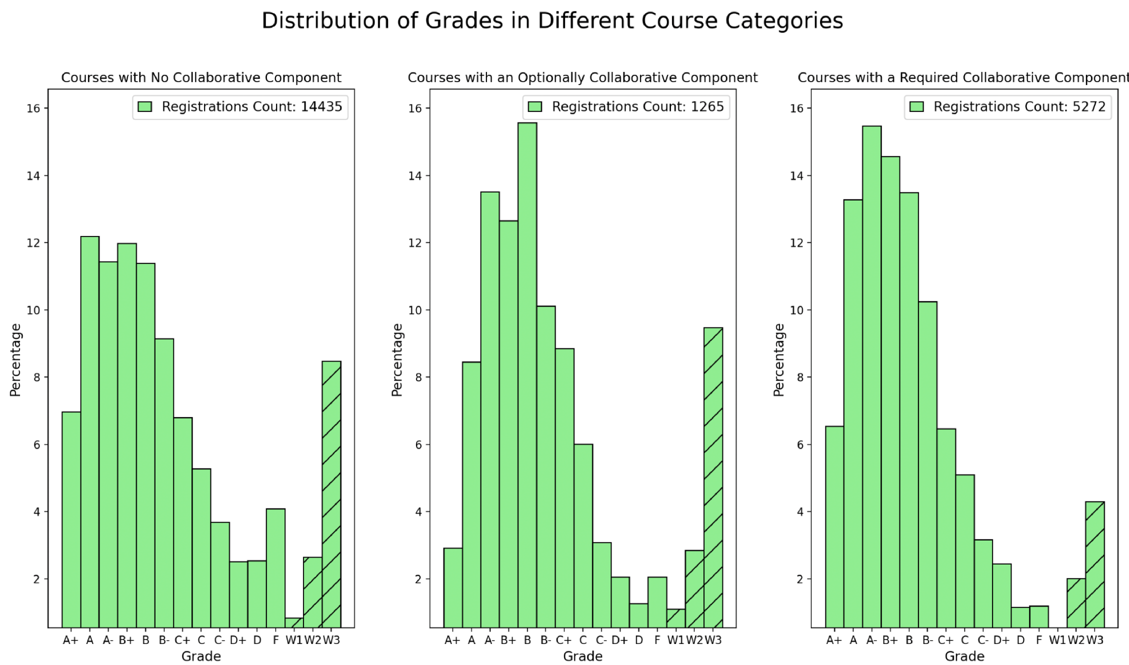

Figure 4.10: Distribution of course grades in different course categories. Courses with an optionally collaborative component have the highest frequency of late withdrawals. Courses with a required collaborative component have the lowest frequency of late withdrawals.

4.1.4 Hypotheses and Analysis

The following subsections detail the hypotheses related to and the analysis methods used to address each research question. Where we indicate that a distribution is not normal, that was determined by applying the Shapiro-Wilk Test (Shapiro & Wilk, 1965) and achieving a p-value smaller than .001. All analysis was conducted by the author of this thesis and reviewed by her supervisor, Carrie Demmans Epp.

All null hypothesis significance tests were followed by statistical power analysis. We performed both post-hoc analysis to determine the observed power of the tests we conducted with the sample we had and a priori analysis to determine the sample sizes that would be required by future work to enable the detection of moderate effects with a statistical power of 80%. Details of the power analysis results for each test are shown in Appendix D. Notable power analysis results are also highlighted in the results and discussion sections of this chapter.

4.1.4.1 RQ1: Grade Differences Across Collaborative Approaches

Building on the positive influence of collaborative learning established by Johnson et al. (2007), we hypothesized that all students achieve higher grades in courses with an optionally collaborative component compared to those without any collaborative component and in courses with a required collaborative component compared to both other course categories.

To evaluate these hypotheses, we employed null hypothesis significance tests to compare mean course grades across different course categories. As the grade distributions of the student groups in our data were not normally distributed and since we were performing comparisons across unpaired groups, we employed Kruskal-Wallis tests (Kruskal & Wallis, 1952) to first determine if there was any difference in course grades across the three different course categories for women, men, international students, and domestic students in their third and fourth academic years. Where the Kruskal-Wallis test revealed a significant difference across the three categories, we conducted Mann-Whitney U tests (Mann & Whitney, 1947) to identify the differences between each pair of course categories.

Finally, we complemented those test results by comparing the mean grades of students who enrolled in more than one course category. Since the subset of students registered in a given year of their program who enrolled in all three course categories was too small, we did not conduct threeway tests and directly conducted two-way Wilcoxon Signed-rank tests (Wilcoxon, 1992) to compare mean grades of students who enrolled in both: (1) courses with no collaborative component and courses with an optionally collaborative component, (2) courses with no collaborative component and courses with a required collaborative component, or (3) courses with an optionally collaborative component and courses with a required collaborative component.

To rebalance the risk of false positives compounded by multiple comparisons, we applied we applied Bonferroni Correction (Bonferroni, 1936) on the Mann-Whitney U and Wilcoxon Signed-rank test results, multiplying resultant p-values by 3, the number of pairwise comparisons performed.

4.1.4.2 RQ2: Grade Differences Across Genders or Across Legal Statuses by Collaborative Approach

Drawing from the insights presented by Margolis and Fisher (2002), relating to women's different perceptions and attitudes towards computer science from those of men, we hypothesized that men and women perform differently across course categories. As international students are often challenged by language barriers in academic environments and assessments (Heywood, 2000; Leki, 2007) and often struggle to adapt to their host environments (Lehmann, 2014), experiencing a diminished self-esteem, decreased mental and psychological well-being, and a decline in physical health (Dávid, 2023), we hypothesized that international students would achieve lower mean course grades across course categories than their domestic peers. We used null hypothesis significance tests to address this question. Since the grade distributions of the student groups in our data are not normally distributed and since we are performing comparisons across unpaired groups, we used Mann-Whitney U tests (Mann & Whitney, 1947).

4.2 Results

In this section, we report the results of the analysis conducted to address each research question.

4.2.1 RQ1: Grade Differences Across Collaborative Approaches

We conducted Kruskal-Wallis tests comparing the mean course grades across course categories, followed by pairwise comparisons using Mann-Whitney U tests when needed. To supplement these results, we conducted Wilcoxon Signed-rank tests. Our hypothesis was that all student subsets have higher grades in courses with an optionally collaborative component than in courses with no collaborative component and in courses with a required collaborative component than in both other course categories

Tables 4.10 shows the results of Kruksal-Wallis tests for third year students. The table shows significant differences in the course grades of third year students across categories for international students and domestic students but not for women or men. Subsequent power analysis, presented in Table D.1 in Appendix D, indicates that the tests comparing the grades across course categories for women and men had an observed statistical power of around 10%.

Table 4.10: Comparing 3rd year students' course grades across course categories for each gender and legal status using Kruskal-Wallis tests.

Subset	**No Collaborative Component**		**Optionally Collaborative Component**		**Required Collaborative Component**		**Kruskal-Wallis Tests**	
	n	***M(SD)***	***n***	***M(SD)***	***n***	***M(SD)***	***H***	***p***
Women	235	2.86 (0.841)	72	2.95 (0.745)	192	2.88 (0.868)	0.544	.762
Men	976	2.89 (0.861)	286	2.87 (0.871)	806	2.91 (0.810)	0.647	.723
International	499	2.92 (0.820)	169	2.87 (0.857)	399	2.77 (0.822)	8.297	.016*
Domestic	712	2.86 (0.882)	189	2.88 (0.842)	599	3.00 (0.808)	8.374	.015*

Note: * indicates $p < 0.05$.

Table 4.11 shows the results of the Mann-Whitney tests comparing the mean course grades across each pair of course categories for domestic students and for international students. Only the comparison of the mean grades of domestic students in courses with a required collaborative component to their mean grades in courses without such a component returned a significant result. Since Kruksal-Wallis tests in Table 4.10 indicate that there is a significant difference in the grades of international students across course categories but the Mann-Whitney U tests in Table 4.11 do not show such a difference, the difference in the course grades of international students is likely other than that predicted by our hypothesis. Power analysis for these tests, shown in table D.2 in Appendix D, indicates that where tests failed to return a significant difference, observed power was consistently below 10%, except in the test comparing the grades of domestic students in courses with an optional collaborative component to their grades in courses where collaboration was required. This test had a moderate observed power of 57% and returned a relatively small, although larger than the significance threshold p-value.

Table 4.11: Comparing 3rd year students' course grades across course categories by collaboration requirement for each legal status using Mann-Whitney U tests.

Subset	**Group 1**			**Group 2**			**Mann-Whitney U Tests**		
	Collaboration Requirement	***n***	***M(SD)***	**Collaboration Requirement**	***n***	***M(SD)***	***U***	***p***	***r***
International	None	499	2.92 (0.820)	Optional	169	2.87 (0.857)	43,217.0	1.000	.02
	None	499	2.92 (0.820)	Required	399	2.77 (0.822)	110,602	1.000	.10
	Optional	169	2.87 (0.857)	Required	399	2.77 (0.822)	36,423.0	1.000	.06
Domestic	None	712	2.86 (0.882)	Optional	189	2.88 (0.842)	67,373.5	1.000	.001
	None	712	2.86 (0.882)	Required	599	3.00 (0.808)	194,638.0	.009*	.07
	Optional	189	2.88 (0.842)	Required	599	3.00 (0.808)	51,501.5	.090	.06

Note: * indicates $p < 0.05$; bold indicates a large effect size. All p-values are Bonferroni corrected.

Table 4.12 shows the results of the Wilcoxon Signed-rank tests comparing the mean course grades across each pair of course categories for each subset of students in their third year. Only two tests returned significant results. Men who enrolled in both course categories achieved higher grades in courses where the collaborative component is required than when it is optional. Domestic students who enrolled in both course categories achieve higher grades in courses with a required collaborative component than in both other course categories. Where tests failed to find a significant result, observed power was between 0% and 21% (see Table D.3 in Appendix D for details), except in the test comparing the grades of domestic students in courses without a collaborative component to courses where collaboration was optional, where observed power was 48%.

Table 4.12: Comparing 3rd year students' course grades across course categories by collaboration requirement for each gender and legal status using Wilcoxon Signed-rank tests.

Subset	**Group 1**			**Group 2**			**Wilcoxon Signed-rank Tests**		
	Collaboration Requirement	***n***	***M(SD)***	**Collaboration Requirement**	***n***	***M(SD)***	***W***	***p***	***r***
Women	None	53	2.92 (0.807)	Optional	53	3.00 (0.703)	413.5	.708	**.61**
	None	163	2.91 (0.755)	Required	163	2.90 (0.887)	5,068.0	.857	**.54**
	Optional	54	2.94 (0.721)	Required	54	2.94 (0.824)	509.5	1.000	**.56**
Men	None	223	2.97 (0.885)	Optional	223	2.93 (0.882)	9,139.5	1.000	**.54**
	None	670	2.92 (0.814)	Required	670	2.95 (0.784)	87,175.0	.663	**.52**
	Optional	285	2.85 (0.861)	Required	285	2.98 (0.747)	6,948.0	.060*	**.60**
International	None	132	3.08 (0.746)	Optional	132	2.92 (0.877)	2,641.0	1.000	**.60**
	None	345	2.99 (0.741)	Required	345	2.79 (0.816)	18,495.0	1.000	**.60**
	Optional	122	2.89 (0.822)	Required	122	2.90 (0.737)	3,086.5	1.000	**.51**
Domestic	None	144	2.85 (0.959)	Optional	144	2.97 (0.826)	3,041.5	.105	**.61**
	None	488	2.87 (0.841)	Required	488	3.04 (0.780)	32,952.0	<.001*	**.63**
	Optional	144	2.85 (0.847)	Required	144	3.03 (0.780)	2,565.5	.024*	**.65**

Note: * indicates $p < 0.05$; bold indicates a large effect size. All p-values are Bonferroni corrected.

Table 4.13 shows the results of Kruksal-Wallis tests for fourth year students. The table indicates that differences in the course grades of fourth year students are different across course categories for all student subsets except international students. Power analysis, presented in Table D.4 in Appendix D, indicates that the test comparing the course grades of international students had a low observed power of only 41%.

Table 4.13.: Comparing 4th year students' course grades across course categories for each gender and legal status using Kruksal-Wallis tests.

Subset	**No Collaborative Component**		**Optionally Collaborative Component**		**Required Collaborative Component**		**Kruskal-Wallis Tests**	
	n	***M(SD)***	***n***	***M(SD)***	***n***	***M(SD)***	***H***	***p***
Women	219	3.11 (0.717)	104	3.06 (0.782)	197	3.32 (0.571)	10.696	.005*
Men	868	3.10 (0.769)	402	2.97 (0.841)	875	3.25 (0.671)	38.625	<.001*
International	399	3.18 (0.721)	179	3.03 (0.832)	367	3.17 (0.682)	3.517	.172
Domestic	688	3.05 (0.776)	327	2.96 (0.828)	705	3.31 (0.634)	63.981	<.001*

Note: * indicates $p < 0.05$.

Tables 4.14 and 4.15 show the results of the Mann-Whitney and Wilcoxon Signed-rank tests, respectively. The tables indicate that in their fourth year, students generally do not perform better in courses with an optionally collaborative component than in courses with no collaborative component and perform better in courses with a required collaborative component than in courses with an optionally collaborative component. The subsets of women, men, and domestic students perform better in courses with a required collaborative component than in courses without a collaborative component. Wilcoxon Signed-rank tests in Table 4.15 however do not support the same hypothesis for international students. Tables D.5 and D.6 in Appendix D present the results of the power analysis of the Mann-Whitney U tests and Wilcoxon Signed-rank tests, respectively. Where test results were not significant, observed power was consistently below 10%.

Table 4.14: Comparing 4th year students' course grades across course categories by collaboration requirement for women, men, and domestic students using Mann-Whitney U tests.

Subset	**Group 1**			**Group 2**			**Mann-Whitney U Tests**		
	Collaboration Requirement	***n***	***M(SD)***	**Collaboration Requirement**	***n***	***M(SD)***	***U***	***p***	***r***
Women	None	219	3.11 (0.717)	Optional	104	3.06 (0.782)	11,549.0	1.000	.01
	None	219	3.11 (0.717)	Required	197	3.32 (0.571)	18,062.0	.006*	.14
	Optional	104	3.06 (0.782)	Required	197	3.32 (0.571)	8,347.5	.012*	.15
Men	None	868	3.10 (0.769)	Optional	402	2.97 (0.841)	188,925.5	1.000	.07
	None	868	3.10 (0.769)	Required	875	3.25 (0.671)	334,064.0	<.001*	.10
	Optional	402	2.97 (0.841)	Required	875	3.25 (0.671)	140,680.0	<.001*	.16
Domestic	None	688	3.05 (0.776)	Optional	327	2.96 (0.828)	118,365.0	1.000	.04
	None	688	3.05 (0.776)	Required	705	3.31 (0.634)	192,460.5	<.001*	.18
	Optional	327	2.96 (0.828)	Required	705	3.31 (0.634)	85,657.0	<.001*	.21

Note: * indicates $p < 0.05$; bold indicates a large effect size. All p-values are Bonferroni corrected.

Table 4.15: Comparing 4th year students' course grades across course categories by collaboration requirement for each gender and legal status using Wilcoxon Signed-rank tests.

Subset	**Group 1**			**Group 2**			**Wilcoxon Signed-rank Tests**		
	Collaboration Requirement	***n***	***M(SD)***	**Collaboration Requirement**	***n***	***M(SD)***	***W***	***p***	***r***
Women	None	93	3.27 (0.557)	Optional	93	3.04 (0.774)	1,136.0	1.000	**.64**
	None	168	3.12 (0.719)	Required	168	3.3 (0.561)	4,696.0	.006*	**.60**
	Optional	79	3.10 (0.761)	Required	79	3.40 (0.505)	616.0	<.001*	**.70**
Men	None	317	3.17 (0.669)	Optional	317	3.00 (0.853)	13,435.5	1.000	**.63**
	None	701	3.11 (0.750)	Required	701	3.29 (0.632)	71,148.0	<.001*	**.62**
	Optional	308	2.95 (0.828)	Required	308	3.29 (0.599)	9,153.0	<.001*	**.70**
International	None	152	3.27 (0.645)	Optional	152	3.07 (0.808)	3,074.5	1.000	**.63**
	None	304	3.19 (0.701)	Required	304	3.20 (0.645)	20,892.0	1.000	.47
	Optional	128	3.01 (0.811)	Required	128	3.22 (0.681)	1,862.5	<.001*	**.67**
Domestic	None	258	3.15 (0.644)	Optional	258	2.97 (0.850)	8,884.0	1.000	**.63**
	None	565	3.06 (0.762)	Required	565	3.34 (0.599)	34,948.0	<.001*	**.68**
	Optional	259	2.97 (0.820)	Required	259	3.35 (0.523)	5,943.0	<.001*	**.71**

Note: * indicates $p < 0.05$; bold indicates a large effect size. All p-values are Bonferroni corrected.

4.2.2 RQ2: Grade Differences Across Genders or Across Legal Statuses by Collaborative Approach

We conducted Mann-Whitney U tests comparing the mean course grades of students across genders and across legal statuses in courses with varying degrees of collaborative learning requirements: none, optional, and required. Our hypothesis was that "men and women will perform differently across course categories" and "international students will achieve lower grades than domestic students across course categories".

Tables 4.16 and 4.17 show the results of the Mann-Whitney U test results for third and fourth year students, respectively.

In both years, our hypotheses were not supported for any comparison between women and men. Tables D.7 and D.8 in Appendix D show that all comparisons between men and women had low observed power, ranging from 5% to 22%.

When comparing the mean course grades of international and domestic students, test results show that domestic students performed better than international students in courses with a required collaborative component. Among third year students, the difference in course grade means was 0.24 grade points, or around a full letter grade. Among fourth year students, the difference was only 0.14 grade points. Comparisons between international and domestic students where tests failed to return a significant result had observed powers consistently below 10%.

Table 4.16: Comparing 3rd year students' course grades across genders and across legal statuses in different course categories using Mann-Whitney U tests.

Course Category	**Group 1**			**Group 2**			**Mann-Whitney U Tests**		
	Subset	***n***	***M(SD)***	**Subset**	***n***	***M(SD)***	***U***	***p***	***r***
No Collaborative Component	Women	235	2.86 (0.841)	Men	976	2.89 (0.861)	111,254.5	.476	.02
	International	499	2.92 (0.820)	Domestic	712	2.86 (0.882)	182,564.0	.795	.02
Optionally Collaborative Component	Women	72	2.95 (0.745)	Men	286	2.87 (0.871)	10,769.0	.544	.03
	International	169	2.87 (0.857)	Domestic	189	2.88 (0.842)	15,978.5	.503	.00
Required Collaborative Component	Women	192	2.88 (0.868)	Men	806	2.91 (0.810)	76,799.0	.872	.005
	International	399	2.77 (0.822)	Domestic	599	3.00 (0.808)	99,082.5	<.001*	.15

Note: * indicates $p < 0.05$; bold indicates a large effect size.

Table 4.17: Comparing 4th year students' course grades across student genders and across legal statuses in different course categories using Mann-Whitney U tests.

Course Category	**Group 1**			**Group 2**			**Mann-Whitney U Tests**		
	Subset	***n***	***M(SD)***	**Subset**	***n***	***M(SD)***	***U***	***p***	***r***
No Collaborative Component	Women	219	3.11 (0.717)	Men	868	3.10 (0.769)	94,624.5	.919	.003
	International	399	3.18 (0.721)	Domestic	688	3.05 (0.776)	150,730.0	.997	.08
Optionally Collaborative Component	Women	104	3.06 (0.782)	Men	402	2.97 (0.841)	22,236.0	.313	.05
	International	179	3.03 (0.832)	Domestic	327	2.96 (0.828)	30,709.5	.822	.04
Required Collaborative Component	Women	197	3.32 (0.571)	Men	875	3.25 (0.671)	89,136.0	.451	.02
	International	367	3.17 (0.682)	Domestic	705	3.31 (0.634)	112,388.5	<.001*	.11

Note: * indicates $p < 0.05$; bold indicates a large effect size

4.3 Discussion

This study used archival data to examine differences in the academic performance of computer science students across collaborative learning approaches.

Exploratory analysis of the used dataset indicated that the number of withdrawals from courses increased from students' first year to their second year and then decreased every following year. Our analysis also showed that students' course grades were lowest in their second year. This observation aligns with the "dip in performance" documented by previous research in the second year of various post-secondary programs (Yorke, 2014). In the context of the computer science department where this study was conducted, this dip might be due to the particularly challenging nature of second-year courses. It is possible that students were not adequately prepared by their first year courses for the challenges posed by the second-year curriculum. Moreover, second-year students may still be unable to discern which courses from the wide array of options the department provides best align with their skills and interests.

Our exploratory analysis also indicated that most withdrawals from courses occur closer to the end of the semester. According to this university's and most large research universities' policies, students who withdraw at that time of the semester are required to pay the full tuition fees of courses they withdraw from. This makes most students less likely to withdraw from courses at that time unless they believe persisting will severely affect their wellbeing or their academic standing. Late withdrawals thus pose a financial and mental burden on most students, and while they were not addressed in this study, late withdrawals need to be investigated and addressed in future work.

Aligning with the findings of previous research related the benefits of collaborative learning on academic achievement in post-secondary education (Johnson et al., 2007; Laal & Ghodsi, 2012; Shibley & Zimmaro, 2002), our analysis showed that collaborative learning was associated with better grades, specifically for women, men, and domestic students.

This effect was not present for international students. In courses where collaboration was required, domestic students performed better than international students in both the third and fourth years. A likely explanation for this phenomenon is that some international students were less prepared by their pre-university education for collaborative learning approaches, especially as they were employed in the context of this department.

Our analysis indicated that students in their fourth year perform worse in courses where collaboration is optional than in courses under any other category. This finding suggests that when presented with the option to either collaborate or work independently, students may not consistently select the option most beneficial to their academic performance.

Generally, our analysis revealed more pronounced results supporting the positive effect of collaborative learning on academic achievement among fourth-year students compared to third-year students. This trend could stem from the fact that first- and second-year students mostly enroll in courses without a collaborative component. As a result, students in their third year might still be acquiring the skills of collaboration and may struggle to fully employ and benefit from collaborative learning as students in their fourth year do.

Students are more likely to leave post-secondary education in their first year than in any other year (Hanson, 2023; Tinto, 1975). Building on the benefits of collaborative learning for academic achievement, sense of community, and the formation of connections, all of which inspire motivation and persistence, we believe that it is important for computer-science departments to employ collaborative learning methods in introductory courses taken by students in the earlier years of their programs.

4.3.1 Limitations

The present study used archival data of student registrations from a large research university in western Canada. The limited representation of students from underrepresented genders hindered our ability to analyze the different intersections of student identities. This unfortunately reflects the unbalanced distribution of students in computer science (National Center for Education Statistics, 2021). A more nuanced understanding of identity would necessitate data collected over a significantly longer time duration. Despite the limited sample sizes, the statistical power was sufficient to detect important effects, and this work has identified important directions for additional investigation. This work also reports the statistical information to allow others to estimate necessary sample sizes so that future studies are sufficiently powered.

4.3.2. Future Work

Future work should aim to expand our dataset to facilitate a more nuanced understanding of students' intersectional identities and experiences and to enhance statistical power. A dataset built over a longer duration could also enable the investigation of the long-term effects of collaborative learning on academic achievement and persistence.

This study highlighted the positive association between collaborative learning and academic achievement for students from different genders and for domestic students. Future work should investigate methods to design collaborative approaches that support both domestic and international students in developing their collaboration skills during the earlier years of their programs and so they can employ those skills later in their degrees and in their careers.

Finally, our analysis highlighted that most students withdrawing from computer-science courses do so late in the semester, likely at a high cost to their mental and financial well-being. Future work should investigate late withdrawals and potential ways their harms could be mitigated, possibly, by employing collaborative learning.

Chapter 5

Conclusion

This thesis comprises two research studies investigating sense of community, social connections, and collaborative learning in post-secondary computer-science education. The first study used data gathered from students through an optional questionnaire and examined the sense of community and the social connections of computer-science students across different demographic variables. The study also investigated the influence of computer science students' social connections on their sense of community and how their sense of community differs across courses with varying collaborative learning requirements. Finally, the study examined differences across courses with varying collaborative learning requirements in students' centrality in their social networks and in the number of strong connections they formed.

The second study used archival data to investigate the differences in the course grades of computer science students across courses with different collaborative learning requirements. Subsequently, the study examined the differences in course grades of students across different demographic groups in courses with varying collaborative learning requirements.

The results of this work highlight important findings, some of which are further discussed below.

5.1 On the Sense of Community of Computer-Science Students

When responding to the questionnaire discussed in Chapter 3, students expressed feeling disconnected from their peers. Particularly, students from underrepresented genders and underrepresented ethnic groups experienced a significantly lower sense of community in computer-science courses than their majority counterparts. Similarly, students in the earlier years of their programs had a lower sense of community than students in later years.

Strayhorn (2018) identified three factors that influence students' sense of community: their background characteristics, their incoming orientations, and their school environment and experiences. Among those factors, university departments can mainly affect their students' school environments and experiences to foster student sense of community. Potential interventions to foster a sense of community among students could involve substituting items found in computer science classrooms with items not typically associated with computer science (Cheryan et al., 2009) and offering research opportunities to students in the earlier years of their programs (Klawe, 2013). These interventions have been successful in supporting the sense of community of students from underrepresented genders in some cases.

Sax et al. (2018) showed that across different demographic groups, computer-science students' sense of community is heightened when they feel supported by their instructors or by their peers. This indicates the potential for supporting sense of community through interventions that encourage supportive communication and interaction amongst students and instructors. Similarly, Meeuwisse et al. (2010) found that students from underrepresented ethnic backgrounds reported a higher sense of community when they had positive formal relationships with both their instructors and their peers. Departments could encourage students to form formal relationships with their peers through incorporating collaborative work in courses and with their instructors through encouraging one-to-one office hours and other supportive formal communication.

5.2 On the Social Connections of Computer-Science Students

Students expressed feeling disconnected from their peers. They also expressed a desire to have more connections and a belief that such connections would support their academic success. Our analysis showed that the number of connections computer-science students had in their courses was a positive predictor of their sense of community.

Dawson (2006) and Royal and Rossi (1996) found that students who engaged in frequent communication with their peers tended to form more connections and experience a stronger sense of community than students who communicate less often. Except where collaborative learning was employed and especially since the COVID-19 pandemic, course tasks in the department under study, and likely in other computer-science departments in similar contexts, were mostly individualistic endeavors that did not encourage frequent communication among students.

As suggested by the findings of RQ8 and RQ9 of the first study, encouraging the formation of connections among students could involve incorporating more collaborative learning into their coursework. Outside of classrooms, computer science departments could also encourage frequent communication by creating “third places” for students in their buildings. Third places, as defined by Oldenburg (1999), are spaces other than where students live or work, where they could voluntarily, informally, and regularly communicate with others in their community. Such spaces bring students together and encourage positive interactions, which, in turn, supports the formation of lasting connections and of a sense of community (Oldenburg, 1999; Temple, 2008).

Banning et al. (2010) found that students associate their third places with the ability to be around and interact with others they know. Students also linked these spaces with activities such as having conversations, socializing, drinking and eating, reading, and studying. Banning et al. reported that most participants (n = 91) had no trouble identifying spaces they considered their third places. However, Banning’s work was conducted with students enrolled in introductory design courses, whose university environments and experiences may be significantly different from those of computer-science students. Further research should investigate whether computer science students in different departments have spaces they consider their third places and what features computer science students associate with or prefer to have in their third places.

Outside the context of post-secondary education, research has shown that residents’ sense of community in their neighborhoods is associated with the proximity and accessibility of third places, as well as the presence of public art, food outlets, seating, nature, and attractive architecture within or near those third places (Francis et al., 2012). Similar research should be conducted to identify which features of third places could positively influence the sense of community of students in post-secondary computer science.

5.3 Experiences of First Year Computer Science Students

Our analysis suggests that students in the earlier years of their programs experience a lower sense of community in their computer-science courses than students in later years. Among all program years, first year students had the lowest mean sense of community scores and the lowest number of connections in their courses.

While these findings align with expectations, considering the transitional nature of the first year where students are still adjusting to the new post-secondary environment, they underscore the need for targeted interventions to enhance the sense of community of first year students, who are more likely to leave post-secondary education than students in any other year (Hanson, 2023; Tinto, 1975).

Building on the benefits of collaborative learning highlighted by this work to the formation of social connections which in turn positively predict sense of community, one such intervention could involve employing more collaborative work in introductory computer-science courses. Analyses conducted in the second study of this thesis, discussed in Chapter 4, indicated that in the department where this work was conducted, students in the earlier years of their programs were offered fewer courses with a collaborative component than students in later years. This pattern likely extends to other departments in similar contexts.

5.4 Experiences of Second Year Computer Science Students

Students in their second year had the highest mean number of connections in their courses. Nonetheless, their sense of community was lower than that of students in all other years except the first. Second-year students also had the highest variance in the number of connections they had in their courses and in their sense of community scores. Of the variance in their CCS-SF and Connectedness scores, 8.2% and 11.6% respectively, were explained by models of the number of supportive connections they had in their courses and outside them.

Our analysis also indicated that students' in their second year had the largest number of withdrawals and the lowest course grades across all program years. This observation aligns with the second year "dip in performance" documented in various post-secondary programs and labeled the "second-year blues" in the United Kingdom and the "sophomore slump" in the United States (Yorke, 2014). Graunke and Woosley (2005) suggested that this phenomenon is influenced by the low sense of community of second year students. Yorke (2014) reported that factors that contribute to this phenomenon include the psychological well-being of students, their orientations, and their self-competency beliefs, which in the context of the department where this work was conducted might be affected by the challenging nature of second-year courses. Moreover, Yorke mentioned that program design and extraneous factors such as the need to undertake part-time work or sort accommodation issues affect the performance of second year students.

While much of the research in post-secondary computer-science education tends to focus on the experiences of first year students, these findings highlight the necessity of investigating the experiences of computer science students in their second year.

5.5 Experiences of International Students in Computer Science

In research addressing the experiences of post-secondary computer-science students, legal status as an aspect of identity is rarely considered. This work explored the experiences of international students, mainly their sense of community and their social connections and how those and their academic achievement are affected by collaborative learning. This work also compared the experiences of international students to those of domestic students.

Our analysis did not find significant differences between international and domestic students for student sense of community and the number of social connections they had. This, however, might be due to the small representation of international students in our questionnaire responses and the consistently low observed statistical power in tests comparing the sense of community scores and the numbers of social connections between international and domestic students. The high proportion of international students in the archival data used by the second study suggests that international students had a lower response rate to the questionnaire distributed by the first study than domestic students.

Our analysis suggested that collaborative learning did not aid international students in feeling that they have a course community to support them in meeting their learning needs. Moreover, while domestic students performed better in courses where collaboration was required than they did in other courses, international students did not experience such an effect. Domestic students additionally performed better than international students in courses where collaboration was required, but not in courses with an optionally collaborative component or in courses without a collaborative component.

A likely explanation for these findings is that international students may have been less prepared than domestic students to benefit from collaborative learning approaches. Figure 4.2

showed that the representation of international students in the department where this work was conducted was generally increasing across semesters. In the last semester documented by the study's dataset, international students made up around 45% of all enrolled computer science students. Given this significant and growing portion of international students, computer science departments should take into consideration the educational backgrounds of their diverse student groups when designing curricula and pedagogical approaches. Future work should investigate methods to design collaborative approaches that support both domestic and international students in developing their collaboration skills during the earlier years of their programs.

5.6 Final Remark

The work discussed in this thesis was motivated by the importance of a sense of community to students' well-being and persistence. We investigated the sense of community of computer-science students across different demographic groups and in different years of their undergraduate degree programs. We focused on social connections and on collaborative learning as factors that influence students' sense of community and academic achievement. The findings of this thesis underscore important directions of work for researchers and departments to support computer-science students from different backgrounds and in different stages of their programs.

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Appendices

Appendix A: Research Ethics Board Approval Letter

4/15/24, 3:41 PM   arise.ualberta.ca/ARISE/sd/Doc/0/MSN6LPL8U6A475GRGF5JHN2SFF/fromString.html

Notification of Approval

Date: July 19, 2021

Study ID: Pro00112537

Principal Investigator: Carrie Demmans Epp

Study Title: Imposter Syndrome in Computer Science Education

Approval Expiry Date: Monday, July 18, 2022

Sponsor/Funding Agency: FoS New Faculty Startup Funds

RSO-Managed Funding:

Project ID	Title	Grant Status	Sponsor	Project Start Date	Project End Date	Purpose	Other Information
RES0039792							
RES0053852	When did you drop out? Identifying barriers to undergraduate success	Submitted	Insight Development Grants	7/1/2021	5/31/2023	Grant	

Thank you for submitting the above study to the Research Ethics Board 2. Your application has been reviewed and approved on behalf of the committee.

Approved Documents:

Recruitment Materials

recruitmenttext_impostersyndrome.docx

Consent Forms

consent_CS_Ed_actionResearch.docx

Questionnaires, Cover Letters, Surveys, Tests, Interview Scripts, etc.

Questionnaire.docx

Any proposed changes to the study must be submitted to the REB for approval prior to implementation. A renewal report must be submitted next year prior to the expiry of this approval if your study still requires ethics approval. If you do not renew on or before the renewal expiry date, you will have to re-submit an ethics application.

Approval by the Research Ethics Board does not encompass authorization to access the staff, students, facilities or resources of local institutions for the purposes of the research.

Sincerely,

Stanley Varnhagen, PhD
Associate Chair, Research Ethics Board 2

https://arise.ualberta.ca/ARISE/sd/Doc/0/MSN6LPL8U6A475GRGF5JHN2SFF/fromString.html   1/2

Figure A.1: Research ethics board approval letter.

Appendix B: Chapter 3 Questionnaire Variables and Items

The study discussed in Chapter 3 involved gathering data through a voluntary questionnaire distributed to students enrolled in 26 undergraduate computer science courses in the department where the study was conducted. The questionnaire comprised five sections. Below are the questionnaire items.

B.1 Participants Sense of Community in their Course

The first section assessed students' sense of community in their courses. It included the Classroom Community Scale - Short Form (CCS-SF) and a free-response question where students could share additional thoughts about their course experience.

The CCS-SF is composed of 8 Likert-type items. Items 1, 2, 5, and 7 relate to feelings of connectedness and contribute to the Connectedness score, while the other four relate to learning support and contribute to the Learning Support score. Each item is rated using a five-point scale, from “strongly disagree” to “strongly agree”. Items 1, 2, 6, 7, and 8 are positively worded, meaning that a rating of “strongly agree” corresponds to a value of 4 while a rating of “strongly disagree” corresponds to a value of 0. Items 3, 4, and 5 are negatively worded, meaning that “strongly agree” corresponds to a value of 0 while “strongly disagree” corresponds to a value of 4.

The items of the Classroom Community Scale - Short Form (CCS-SF) measuring students sense of community in their courses are as follows:

1. I feel that students in this course care about each other.
2. I feel connected to others in this course.
3. I feel that it is hard to get help when I have a question.
4. I feel uneasy exposing gaps in my understanding.
5. I feel reluctant to speak openly.
6. I feel that I can rely on others in this course.
7. I feel that I am given ample opportunities to learn.
8. I feel confident that others will support me.

The free-response question was worded as follows:

Is there anything you would like to share about your experience in {course code}? [Optional]

B.2 Participants' Social Connections in their Course

The second section gathered data on students' social connections. This section also included a free-response question where students could share additional thoughts about their social connections and how they support their academic success. The following are the questions of the second section:

1. Please list the names of students currently enrolled in {course code} who fit any of the following descriptions:
    a. Students you most often interact with in academic activities related to this class. This includes, among other things, students you work with on assignments or study with.
    b. Students you consider your friends
    c. Students you consider your friends from before this class started.

    List up to 20 names and check the description/descriptions that fit each name. One name can fit more than one description (e.g. "a friend from before this class started" can also be "a friend", and so on).

    Please provide both first and last names, and when possible, please include {university domain emails} in parentheses.

    If no one fits any of these descriptions, please write 'none' in place of the first name.
2. Please list people not enrolled in {course code} who support you in activities related to this course.

    In this question, you don't need to provide names; instead, you can describe people by their relationship to you (e.g., 'my sister,' 'a friend who is also in computing science but is not enrolled in the course').

    If no one fits this description, please write 'none' in the first box.
3. Please enter your first and last name.
4. Is there anything you would like to share about your social connections and how your connections support your academic success in {course code}? [Optional]

B.3 Participants' Sense of Community in the Department

The third section was optional, that is, students could complete the questionnaire without responding to the third section. The third section asked students who chose to answer it to respond to items related to their sense of community in the computer science department where the study was conducted. Here again, we used the CCS-SF and a free-response question, both worded slightly differently than in the second section related to sense of community in courses. CCS-SF, Connectedness, and Learning Support scores for students' sense of community in the department are calculated the same way as in the second section for their sense of community in their courses. However, responses to this section were not used in the research discussed in this thesis but will be used in future research.

The same base items from the CCS-SF were used in addition to the updated free-response item:

> Is there anything you would like to share about your experience in the {department name}? [Optional]

B.4 Demographic and Program Information

The fourth section gathered information related to students' demographic backgrounds and to their current degree program at the university where the study was conducted. All questions in this section were optional. Responses to some questions in this section were not used in the research discussed in this thesis but will be used in future work. Below are the questions of the fourth section. The response type for each question is shown in italics:

1. What is your gender?
   One-answer multiple choice question with the following options:"I prefer to describe myself (with a textbox to enter gender identity)", "Female", "Male", "Non-binary/Other", "I prefer not to share this information"
2. In which year were you born?
   A slider ranging from 1950 to 2010
3. Which languages do you speak fluently? Please list them all, separated by commas.
   Single-line text entry
4. In which country did you grow up?

One-answer multiple choice question with an alphabetically ordered list of all countries as options

5. What is your status in Canada?
   One-answer multiple choice question with the following options: "Canadian citizen", "Permanent resident", "Student on a study permit", "Temporary resident on a visa other than a study permit", "I prefer not to share this information"
6. What population groups are you a member of? Select all that apply.
   Multiple-answer multiple choice question with the following options: "Arab or Middle Eastern", "Black", "Chinese", "Filipino", "Indigenous: First Nations, Métis, Inuk (Inuit)", "Japanese", "Korean", "Latin American", "South Asian", "South East Asian", "West Asian (e.g. Iranian, Lebanese)", "White", "I prefer not to share this information"
7. What is the highest level of education your first parent/guardian has completed?
   One-answer multiple choice question with the following options: "No certificate, diploma or degree", "Secondary (high) school diploma or equivalency certificate", "Apprenticeship or trades certificate or diploma", "College, CEGEP or other non-university certificate or diploma", "University certificate or diploma below bachelor level", "University certificate, diploma, or degree at bachelor level", "University certificate, diploma, or degree above bachelor level", "Other/Unknown", "I prefer not to share this information"
8. What is the highest level of education your second parent/guardian has completed?
   One-answer multiple choice question with the following options: "No certificate, diploma or degree", "Secondary (high) school diploma or equivalency certificate", "Apprenticeship or trades certificate or diploma", "College, CEGEP or other non-university certificate or diploma", "University certificate or diploma below bachelor level", "University certificate, diploma, or degree at bachelor level", "University certificate, diploma, or degree above bachelor level", "Other/Unknown", "I prefer not to share this information"
9. What program are you currently in?
   One-answer multiple choice question with the following options: "BA in any field", "BSc in a field other than Computing Science (e.g., Biology, Psychology, Physics, Chemistry)", "BSc Honors in a field other than Computing Science (e.g., Biology, Psychology, Physics,

Chemistry)", "BS Specialization in an area of Computing Science", "BSc Honors in Computing Science", "BS General in Computing Science", "After degree program in Computing Science", "MSc in Computing Science (Course-based)", "MSc in Computing Science (Thesis-based)", "PhD", "Other", "I prefer not to share this information"

10. What year of your program are you currently in?
    One-answer multiple choice question with the following options: “1”, “2”, “3”, “4”, ‘5”, “6+”, "I prefer not to share this information"
11. What is your grade point average (GPA) so far ?
    One-answer multiple choice question with the following options: “less than 1.5”, “1.5 - 2.5”, “2.5 - 3.5”, “3.5 - 4.5", “This is the first semester of my degree and I still do not have a GPA”. “I prefer not to share this information”

B.5 Permission to Obtain Participants’ Course Grades

The fifth section asked students for permission to obtain their final course grades when the course is over. Responses to this section were not used in the research discussed in this thesis but will be used in future work.

The first question is a multiple choice items with the options “yes” and “no”:

1. To better understand the relationship between student experiences and their performance, we would like to link your answers to the previous questions with your course grade.
   Neither your name nor grade will be included in any report we write on the results of analyzing this data. Even if you choose to not give us permission to access your course grade, your other answers to this questionnaire would still be useful to us.
   May we obtain your {course code} grade after the course ends?

The second question is a text-entry question only shown to students if the select “yes” in the first question:

2. Thank you for choosing to give us permission to obtain your {course code} grade after the course ends. Please enter your {university email} to allow us to link your grade to your responses.

Appendix C: Chapter 3 Power Analysis Tables

When conducting our analysis, we followed null hypothesis significance tests by statistical power analysis. We performed both post-hoc analysis to determine the observed power of the tests we conducted on the samples we had and a priori analysis to determine the sample sizes that would be required by future work to enable the detection of moderate effects with a statistical power of 80%. We used the statsmodels Python package (Perktold, 2023) to conduct power analysis. This Appendix presents the results of the power analysis conducted for the study discussed in Chapter 3.

For some tests, the value in the column titled "*n* for Power = .80", which reports the sample size required to achieve a power of 80%, has a value of "Failed to converge". A failure to converge means that the power solver was unable to find a sample size that enables the detection of a moderate effect size with a power of 80%. This suggests that the tested effect, if it exists, is very small.

Tables C.1 and C.2 show the power analysis results related to the first research questions comparing students' sense of community across genders, ethnic groups, legal statuses, and program years. Table C.1 shows the power analysis results of the conducted Kruskal-Wallis tests, while Table C.2 shows the results of the conducted Mann-Whitney tests.

Table C.1: Power analysis for comparison of participants' CCS-SF scores, Connectedness scores, and Learning Support scores across ethnic groups and across program years using Kruskal–Wallis tests.

Subsets	**CCS-SF Score**		**Connectedness Score**		**Learning Support Score**	
	Observed Power	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**
East Asian *(n = 44)* South Asian or South-East Asian *(n = 74)* White *(n = 65)* Underrepresented Ethnic Groups *(n = 46)*	.21	1,135	.71	275	.33	671
1st Year *(n = 19)* 2nd Year *(n = 82)* 3rd Year *(n = 72)* 4th Year *(n = 62)*	.20	1,190	.32	710	.18	1,395

Note: bold indicates power >= 0.80.

Table C.2: Power analysis for comparison of participants' CCS-SF scores, Connectedness scores, and Learning Support scores across genders, legal statuses, and ethnic groups using Mann-Whitney U tests.

Subset 1	**Subset 2**	**CCS-SF Score**		**Connectedness Score**		**Learning Support Score**	
		Observed Power	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**
Underrepresented Genders *(n = 104)*	Men *(n = 124)*	**.95**	64	.71	146	**.96**	62
International *(n = 75)*	Domestic *(n = 160)*	.03	Failed to converge	.02	Failed to converge	.05	2,587,602
East Asian *(n = 44)*	South Asian or South-East Asian *(n = 74)*	-	-	.00	Failed to converge	-	-
East Asian *(n = 44)*	White *(n = 65)*	-	-	.00	Failed to converge	-	-
Underrepresented Ethnic Groups *(n = 46)*	East Asian *(n = 44)*	-	-	**.96**	25	-	-
South Asian or South-East Asian *(n = 74)*	White *(n = 65)*	-	-	.01	Failed to converge	-	-
Underrepresented Ethnic Groups *(n = 46)*	White *(n = 65)*	-	-	.58	103	-	-
Underrepresented Ethnic Groups *(n = 46)*	South Asian or South-East Asian *(n = 74)*	-	-	.31	255	-	-

Note: bold indicates power >= 0.80; a dash indicates this test was not performed due to insignificant Kruskall-Wallis results.

Table C.3 shows the power analysis results related to the third research questions comparing the numbers of strong and weak connections students have.

Table C.3: Power analysis for comparison of the number of strong connections and number of weak connections participants have in their courses for each subset using Mann-Whitney U tests.

Student Subset	**n**	**Observed Power**	***n* for Power = .80**
Underrepresented Genders	104	**.96**	59
Men	124	**1.00**	37
International	75	**.98**	35
Domestic	160	**1.00**	54
East Asian	44	.54	88
South Asian or South-East Asian	74	**.97**	37
White	65	**.92**	44
Underrepresented Ethnic Groups	46	.74	55
1st Year	19	.42	55
2nd Year	82	**.98**	38
3rd Year	72	**.86**	60
4th Year	62	**.93**	40

Note: bold indicates power >= 0.80.

Tables C.4 and C.5 show the power analysis results related to the fourth research questions comparing the numbers of different social connections students have across genders, ethnic groups, legal statuses, and program years. Table C.4 shows the power analysis results of the conducted Kruskal-Wallis tests, while Table C.5 shows the results of the conducted Mann-Whitney tests.

Table C.4: Power analysis for comparison of the numbers of different types of connections participants have across ethnic groups and participants' years in their programs using Kruskal–Wallis tests.

Subsets	**No. of Friends**		**No. of Friends Before Course**		**No. of Students they Work With**		**No. of External Connections**	
	Observed Power	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**
East Asian *(n = 44)* South Asian or South-East Asian *(n = 74)* White *(n = 65)* Underrepresented Ethnic Groups *(n = 46)*	.54	392	.52	412	.43	504	.47	462
1st Year *(n = 19)* 2nd Year *(n = 82)* 3rd Year *(n = 72)* 4th Year *(n = 62)*	**.89**	190	**0.95**	154	**.95**	154	**1.00**	87

Note: bold indicates power >= 0.80.

Table C.5: Power analysis for comparison of the numbers of different types of connections participants have across genders, legal statuses, ethnic groups, and participants years in their programs using Mann-Whitney U tests. The number of samples used to conduct the Kruskal-Wallis tests could be found in Table 3.2 in the third chapter of the main text.

Subset 1	**Subset 2**	**No. of Friends**		**No. of Friends Before Course**		**No. of Students they Work With**		**No. of External Connections**	
		Observed Power	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**
Underrepresented Genders *(n = 104)*	Men *(n = 124)*	.14	2,175	.07	25,221	.04	Failed	**.81**	112
International *(n = 75)*	Domestic *(n = 160)*	.00	Failed	.00	Failed	.02	Failed	.06	18,071
East Asian *(n = 44)*	South Asian or South-East Asian *(n = 74)*	-	-	.69	76	-	-	-	-
East Asian *(n = 44)*	White *(n = 65)*	-	-	.12	1,425	-	-	-	-
Underrepresented Ethnic Groups *(n = 46)*	East Asian *(n = 44)*	-	-	.02	Failed	-	-	-	-
South Asian or South-East Asian *(n = 74)*	White *(n = 65)*	-	-	.00	Failed	-	-	-	-
Underrepresented Ethnic Groups *(n = 46)*	White *(n = 65)*	-	-	.43	160	-	-	-	-

Underrepresented Ethnic Groups *(n = 46)*	South Asian or South-East Asian *(n = 74)*	-	-	.05	234,127	-	-	-	-
1st Year *(n = 19)*	2nd Year *(n = 82)*	-	-	-	-	-	-	.21	186
1st Year *(n = 19)*	3rd Year *(n = 72)*	-	-	-	-	-	-	.74	35
1st Year *(n = 19)*	4th Year *(n = 62)*	-	-	-	-	-	-	.00	11
2nd Year *(n = 82)*	3rd Year *(n = 72)*	-	-	-	-	-	-	.60	124
2nd Year *(n = 82)*	4th Year *(n = 62)*	-	-	-	-	-	-	**.98**	37
3rd Year *(n = 72)*	4th Year *(n = 62)*	-	-	-	-	-	-	.33	227

Note: bold indicates power >= 0.80; a dash indicates this test was not performed due to insignificant Kruskall-Wallis test results. Due to space limitations, values of “Failed to converge” are reported in this table as “Failed”.

Tables C.6 and C.7 show the power analysis results related to the seventh research questions comparing students' sense of community across course categories by collaborative learning requirement. Table C.6 shows the power analysis results of the conducted Kruskal-Wallis tests, while Table C.7 shows the results of the conducted Mann-Whitney tests.

Table C.6: Power analysis for comparison of participants' CCS-SF scores, Connectedness Scores, and Learning Support Scores course categories by collaborative learning requirement for each student subset using Kruskal–Wallis tests. The number of samples used to conduct the Kruskal-Wallis tests could be found in Table 3.23 in the third chapter of the main text.

Subset	**CCS-SF Score**		**Connectedness Score**		**Learning Support Score**	
	Observed Power	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**	**Observed Power**	***n* for Power = .80**
Underrepresented Genders	.34	313	.15	786	.53	188
Men	.11	1,487	.39	320	.07	5,647
International	.66	101	.22	355	**.89**	61
Domestic	.33	493	.41	387	.11	2,009
East Asian	.20	230	.22	204	.28	158
South Asian or South-East Asian	.16	517	.28	269	.27	276
White	.12	669	.35	186	.20	348
Underrepresented Ethnic Groups	.34	132	.22	214	.39	116
3rd Year	.20	395	.17	490	.34	211
4th Year	.47	128	.47	128	.36	171

Note: bold indicates power >= 0.80.

Table C.7: Power analysis for comparison of Learning Support scores of participants who identified as international students across course categories by collaboration requirement using Mann-Whitney U tests.

Group 1		Group 2		Power Analysis	
Collaboration Requirement	***n***	**Collaboration Requirement**	***n***	**Observed Power**	***n* for Power = .80**
None	47	Optional	9	.03	Failed to converge
None	47	Required	19	.36	101
Optional	9	Required	19	.29	61

Note: bold indicates power >= 0.80.

Tables C.8 and C.9 show the power analysis results related to the eighth research questions comparing students' degree centralities across course categories by collaborative learning requirement. Table C.8 shows the power analysis results of the conducted Kruskal-Wallis tests, while Table C.9 shows the results of the conducted Mann-Whitney tests.

Table C.8: Power analysis for comparison of participants' degree centralities in their course social networks across course categories for each subset using Kruskal–Wallis tests.

Student Subset	**No Collaborative Component**	**Optionally Collaborative Component**	**Required Collaborative Component**	**Power Analysis**	
	n	***n***	***n***	**Observed Power**	***n* for Power = .80**
Underrepresented Genders	149	22	64	.71	128
Men	70	10	24	**.87**	105
International	77	11	36	**.98**	40
Domestic	47	9	19	**.91**	118
East Asian	102	13	45	**.83**	41
South Asian or South-East Asian	19	8	17	.51	138
White	46	5	23	.32	204
Underrepresented Ethnic Groups	49	4	12	.49	89
3rd Year	31	3	12	**.93**	51
4th Year	34	9	29	.70	77

Note: bold indicates power >= 0.80.

Table C.9: Power analysis for comparison of the degree centralities in course social networks of participants who identified as men, domestic students, or students in their 4th year across course categories by collaboration requirement using Mann-Whitney tests.

Subset	Group 1		Group 2		Power Analysis	
	Collaboration Requirement	***n***	**Collaboration Requirement**	***n***	**Observed Power**	***n* for Power = .80**
Men	None	77	Optional	11	.00	Failed to converge
	None	77	Required	36	**.84**	44
	Optional	11	Required	36	.77	19
Domestic	None	102	Optional	13	.02	Failed to converge
	None	102	Required	45	**.98**	28
	Optional	13	Required	45	.73	25
4th Year	None	30	Optional	11	.03	Failed to converge
	None	30	Required	21	**.90**	18
	Optional	11	Required	21	.68	20

Note: bold indicates power >= 0.80.

Finally, Table C.10 shows the power analysis results related to the ninth research questions comparing the number of strong connections students formed across course categories.

Table C.10: Power analysis for comparison of the number of students participants identified as their friends but not their friends before the course began across course categories for each subset using Kruskal–Wallis tests.

Subset	No Collaborative Component	Required Collaborative Component	Power Analysis	
	n	*n*	Observed Power	*n* for Power = .80
Underrepresented Genders	70	24	.57	66
Men	77	36	.00	Failed to converge
International	47	19	.23	204
Domestic	102	45	.02	Failed to converge
East Asian	19	17	.12	486
South Asian or South-East Asian	46	23	.01	Failed to converge
White	49	12	.05	123,274
Underrepresented Ethnic Groups	31	12	.22	132
3rd Year	34	29	.00	Failed to converge
4th Year	30	21	.59	43

Note: bold indicates power >= 0.80.

Appendix D: Chapter 4 Power Analysis Tables

This Appendix presents the results of the statistical power analysis conducted for the study discussed in Chapter 4. We employed the same methods for power analysis related to the study discussed in Chapter 4 as we did for the analysis related to the study discussed in Chapter 3. Refer to Appendix C for details on power analysis methods.

Tables D.1 to D.6 show the power analysis results related to the first research question comparing grades across course categories by collaborative learning requirements Tables D.1 to D.3 for students in their third year. Table D.1 shows the power analysis results of the conducted Kruskal-Wallis tests Table D.2 shows the results of the Mann-Whitney tests. Finally, Table D.3 shows the results of the Wilcoxon Signed-rank tests.

Table D.1: Power analysis for comparison of 3rd year students' course grades across course categories for each gender and legal status using Kruksall-Wallis tests.

Subset	**No Collaborative Component**	**Optionally Collaborative Component**	**Required Collaborative Component**	**Power Analysis**	
	n	***n***	***n***	**Observed Power**	***n* for Power = .80**
Women	235	72	192	.10	6,651
Men	976	286	806	.12	21,334
International	499	169	399	.64	1,507
Domestic	712	189	599	.74	1,729

Note: bold indicates power >= 0.80.

Table D.2: Power analysis for comparison of 3rd year students' course grades across course categories by collaboration requirement for each legal status using Mann-Whitney U tests.

Subset	**Group 1**		**Group 2**		**Power Analysis**	
	Collaboration Requirement	***n***	**Collaboration Requirement**	***n***	**Observed Power**	***n* for Power = .80**
International	None	499	Optional	169	.01	Failed to converge
	None	499	Required	399	.00	Failed to converge
	Optional	169	Required	399	.002	Failed to converge
Domestic	None	712	Optional	189	.08	26,539
	None	712	Required	599	**.91**	461
	Optional	189	Required	599	.56	570

Note: bold indicates power >= 0.80.

Table D.3: Power analysis for comparison of 3rd year students' course grades across course categories by collaboration requirement for each gender and legal status using Wilcoxon Signed-rank tests.

Subset	**Group 1**		**Group 2**		**Power Analysis**	
	Collaboration Requirement	***n***	**Collaboration Requirement**	***n***	**Observed Power**	***n* for Power = .80**
Women	None	53	Optional	53	.21	470
	None	163	Required	163	.03	Failed to converge
	Optional	54	Required	54	.04	Failed to converge
Men	None	223	Optional	223	.01	Failed to converge
	None	670	Required	670	.22	5,544
	Optional	285	Required	285	.72	261
International	None	132	Optional	132	.00	Failed to converge
	None	345	Required	345	.00	Failed to converge
	Optional	122	Required	122	.06	87,576
Domestic	None	144	Optional	144	.48	348
	None	488	Required	488	**1.00**	139
	Optional	144	Required	144	.82	136

Note: bold indicates power >= 0.80.

Tables D.4 to D.6 show the power analysis results related to the first research question for students in their fourth year. Tables D.4, D.5, and D.6 show the results of the Kruskal-Wallis tests, Mann-Whitney tests, and Wilcoxon Signed-rank tests, respectively.

Table D.4: Power analysis for comparison of 4th year students' course grades across course categories for each gender and legal status using Kruksall-Wallis tests.

Subset	**No Collaborative Component**	**Optionally Collaborative Component**	**Required Collaborative Component**	**Power Analysis**	
	n	***n***	***n***	**Observed Power**	***n* for Power = .80**
Women	219	104	197	**.91**	385
Men	868	402	875	**1.00**	538
International	399	179	367	.41	2,248
Domestic	688	327	705	**1.00**	267

Note: bold indicates power >= 0.80.

Table D.5: Power analysis for comparison of 4th year students' course grades across course categories by collaboration requirement for men, women, and domestic students using Mann-Whitney U tests.

Subset	**Group 1**		**Group 2**		**Power Analysis**	
	Collaboration Requirement	***n***	**Collaboration Requirement**	***n***	**Observed Power**	***n* for Power = .80**
Women	None	219	Optional	104	.02	Failed to converge
	None	219	Required	197	**.95**	122
	Optional	104	Required	197	**.94**	84
Men	None	868	Optional	402	.00	Failed to converge
	None	868	Required	875	**1.00**	259
	Optional	402	Required	875	**1.00**	82
Domestic	None	688	Optional	327	.001	Failed to converge
	None	688	Required	705	**1.00**	93
	Optional	327	Required	705	**1.00**	51

Note: bold indicates power >= 0.80.

Table D.6: Power analysis for comparison of 4th year students' course grades across course categories by collaboration requirement for each gender and legal status using Wilcoxon Signed-rank tests.

Subset	**Group 1**		**Group 2**		**Power Analysis**	
	Collaboration Requirement	***n***	**Collaboration Requirement**	***n***	**Observed Power**	***n* for Power = .80**
Women	None	93	Optional	93	.00	Failed to converge
	None	168	Required	168	**1.00**	81
	Optional	79	Required	79	**.99**	30
Men	None	317	Optional	317	.00	Failed to converge
	None	701	Required	701	**1.00**	92
	Optional	308	Required	308	**1.00**	31
International	None	152	Optional	152	.00	Failed to converge
	None	304	Required	304	.08	31,665
	Optional	128	Required	128	**.95**	76
Domestic	None	258	Optional	258	.00	Failed to converge
	None	565	Required	565	**1.00**	41
	Optional	259	Required	259	**1.00**	22

Note: bold indicates power >= 0.80

Tables D.7 and D.8 show the power analysis results related to the second research question comparing mean course grades across gender and legal statuses for different course categories. Table D.7 shows the results for the analysis using the grades of students in their third year, while Table D.8 shows the results for the analysis using the grades of students in their fourth year.

Table D.7: Power analysis for comparison of 3rd year students' course grades across genders and across legal statuses in different course categories using Mann-Whitney U tests.

Course Category	Group 1		Group 2		Power Analysis	
	Subset	***n***	**Subset**	***n***	**Observed Power**	***n* for Power = .80**
No Collaborative Component	Women	235	Men	976	.09	9,301
	International	499	Domestic	712	.002	Failed to converge
Optionally Collaborative Component	Women	72	Men	286	.14	1,220
	International	169	Domestic	189	.06	103,667
Required Collaborative Component	Women	192	Men	806	.08	8,671
	International	399	Domestic	599	**1.00**	156

Note: bold indicates power >= 0.80.

Table D.8: Power analysis for comparison of 4th year students' course grades across genders and across legal statuses in different course categories using Mann-Whitney U tests.

Course Category	Group 1		Group 2		Power Analysis	
	Subset	***n***	**Subset**	***n***	**Observed Power**	***n* for Power = .80**
No Collaborative Component	Women	219	Men	868	.05	76,132
	International	399	Domestic	688	.00	Failed to converge
Optionally Collaborative Component	Women	104	Men	402	.18	1,204
	International	179	Domestic	327	.006	Failed to converge
Required Collaborative Component	Women	197	Men	875	.22	1,775
	International	367	Domestic	705	**.95**	295

Note: bold indicates power >= 0.80.