Retention in Computer Science Undergraduate Programs in the U.S.

Data Challenges and Promising Interventions

acm Association for Computing Machinery

Advancing Computing as a Science & Profession

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The ACM Education Board Retention Committee:
Chris Stephenson (co-chair)
Alison Derbenwick Miller (co-chair)
Christine Alvarado
Lecia Barker
Valerie Barr
Tracy Camp
Carol Frieze
Colleen Lewis
Erin Cannon Mindell
Lee Limbird
Debra Richardson
Mehran Sahami
Elsa Villa
Henry Walker
Stuart Zweben

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EXECUTIVE SUMMARY

In recent years, the lack of diversity in computing fields in the United States has been the focus of a number of conversations: in technology companies, in the popular media, in government, and in academia. Although the possible reasons for diversity challenges remain the subject of debate, one thing is clear: if we are not attracting and retaining a diverse population of students in computer science programs during the students' academic careers, we will not see a diverse workforce in computing emerge. Diversity challenges begin in schools, carry through into higher education, and ultimately persist in the workforce.

Diversity in computing is a vitally important issue. First and foremost, computer science (CS) and the technologies it enables provide numerous opportunities for economic growth, stability, and success. To expand equity and social justice across society, all students must have access to CS education and the myriad educational, occupational, and financial opportunities it affords. Additionally, increased diversity in computing is at the heart of robust innovation resulting in products that may also serve a diverse population. And, understanding how computing both expands and limits the information to which people have access is critical to ensuring active and meaningful participation in civic life and the support of democracy.

Yet, even as "CS for All" has taken on a life of its own in the United States and an increasing number of schools are offering CS courses, the demographics of the students involved in computing remain stubbornly consistent. Despite recent increases in enrollment, by the time students start high school, CS is predominately the domain of White boys. The percentage of girls and minorities enrolled in CS classes is far smaller than the percentage of girls and minorities enrolled in school; their representation in computing is disproportionately small. Similar demographics persist in higher education.

This report on retention in undergraduate CS programs in the United States reveals that retention is an incredibly complex issue and that empirical data to examine retention is both limited and messy. The changing demographics will undoubtedly require a broad set of tactics that address issues in both recruitment and retention. Girls and other groups underrepresented in computing must be invited into CS, and once they are there, they must be retained. This sounds fairly simple, but it is not.

For example, *retention* itself is difficult to define and isn't used consistently across institutions or conversations. Questions about both student and institutional intent in taking and offering courses designed for first-year students come into play. If a student taking a first-year CS course never intended to pursue further CS studies and follows through on that intent, is that a retention problem? From a purely quantitative perspective it may appear to be so, but to follow the quantitative data alone may lead to incorrect conclusions about the problem.

Institutional priorities can also be a factor. In some cases, retaining a student at an institution is more important than retaining a student in any given program or school, and the data the institution collects to measure retention may reflect this perspective. Inconsistent data collection and terminology use can make it difficult—if not impossible—to aggregate existing data across institutions in a way that can provide correct and insightful information on retention in CS specifically.

And yet, if diversity in computing is to be increased, retention issues must be tackled. To address this, the Association for Computing Machinery (ACM) formulated a committee of faculty from diverse institutions to explore currently available data, tease out the knowns and unknowns, and make recommendations. This report is a substantial first step in attempting to use empirical data to examine and understand retention in U.S. undergraduate CS programs. It examines existing datasets and ultimately reveals that significantly better data is needed to draw any broad conclusions about retention in CS programs. This report also includes case studies from specific institutions that provide important insights into both how a broader, cross-institutional study could be approached and the ways in which different institutions are understanding and addressing retention. Finally, this report includes an examination of interventions that have been used to improve retention at existing institutions.

Based on the data examination, analysis, and case studies, this report makes a number of recommendations regarding data collection, successful interventions, and future research:

- Additional research is needed to provide a more nuanced understanding of the dynamics of attrition and retention, to identify the factors that decrease retention, and to find ways to address these factors.
- Individual programs should plan data-gathering efforts that regularly capture information about student progressions through courses and programs.
- Where possible, institutions should hire data specialists with the expertise and time to provide complete datasets and assist faculty with analysis.
- Institutions should collaborate to determine the types of data that could consistently be captured across institutions and how this data might be regularly aggregated and evaluated.
- Instructors of introductory courses need to be involved in data collection.
- Administrators need to help enable data collection by marshaling the resources necessary to gather, clean, and analyze data.
- Data should be evaluated in different contexts, using different denominators to determine how women and other groups are represented in computing in the context of their participation in higher education and their representation in society.
- Educators and administrators need to be aware of barriers to entry as leaks in the retention pipeline are identified.
- Institutions should not wait for more research before launching new interventions and using new insights to continuously refine and improve these interventions.
- Educators should provide students with a well-rounded understanding of the discipline of CS and seek to overcome misconceptions.
- Institutions should provide funding and educators should adopt pedagogical strategies to ensure that all students perceive classrooms and labs as welcoming environments.
- Educators should adopt pedagogical strategies that incorporate collaboration and team-based learning.
- Institutions should provide programs, services, and pathways that enable students entering the institution with varying computational backgrounds to succeed in their intended major (especially with regard to computing and mathematics).
- Educators need resources to help them incorporate real-life problems into courses so students have early exposure to the positive societal role of CS.
- Educators need funding for undergraduate research programs (especially at minority-serving institutions (MSIs)) because many students cannot afford to participate in summer programs unless they are compensated at a level equal to what they would earn in a summer job.
- Institutions need support to investigate and adopt the ACM Committee for Computing Education in Community Colleges (CCECC) transfer guidelines to encourage and facilitate transfer from two-year and community colleges to four-year institutions.
- Institutions need to provide proactive advising to ensure that students are exposed to career opportunities and pathways early in their undergraduate experience and are able to complete their intended major on time.

The ACM Retention Committee hopes that this document, despite its limitations, will be a useful resource and an inspiration for additional empirical work for CS faculty, departments, undergraduate institutions, and researchers as we work together to better understand the complexities of tracking and understanding student retention and develop interventions that will improve the engagement and retention of all students.

CONTENTS

The Long-Standing Lack of Diversity in Computer Science in the United States

Though recent media attention on the lack of women and people from groups underrepresented in technology jobs in the United States might lead one to conclude this is a recent problem, it is not. Instead, it reflects a decades-old change in the demographics of students who choose to pursue computer science (CS) as a field of study. The current problem results from society's reaping what we collectively sowed starting in the late 1980s and early 1990s, when the percentage of women graduating with degrees in computing in the U.S. dropped to levels generally between 10% and 18% depending on which areas of computing were considered (Zweben and Bizot, 2016), and the study of CS became predominantly the domain of White men (Myers, 2018; Google and Gallup, 2016). Even with reported recent gains in the representation of women in CS (Computing Research Association, 2017), this representation still does not exceed 18%.

In recent years, several cultural and systemic hypotheses have been put forward to explain the lack of diversity in modern computing jobs. History tells us this problem does not begin in the workforce; the current workforce must necessarily reflect the educational demographics of students past. Therefore, the current workforce diversity problem is not just a workforce problem. Rather, it is a pipeline and retention problem that begins in middle and high school, persists through university undergraduate and graduate programs, and ultimately manifests in the labor pool and in industry.

The extent of the diversity challenge in pre-college schooling is clearly demonstrated in data provided by The College Board for its CS Advanced Placement exams. Analysis conducted by Barbara Ericson (Georgia Tech College of Computing, 2017) on the 2017 AP CS data revealed that despite (1) an 11.2% increase in AP CS A student test takers and (2) the introduction of the new Computer Science Principles course and exam which attracted 43,780 students, young women represented only 27% of all AP CS test takers, Black students accounted for only 5%, and Latinx students for only 15%, all well below their overall shares of school enrollment.

This same pattern of underrepresentation of female students persists in post-secondary CS programs. According to the National Science Foundation's Engineering and Science Indicators for 2016, despite the fact that women earned 57.3% of bachelor's degrees overall, and 50% of bachelor's degrees in science and engineering, they accounted for only 17.9% of bachelor's degrees in the computing sciences. That percentage dips even lower for women of color (National Science Foundation, 2016). The Integrated Postsecondary Education Data System (IPEDS) data for doctoral-granting units (CRA, 2017) found similar results. For these institutions, women comprised 15.3% of CS bachelor's degrees granted in 2015. The percentage of women was only slightly higher in non-doctoral granting institutions in 2015, with women representing 16.6% of bachelor's degrees granted in CS.

The lack of representation in undergraduate CS programs in the United States is even more dire for people from other groups underrepresented in computing. According to IPEDS data from the National Center for Education Statistics (NCES) (CRA, 2017) (using only codes 11.0101 and 11.0701 in defining CS) for all bachelor's degrees granted in CS in 2015:

- 8.4% were Latinx students at doctoral-granting institutions
- 8.5% were Latinx students at non-doctoral-granting institutions
- 4.3% were Black students at doctoral-granting institutions
- 8.6% were Black students at non-doctoral-granting institutions

This NCES data for institutions of all types (National Center for Educational Statistics, 2018) is consistent with data provided by the annual Taulbee study of doctoral-granting institutions. The Taulbee data for 2015 shows that students from groups underrepresented in computing collectively comprised only 13% of CS bachelor's degree graduates (Zweben and Bizot, 2017). In non-doctoral granting institutions, people from groups underrepresented in computing fared only slightly better. IPEDS data shows that for most of the years from 2007-2015, people from groups underrepresented in computing collectively remained at close to 18% of all CS bachelor's degrees granted.

The persistent disproportional participation of people from groups underrepresented in computing continues into the workforce. Data from the United States Bureau of Labor Statistics indicates that women's representation in the information technology and computing workforce has been steadily dropping since its peak in the mid-1980s. According to the National Center for Women in Information Technology (2018a), the percentage of women in computing declined from 2000 to 2011 and is now just holding steady. In addition, women in computing fields, with a quit rate of

more than 56%, are more likely to leave their computing careers at 10 to 20 years than in any other science and engineering field and at twice the rate of their male peers.

Why Diversity in CS Matters

Why is this lack of diversity in CS a problem? The underrepresentation of women and people from groups underrepresented in computing raises concerns for a variety of reasons, including (1) issues of equity and fairness, (2) the economic and competitive imperative of ensuring a large and diverse U.S. workforce, (3) the fact that better solutions are developed by teams with a diversity of people and perspectives, and (4) the increasing interdependency between American democracy and the ability to understand and navigate the presentation of information through technology.

Equity and Fairness

Given the near ubiquity of computing across industries, the increasing number of computing-related jobs (Burning Glass and Oracle Academy, 2016), the value of computing skills in almost all jobs, and the fact that CS offers numerous lucrative career pathways (Burning Glass and Oracle Academy, 2017), it is only fair that all students should have access to the educational experiences and prerequisites that are essential to these jobs. As research scientist Jane Margolis has articulated, CS knowledge is "a kind of high-status knowledge that taps a student into the grid of twenty-first century opportunities" (Margolis, Estrella, Goode, Holme, and Nao, 2008, 4). As described earlier, the continued absence of specific groups in the computing field is well documented. Consequently, rather than CS serving as a powerful tool for social and economic equalization, the systematic details of inequality, mechanisms, and beliefs that channel some groups (particularly students of color) away from computing in fact denies those populations a wide range of educational, occupational, and financial opportunities.

Economic and Competitive Imperatives

Many countries believe that a large and diverse workforce is essential to continued innovation and economic growth. In the United States, the current shortfall of CS graduates prepared to fill current and future computing jobs is a pressing concern in education and in industry. According to the University of Washington's Ed Lazowska (2016), computing occupations "are projected to account for 73% of all newly created STEM jobs during the decade (488,500 jobs), and 55% of all available STEM jobs, whether newly created or available due to retirements (1,083,800 jobs over the decade)." Code.org noted that in 2017 there were more than 500,000 open computing jobs available nationally and in that same year fewer than 50,000 students graduated from CS programs—the main source of preparation for these jobs (Code.org, 2018). If the U.S. cannot supply graduates with the knowledge and skills to fill available computing jobs, then innovation will lag, and possibly cease.

Better Solutions Through Diversity

Numerous Fortune 100 CEOs, including Google's Sundar Pichai, Microsoft's Satya Nadella, and Oracle's Safra Catz, have pointed out that underrepresentation in CS can have a debilitating impact on innovation and the design of technology-based products because a diverse mix of voices leads to better discussions, decisions, and outcomes. Evidence of this, from the still-present dangers to women caused by automobile testing using "male" -sized and -shaped crash test dummies in the 1960s, speech recognition systems that primarily recognize male voices, and facial recognition systems that cannot recognize people of color, is well documented by Carol E. Reiley, co-founder and president of Drive.ai. She writes, "The lack of diversity in AI [artificial intelligence] is not merely a social or cultural concern. It's really a life or death safety issue" (Reiley, 2016). Respected researcher Orit Hazzan also has pointed out, "[I]t is in the interest of the computing world, rather than in the interest of any specific underrepresented group in this community, to enhance diversity in general" (Hazzan, 2006, 1).

Computer Science Supports Civic Participation

The year 2018 will be notable as the year the American public became broadly aware of the ways in which technology can be used to manage, control, and manipulate information and perceptions of fact. With new, publicized attention to alleged Russian interference in the 2016 U.S. Presidential election and the role companies like Facebook and Twitter can play in affecting the information individuals see, Americans became sharply aware why it matters that citizens, policy makers, and the general public understand the computing and algorithms behind the headlines. To participate fully in civic life, to make informed decisions, and to engage in political decision-making at all levels, citizens must be able to think critically and analytically. They must also understand how to interpret and validate information presented to them.

The growing use of machine learning provides a clear example of how new technologies are shaping multiple fields and directly impacting human lives. For example, something as simple as a news feed populated by algorithms based on what one has already read can result in a dangerous narrowing of perspective and a limited understanding of reality. Algorithms may be based on faulty assumptions, contain logical errors, or include assumptions that are violated in some applications. Datasets may highlight incomplete or inconsistent values, contain implicit biases, or focus upon limited populations. Thus, when computers are making choices for individuals, it is vital that those individuals understand how those choices are formulated. Without a foundational knowledge of computing, they cannot be fully engaged in civic life, and they cede power to those who do understand computing.

Clearly, diversity in CS is vital, and the lack of diversity has important consequences for those who are not

represented—namely women and people from the other groups underrepresented in computing. What is to be done to change things? Although those in education and industry have put forward many theories, two things remain stubbornly opaque: why the CS diversity problem persists despite specific efforts to engage and retain girls and people from groups underrepresented in computing, and whether data-driven interventions would be more success-ful in moving the field closer to parity.

The Formation of the ACM Retention Committee

In November 2016, the Education Board of the ACM estab-lished a committee to explore these diversity concerns at the undergraduate level. The diversity issue is enormously complex, and the committee was deliberately created with a limited scope to help lend focus and structure to the work. The committee's purpose was to examine and address the current issue of retention in four-year, post-secondary CS education programs in the United States, specifically the retention of women and students from other groups underrepresented in computing following CS1 and CS2. In part because of the paucity of data-driven analyses and recommendations in the general literature, the committee's goals were to explore existing datasets and data challenges, identify factors contributing to the leaky pipeline, and recommend potential interventions to improve retention. Although retention of students at each stage of an undergraduate computing program merits review, the committee focused primarily on introductory levels (the first and second courses in a CS major program, which the committee decided to refer to as CS1 and CS2), rather than on program graduation rates, as this is the first opportunity for CS bachelor's programs to impact retention for a large number of students.

The committee consisted of a varied group of CS faculty and was co-chaired by two representatives from industry (Alison Derbenwick Miller from Oracle and Chris Stephenson from Google). Other members of the commit-tee included:

- Christine Alvarado: University of California, San Diego
- Lecia Barker: NCWIT (National Center for Women in Information Technology)
- Valerie Barr: Mount Holyoke College
- Tracy Camp: Colorado School of Mines
- Carol Frieze: Carnegie Mellon University
- Colleen Lewis: Harvey Mudd College
- Erin Cannon Mindell: Google
- Lee Limbird: Fisk University
- Debra Richardson: University of California, Irvine
- Mehran Sahami: Stanford University
- Elsa Villa: University of Texas, El Paso
- Henry Walker: Grinnell College
- Stuart Zweben: The Ohio State University

The questions which drove the committee's work included:

- What sources of data exist from which to study retention on a broad scale? (For example, CRA's Taulbee Survey and National Center for Education Statistics IPEDS.)
- What are the barriers to the collection/provision of more comprehensive data?
- What methods, tools, incentives might facilitate better data collection and analysis?

The committee also started to explore factors poten-tially contributing to students choosing to leave their CS programs along with factors that contributed to staying. These included:

- What is known about the intentions of students entering CS1/CS2? Do they know whether they want to major or minor in CS before taking CS1? Do intentions and/or commitment levels differ by gender prior to starting CS1? Understanding this is a more challenging issue in institutions where students do not matriculate into the institution with a declared major.
- Does intent change differently for women, students from other groups underrepresented in computing, and men after the first year of CS courses?
- What is known about the intentions of the institution or department in developing and offering CS1/CS2? Is the course a "funnel" course designed to attract students into CS? Is the course a "filter" course designed to encourage some students to opt out and help the institution manage interest/demand versus supply challenges?
- Does prerequisite experience (e.g., high school CS courses, community college transfer students, summer jobs or internships in computing areas) play a role in retention?
- Do the faculty/teaching demographics of the individual programs impact retention of women and students from other groups underrepresented in computing?
- How do the CS dropout rates for women and people from other groups underrepresented in computing compare to dropout rates for these groups for other similar disciplines?
- Where do students go when they leave CS after CS1/CS2?
- What factors contribute to the retention of students?
- Are the challenges and issues similar or different at majority-minority institutions?

From the outset, the committee recognized that retention is highly complex. In addition to the factors above, the audience for CS1 and CS2 is varied and introductory computing courses must meet incoming students where they are. Although challenges with meeting the needs of students with different backgrounds and experience levels

have been present in introductory CS courses for years, the need to address non-homogeneous populations and the related difficulties in doing so have been exacerbated by recent record-setting enrollments in computing majors and client disciplines (disciplines that value and rely on computation and computational analysis as a tool and look to CS departments to teach their majors basic CS concepts and skills). By definition, teaching introductory CS to students majoring in client disciplines means that not every student who takes CS1 and/or CS2 will go on to take more advanced CS classes or become a CS major. How do we account for this when researching retention issues? Additionally, overall retention in higher education is currently a challenge. National Student Clearinghouse data shows that only 61% of students starting college in 2015 returned to their starting institution in 2016 (Field, 2018). These issues contribute to the difficulty of studying the retention of women and other underrepresented populations in computing.

Additionally, as the committee began its work and started exploring available data, the committee found that defining, collecting, collating, and organizing retention data both within and across institutions is extraordinarily challenging. It quickly became clear that even though all the factors and questions the committee considered are important and merit further evaluation, to address them all using existing datasets would not be possible. This is more fully explored in "Challenges to Collecting Retention Data" below.

Retention Versus Persistence

As the committee began its work, it became clear that the word *retention* means different things at different institutions and that it would be important to define *retention* as it is used in this work.

In some cases, *retention* may simply mean that someone enrolled and stayed at the same institution until graduation, no matter the program they completed versus where they began when they first were enrolled at the institution. In this case, *retention* is not concerned with majors or departments—only that an entering student stays at the same institution through graduation.

In other cases, *retention* can mean "once accepted into a program of study, the student stayed in that program until completion of the program," or even more generally, given two points in time, the student is in the same program (presumably but not necessarily at the same institution) at the beginning point and at the end point.

In the first case, *retention* is relative to the institution; in the second case, it is relative to the program of study. This second case—whether a student remains in a declared major year-over-year—is sometimes also or alternatively referred to as *persistence*. And while *persistence* is widely used to reflect a student staying in a program within an institution, it can also be used to reflect a student remaining in a major regardless of institution.

From a college or university administration perspective, both retention and persistence are important to gauge the success of the institution and the schools, departments, and majors within that institution, and institutions have good reasons for using the methodologies and terminologies they do in the contexts of their own organizations. However, this can all become very complex and confusing when one is trying to request, understand, and aggregate data from multiple institutions and sources, and if not carefully attended to, can lead to misunderstandings and misrepresentations of the retention landscape.

The committee was specifically interested in whether a student who enrolled in CS1 subsequently enrolled in CS2 at the original institution or at another institution. For the purposes of this project, this is what the committee defined as *retention*. The challenges with obtaining this data—including knowing what language to use in requesting data from institutions—are explored in more detail in the section entitled "Challenges to Collecting Retention Data."

Challenges with Defining and Measuring Diversity in Computing

Studying retention data alone may lead to erroneous conclusions about the diversity problem itself, the size and scope of the problem, and potential solutions to the problem. Additionally, looking at gender and race/ethnicity data for CS graduates without cross-correlating socioeconomic status and level of preparation for college may result in misidentification of the true source of diversity challenges: is there a unique diversity problem in computer science, or does the lack of diversity in computer science reflect or amplify a lack of diversity in higher education? And, as discussed earlier, is the issue one of retention, or is the root of the problem really recruitment?

New work by Valerie Barr (Barr, 2018) presents a compelling challenge to the traditional analysis of diversity in computing, suggesting that to truly understand the issue, one must look at the number of degrees earned in CS by a specific cohort versus all degrees earned by that cohort, and not versus the total number of degrees earned in CS. She argues this is particularly critical for longitudinal analysis of the problem, as the demographics of the undergraduate population are not constant over time.

Barr argues that "a by-cohort analysis…gives an accurate way to compare the attractiveness of the field across different student populations" (Barr, 2018, 41). When she slices the data by gender (i.e., men earning CS degrees as a percentage of all degrees earned by men versus women earning CS degrees as a percentage of all degrees earned by women) it becomes clear that the disengagement of women from computing is even more severe than the typical analysis shows. At the highest point, in 1986, women earned 2.97% of their degrees in computer science. In 2015, that number was 0.86%. Contrast that with men, who earned 5.52% of their degrees in CS in 1986, and 5.3% of

their degrees in CS in 2015 (Barr, 2018, 41-42). The decline in women's engagement in computer science is clear.

A similar analysis of race and ethnicity in CS reveals something different: since 1995 (the earliest data available), Blacks, Native Americans, and Hispanics have consistently earned around 2.5% of their total cohort degrees in computer science. As a percentage of their respective degree-earning populations, representation in computer science has stayed nearly constant (Barr, 2018, 43-44). In absolute numbers, though, the number of CS graduates is small; this reflects the troubling fact that for all three of these cohorts, their representation as a percentage of total college degrees earned is far less than their representation as a percentage of the total U.S. population.

In contrast, Asians earn CS degrees at a consistently higher rate. In 2015, nearly 5% of all degrees earned by Asians were earned in CS. In that same year, Asians made up just over 5% of the total US population, and earned 6.8% of all college degrees. In a cohort-based analysis, Asians earn CS degrees at a level that aligns with their overall representation in the population, and at levels much closer to parity with degrees earned in other fields. However, in an analysis that compares CS degrees earned by Asians with the overall number of CS degrees earned, Asians earn 12% of all CS degrees. This could lead one to conclude that Asians are over-represented in computing, when in fact, they earn CS degrees in proportion to their overall representation in the population (Barr, 2018, 43).

This analysis reveals that, if a true understanding of retention and representative diversity in computing is to be achieved, it is critical that data be evaluated in different contexts, using different denominators. For women, the perceived underrepresentation of women in computing when measured in the context of all CS degrees earned is actually even more severe when viewed through a cohort-based lens that accounts for all degrees earned by women. For Asians, representation in CS is on par with representation in the population, and far better than other groups (including Whites) when considered in the context of all degrees earned by Asians. For Blacks, Hispanics, and Native Americans, if the analysis only considers the attainment of CS degrees by these cohorts as a percentage of the total degrees earned in CS, it leads to the incorrect conclusion that these groups are underrepresented in computing, when in fact, these groups are underrepresented in higher education overall.

Without a multifaceted analysis, retention and participation data can potentially lead administrators, faculty, policy makers, and others to focus on solutions to the wrong problems. It is therefore critical that data be evaluated in different contexts, using different denominators to evaluate how women and other groups are represented in computing in the context of their participation in higher education and their representation in society, and not just as a fraction of the number of CS degrees granted.

Limitations of This Project

This project is limited by the fact that the committee's focus was strictly on the U.S. and, as such, is set within a specific social, cultural, and political environment. For this reason, the results and conclusions cannot be extrapolated or generalized to any other country. As Schinzel (2002) noted with specific reference to studying gender representation, CS enrollment globally is culturally diversified and gender itself is not a consistent construction across cultures.

In addition, while the committee's goal was to include students of all gender identities, ethnic backgrounds, cultural perspectives, socio-economic statuses, and intellectual/career interests, the data the committee was able to source at this time simply did not support those goals. The data also did not support the analysis of specific cohorts of students or retention for transfer students. Currently available data limited the committee's quantitative analysis to gender, racial, and ethnic diversity in a shifting, multi-institutional student population over a four-year period. (The committee's exploration of existing datasets and related data analysis are described in detail in later sections.) Further work should be done to develop new recommendations for institutions about collecting data to support understanding "diversity" in a broader way. This would also contribute to a richer, more sophisticated understanding of retention in CS based on a wider range of variables.

Finally, the datasets the committee was able to obtain do not support generalization of the committee's findings to the broader U.S. student population. The committee's scope did not include creating a new dataset, and existing datasets were neither random nor sufficiently large to support large-scale generalizations. The unfortunate side effect of this is that the committee was unable to identify definitively, based on quantitative data, whether there is a retention problem or rather an engagement problem in CS and what the contributing factors might be to the dismal diversity data points discussed earlier.

However, the committee is able to provide a far more detailed picture of the data that is available, as well as several interesting case studies using data from specific institutions that reveal both cautionary tales and some surprising retention successes. Finally, the committee is able to recommend interventions that have been used successfully at different institutions, including some where remarkable improvements in the diversity of CS majors are clear.

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SPECIAL CHALLENGES FOR MINORITY-SERVING INSTITUTIONS

In the committee's investigation of retention in CS1 and CS2 courses, it became apparent that retention challenges are uniquely experienced in different kinds of undergraduate institutions. Minority-serving institutions (MSIs), for example, have a number of characteristics that differentiate them from other four-year undergraduate institutions. This section explores some of those characteristics to provide a more nuanced view of retention in CS. The committee's intention is not to suggest that MSIs alone face these challenges, but rather to highlight that there are systemic challenges which impact these institutions and tend to exacerbate any set of challenges, including those underlying retention in CS. By and large, these systemic challenges result from a relative lack of resources which impacts what faculty are able to do, thereby making it difficult to provide a sufficiently rich experience for students. After definitions and context, the committee provides some illustrative examples of challenges faced and suggestions for how some of the needs of MSIs can be addressed.

About Minority-Serving Institutions

The U.S. Department of Education (DoE) is charged with promoting educational excellence for all Americans, and in this capacity, has an interest in supporting higher education institutions that enroll undergraduate populations with significant percentages of students from underrepresented groups. Although there are a number of federal programs within and beyond the DoE that provide funding to institutions that meet this general criterion, there "are no statutory or regulatory definitions of the term 'minority-serving institution'" (U.S. Department of Education, 2018a) and as a result, different programs and different departments may use different rules, regulations, and criteria to define "minority-serving institution."

There are a number of institutions serving different minority populations that are eligible to receive funds under Section F of the Higher Education Act, 20 U.S. Code § 1067q, as minority-serving institutions, including historically Black colleges and universities (HBCUs), Hispanic-serving institutions (HSIs), Tribal colleges and universities (TCUs), Alaska Native-serving institutions, Native Hawaiian institutions, predominantly Black institutions, Asian-American and Native American Pacific Islander-serving institutions, and Native American-serving nontribal institutions.

Importantly, the DoE has historically offered a program called the Minority Science and Engineering Improvement Program (MSEIP) that "assists predominantly minority institutions in effecting long-range improvement in science and engineering education programs and increasing the flow of underrepresented ethnic minorities, particularly minority women, into science and engineering careers." (U.S. Department of Education, 2018b). Institutions of higher education eligible for this program are identified as "minority institutions" (MIs) under § 365(3) of the Higher Education Act (20 U.S.C. 1067k(3)), and must have minority enrollments of at least 50% of the total enrollment (U.S. Department of Education, 2018c). This is a narrower definition and only applies to programs whose statutes or regulations specifically reference this definition of MI (U.S. Department of Education, 2018d).

For purposes of this project, the committee used the broader MSI designation and focused on three specific types of MSIs: HBCUs, HSIs and TCUs.

HBCUs

Historically Black colleges and universities were originated to address the fact that Black students were historically excluded from admission to colleges and universities nationwide. Today, many African-American students at HBCUs are first-generation college attendees. Many others are second- and third-generation students attending a particular HBCU as "legacy" attendees. As at other MSIs, infrastructure resources at HBCUs are often limited, and philanthropic investments tend to focus on strengthening scholarship assistance for students to support the underlying mission of HBCUs (Ezzell and Schexnider, 2018).

Students at HBCUs have a prevalent interest in making a positive societal impact and creating a society with fewer economic, social, and health disparities (Hanson, 2004, 2007; Hill, Corbett, and St. Rose, 2010; Johnson, 2007). This motivation to serve others through science and connect research with larger personal goals has been termed "altruistic science" (Carlone and Johnson, 2007). As a result, it is not uncommon for a majority of students entering HBCUs to aspire to professions in health care, law, or similar professions that they identify with having transformative potential for society. Because professions such as those in CS and data science may not be perceived as life-serving by students or their families, it is a particular challenge for these professions to attract diverse talent (Johnson, 2007). Areas such as precision medicine, for example, have begun to provide examples of data interrogation that are life-serving, but overall there remains a lack of generalized societal understanding of the diverse ways in which computational

skills and careers in CS can lay the groundwork for societal contributions that move the needle of justice. Meeting this gap in understanding, as a society, would help attract more diverse talent to these professional disciplines.

HSIs

During the 1980s and 1990s, in response to increasing disparities in the undergraduate enrollments of non-Hispanic White students and Hispanic students, Congress amended Title V, Part A of the Higher Education Act to define and create supplemental funding for HSIs (20 U.S.C. 1101 *et seq*.). In addition to requiring that an institution has an undergraduate enrollment of at least 25% full-time-equivalent Hispanic students at the end of the grant year immediately preceding the year in which the institution was applying for funding, Congress imposed a number of eligibility requirements for institutions, including that the institution spend less per student than the national average and have an "enrollment of needy students" at levels defined by law (20 U.S.C. 1101(a)).

Today, HSIs enroll almost half of Hispanic students attending college (Conrad and Gasman, 2015), yet HSIs represent less than 6% of postsecondary institutions in the United States. According to *Excelencia* in Education (2015), 7% of STEM baccalaureate degrees were earned by Hispanics in 2013, and a mere 4% and 3% were master's and doctoral STEM degrees, respectively (National Science Foundation, 2018).

While a greater percentage of Hispanic high school graduates (49%) enroll in college than White non-Hispanic high school graduates (Lopez and Fry, 2013), students who are Hispanic are more likely to enroll in a two-year college (Kurlaender, 2006) and be first in their families to attend college (Pérez and Ceja, 2010). Hispanic students at two-year colleges, however, tend not to transfer to four-year institutions (Crisp and Nora, 2010). HSIs are also typically under-resourced, with many receiving little to no NSF funding (National Science Foundation, 2017). This poses challenges in supporting evidence-based programmatic support, both curricular and co-curricular, including faculty professional development and research experiences for undergraduates.

TCUs

Tribal colleges and universities are defined, authorized, and may receive federal funding under a combination of Executive Orders and congressional acts, originating with the Tribally Controlled College and University Assistance Act of 1978, 25 U.S.C. 1801(a)(4) (U.S. Department of Education, 2018e). Unlike for HSIs, where Congress acted to address enrollment disparities, in authorizing funding for TCUs, Congress's goal was to support "the operation and improvement of tribally controlled colleges or universities to insure continued and expanded educational opportunities for Indian students." (25 U.S.C. 1802). As with HBCUs

and HSIs, challenges exist for retaining and graduating Native Americans with evidence indicating they leave postsecondary institutions at higher rates than other groups underrepresented in computing and are also underrepresented in graduate programs (Jackson, Smith, and Hill, 2003).

Challenges of MSIs

The following are some illustrative, though not exhaustive, examples of the challenges faced by minority-serving institutions and the students who attend them:

- As noted above in the HBCUs subsection, students from groups underrepresented in CS often express a desire for socially relevant professions. Unfortunately, many students and their parents do not see the direct positive impact of CS careers. This challenge can be exacerbated when MSIs are isolated (not in urban areas and not partnered with other institutions).
- We know that early and frequent research opportunities are beneficial for students (Russell, Hancock, and McCullough, 2007). These opportunities give students the opportunity to dive deeply into a single problem, help them gain valuable experience that changes the way they approach future courses, and make them more competitive for opportunities after graduation. Unfortunately, the lack of resources at many MSIs makes it very difficult to provide students with research experience. Faculty at MSIs frequently have high teaching loads, lack funds to travel to and participate in professional meetings, and have minimal or no professional training that prepares them to develop research projects and grant proposals. The lack of resources also makes it difficult for faculty to learn new pedagogical methods that help students develop the skills necessary for pursuing research.

Many students at MSIs are the first in their families to attend college. This poses additional challenges which institutions and faculty need to address. For example:

- Within their families, students tend not to have role models of people who work computationally. Students also lack sufficient examples in the popular press or in the entertainment industry that can serve as an inspiration for their career planning.
- There is a lack of "navigational capital" in that families do not have models for how to support children who go to college (Yosso, 2006).
- A large portion of these students start at community college (CC), but the computer science transition from CCs to four-year institutions can be difficult due to problematic linkage between CC curriculum and four-year curriculum. Schools need support to investigate and adopt the ACM CCECC transfer guidelines (ACM, 2018).

- Proactive advising is critical to ensuring that career opportunities are presented early and students can follow the correct curricular path, rather than end up needing (expensive) additional years to complete requirements.

Many colleges and universities face the challenge of developing strong mentoring and support programs while, at the same time, maintaining standards. Student success must be balanced against both the need for a rigorous curriculum that prepares students to succeed at the next level and competency-based evaluation and assessment. Students from groups underrepresented in computing will already face an uphill struggle in the workforce due to their minority status; reducing rigor to retain these students in computing as undergraduates (and therefore graduating them with less competence) will do them a disservice at the next level and throughout their careers.

While the retention challenges facing MSIs are complex, there are new developments that may help address some of the issues noted above. The National Science Foundation's *Improving Undergraduate STEM Education: Hispanic-Serving Institutions* program is providing additional funding to increase retention and graduation rates of students pursuing associate or baccalaureate degrees in STEM (National Science Foundation, 2017).

In addition, Mount Holyoke College has developed a freely available mentoring and support curriculum called MaGE to train peer tutors (Pon-Barry, St. John, Wai-Ling Packard, and Stephenson, 2017). It should be noted, however, that faculty also need training and release time for course development and program supervision, and additional course coverage may be necessary as faculty are re-deployed to run mentoring efforts.

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CHALLENGES TO COLLECTING RETENTION DATA

Data collection is a critical part of quantitatively understanding the issues related to student retention. However, as outlined previously, retention is a highly complex topic, and data collection is extraordinarily challenging for several reasons. Some of these reasons are described here.

Challenges with Data Collection at the Institutional Level

While retention is an important measure of student success in a program, a number of institutions do not actively collect and curate retention data in an intentional way. As a result, such data must often be pieced together after the fact, for example, comparing the number of students who take a CS1 course in a given term with the number that then take a CS2 course in the next term. Even when such data is gathered, it can often be diluted by factors such as students placing out of or repeating classes, taking courses in a non-linear progression, taking substitute courses at other institutions, or transferring to another institution altogether. Some of these issues can be mitigated by gathering data at the student level (i.e., tracking individual students from course to course) rather than using aggregated class statistics. However, gathering such data at the student level is often beyond the scope of what many institutions can do expediently and still may not entirely eliminate some of the possible confounds in the data.

Challenges with Data Aggregation across Multiple Institutions

In addition to the challenges of collecting retention data within an institution, it is even more problematic to effectively aggregate retention data across multiple institutions. Logistically, there is generally a lack of consistent data collection (e.g., at regular, consistent intervals) across institutions. Even in cases where semantically consistent data might exist, it is often stored in different formats (potentially for different uses) across different institutions. While this may be a theoretically solvable problem, the time and effort required to do so in practice may make it prohibitive to actually aggregate this data.

Furthermore, different institutions may have differing models for when students declare their majors. For example, some institutions admit students directly into the CS major at the time of admission to the institution.

At these institutions, students who are not admitted to the CS major might still have an opportunity to take CS1 or CS2 but may have no incentive (or potentially not even be allowed) to take additional advanced CS coursework. Other institutions may allow students to choose a major after being admitted to the institution but may then have barriers to entry for the CS major (e.g., minimum GPA requirements, limited class sizes, etc.). As a result, a student's decision to take follow-on CS courses may not be entirely under his/her control. Still other institutions may have no specific barriers to pursuing a CS major once a student is admitted to the institution. Thus, even if these institutions measured what on the surface may look like the same data (e.g., students advancing from CS1 to CS2 to CS3) and stored that data in the same format, the semantics of the data are actually somewhat different. Aggregating this data to determine more global measures of retention across programs results in an amalgam of data without clear semantics, limiting what can truly be claimed despite what the numbers alone might seem to indicate.

Challenges in Institutional Definitions and Goals around Retention

Another challenge in gathering retention-related data is the different definitions and goals pertaining to retention at different institutions and programs. For example, in some programs if a student transfers to another institution of higher learning, that student is not considered "retained" even if the student continues to pursue CS at the new institution. This can create confusion particularly in the case where an institution may actually encourage its strongest students to transfer to more selective schools.

Conversely, some institutions only track retention for students considered "first-time, full-time," which means the student has not previously taken courses at an institution of higher learning and is a full-time student. Such measures, however, leave out transfer and part-time students which may make up a considerable percentage of the student body at some schools.

On a related note (and alluded to earlier in this report) there is also considerable variability in institutional goals with respect to retention. For example, some schools may emphasize graduation rates (regardless of major) as the primary retention measure to maximize. In such cases, trying to retain students within a particular major or program is de-emphasized compared to keeping the student at the institution.

Protecting Privacy as a Legitimate Reason to Not Share Data

Issues of privacy may limit the amount of data sharing that might be possible within or across institutions. At the level of data about individual students, privacy concerns are justifiably serious, and, as a result, almost all institutions would only consider providing aggregated data. Even then, when student numbers are small (especially in groups underrepresented in computing), an institution may be reluctant to share (or even be prohibited from sharing) aggregated retention data with others. The potential for data deanonymization, even for aggregated data, is often a risk that many institutions, especially smaller ones, are unwilling to take. This, in turn, can create selection bias in aggregated datasets, which can potentially lead to distortions in the data.

Intention: A Critical, and Often Hidden, Variable

Collecting aggregated, or even individual, data on retention requires careful deliberation and planning. Indeed, when data is collected after the fact by simply looking at the number of students enrolled in courses or even at individual student progressions through classes, a critical variable is often not captured: the student's intent in taking a course. For example, some students may take CS1 with the intent of potentially majoring in CS. Others may take the course because it is a requirement for another (already chosen) major. Still others may be taking the course as a general education requirement, simply out of general interest, or for a potential host of other reasons (e.g., taking a class with their roommate, taking a course based on the instructor's reputation, etc.). Without an articulation of students' intent for taking a class, it is difficult to meaningfully determine whether their choices to continue on to a subsequent CS course are an indication of retention (or lack thereof) in a CS program or simply a by-product of some intention for taking the course other than the pursuit of a CS major.

As mentioned previously, institutions may have different timelines for when students declare a major, for example, at the time of admission to the institution versus sometime in students' first two years at the institution. This timeline difference makes it difficult to make consistent inferences regarding intent. For a student who is admitted as an incoming student to a CS major and then does not take any CS classes beyond CS1, it can reasonably be inferred that the student was not retained in the CS program. However, for the student who can choose any major prior to junior year, the choice to not take another CS course after CS1 may not allow the inference of anything with regard to intention to major in CS.

Retention versus Failure to Engage

The previous example of a student admitted directly to a CS program versus one who has the freedom to choose any major prior to junior year highlights another important difficulty in measuring retention: the difference between failing to retain a student in a CS program versus failing to engage a student sufficiently for him/her to join a CS program. Here the student's underlying intent is the critical factor to consider. Students who are admitted directly to a CS program have, in essence, made their intent explicit. They have chosen to major in CS and if they do not complete the program it can be argued that this was a failure in retention. For students who have the freedom to choose their majors prior to junior year, it becomes difficult to know if the choice to not continue beyond some introductory CS courses is actually a retention issue (i.e., a student at some point intended to major in CS, but chose another major instead) or a student simply chose another major because she/he had not intended to major in CS and was not sufficiently engaged by an introductory CS course to change her/his existing intent.

A Case Study in Understanding Intent: The Transition from CS1 to CS2 at Stanford University

Without a clear understanding of students' intents, it is very easy to be misled by cursory statistics. The following case study using data from Stanford University helps to illustrate this point. At Stanford, students do not need to declare their major until their junior year and there are no barriers to entry for the major. The introductory CS1 course there is taken by a large percentage of all undergraduates and is aimed at being a "funnel" course to attract students into CS.

In examining the cursory statistics of the percentage of men and women in the CS1 course versus the follow-on CS2 course, it appeared that the percentage of women declined significantly between the two courses. To make this example concrete, we examined the enrollment of CS1 in the fall of 2016-17, finding that 47.5% of the class were women. We then looked at the CS2 class that was offered in winter 2016-17 (i.e., the immediate follow-on class in the introductory CS sequence) and found the course to be 38.6% women. The decrease in the percentage of women in CS2 might lead one to (wrongly) believe that the CS1 course was not as welcoming to women as to men. Why is this the wrong conclusion? The answer lies in understanding student intent.

Our first evidence that there was a gender disparity in student intent for taking CS1 came from stratifying the undergraduate men and women taking CS1 that term by their class year. We found that men tended to "front-load" the class, taking it early in their academic careers, whereas more women took the class in their sophomore year or later. Figure 1 shows the number of men and women taking the course, separated by class year.

As seen in Figure 1, it is only in the freshman year that men outnumber women by a large margin. In every other class year, there are more women than men. Seeing this result indicated that perhaps the reason for taking CS1 was different for many more of the women than for the men.
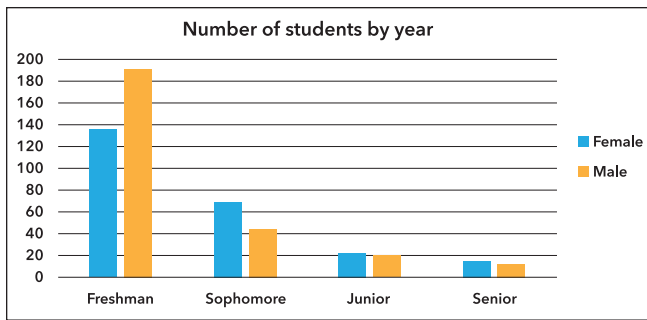
Figure 1. Number of Undergraduate Men and Women Taking CS1 in fall 2016-17 at Stanford University.

Indeed, someone taking CS1 in his/her senior (or even junior) year is unlikely to be considering a CS major as a real possibility.

Having observed this same phenomenon in prior terms, we decided to gather data on intent with regard to majors. In the first week of the class, all students were required to fill out a survey which included a question on whether or not they intended to major in CS. The results, shown in Figure 2 below, showed a clear gender disparity.
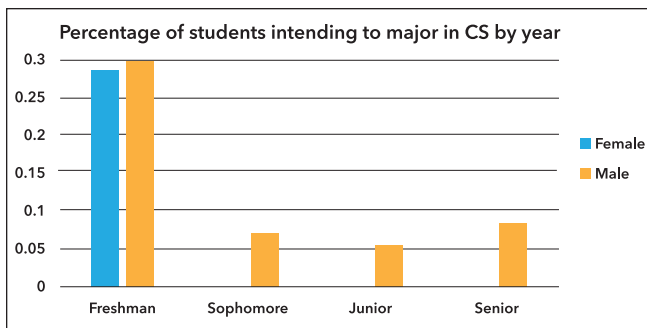
Figure 2. Percentage of Undergraduate Men and Women Per Class Year Intending to Major in CS. (The lack of bars for women in the sophomore, junior, and senior years reflects that no women in any of those years intended to major in CS.)

As seen in Figure 2, the percentage of freshmen taking CS1 who intend to major in CS is roughly comparable across genders (although it is slightly higher for men). Recall, however, that there are many more men than women in their freshman year in the class. Moreover, at the sophomore level and in the later years, while there are more women than men in the class, none of these women indicated an intent to major in CS. Rather they were likely taking CS1 for a requirement in another major or for some other reason. Interestingly, there were men in the sophomore year and later taking CS1 who were intending to major in CS, including the astounding fact there were senior CS majors in CS1!

While the fall quarter CS1 class was 47.5% women, accounting for intent, we found that only 38.6% of the undergraduates in CS1 intending to major in CS were women. Recall that the winter quarter CS2 class was 38.6% women. The fact that these percentages match exactly is coincidental. We should not infer that all the women intending

to major in CS from the CS1 course were retained in the subsequent CS2 course as we do not know if these were the same students. More likely, there were some women in the winter quarter CS2 class who did not take the fall CS1 class and some women from the fall CS1 class who did not take the winter CS2 class, and these numbers tended to offset each other. Also, it is likely that there were more men taking the winter CS2 class without having taken CS1 in the fall, as a prior study (Redmond, Evans, and Sahami, 2013) indicated that more men than women interested in CS at Stanford had computing experience prior to entering college. Still, once we have explicit data regarding student intent, we find strong evidence that the CS1 course is not in fact deterring women who intended to pursue a CS major any more than men who intended to pursue a CS major. It also makes clear why explicitly determining student intent is critical to not making erroneous conclusions based just on statistics of the numbers of men and women in a course as compared to its follow-on course.

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EXPLORING AVAILABLE DATA SETS

As previously described, the committee sought to answer the question of "what sources of data exist" from which some comprehensive quantitative understanding of retention in CS programs could be derived. In studying this question, it proved difficult to identify any source of what might be considered comprehensive data about retention. Most articles about retention in CS appear to study a local situation in the institution or institutions of the authors, so that a particular methodology for improving retention can be investigated in detail and so that specific type of data can be collected (e.g., Giannakos, Pappas, Jaccheri, and Sampson, 2017). More comprehensive datasets about computing programs exist, but each appears to have its limitations relative to studying retention. Some of the more popular datasets and their limitations are enumerated below.

IPEDS

The Integrated Postsecondary Education Data System (IPEDS) allows the user to obtain and create reports covering all disciplines and all institutions that submit data to the National Center for Education Statistics (NCES). Because of NCES's role within the U.S. Department of Education as the primary federal entity for collecting data related to U.S. education, the data elements it contains are nearly universally populated and have been for decades. The data is updated annually (IPEDS, 2018). IPEDS is a well-cited source of information about CS.

IPEDS data at the disciplinary level is limited. Disciplinary data can be ascertained by using Classification of Instructional Program (CIP) codes. These are six-digit numeric codes under which institutions report each of their educational programs. The disciplinary data available in IPEDS includes degree and certificate completions at all levels of postsecondary education, with associated breakdowns by gender, ethnicity, and type of institution. This allows analysis of overall trends for these important variables. Beyond program completion data, however, there is no data in IPEDS from which to study disciplinary characteristics associated with retention. No enrollment data is provided at the disciplinary level, and degree completion data is insufficient to compute or estimate any meaningful retention statistics.

CRA Taulbee Survey

A widely used source of data specific to the computing field is the annual Taulbee Survey (Taulbee Survey, 2018) conducted by the Computing Research Association (CRA).

For more than 45 years, this survey has reported data from U.S. and Canadian departments that grant doctoral degrees in CS, Computer Engineering and, for the past decade, the Information area of computing. The survey's response rate is routinely 75-80% from U.S. CS departments, making the reported data highly representative of U.S. doctoral-granting departments in CS. Data is reported about enrollments and degree production at the bachelor's, master's, and doctoral levels within these departments, with breakdowns in gender and ethnicity also reported by most of the 140-150 respondents. Data about new majors at each degree level is also reported, although there are no breakdowns for gender and ethnicity for this data. During the past two years, the survey has also been collecting enrollment data from a representative bachelor's level course at each of the introductory, intermediate, and advanced levels.

The Taulbee Survey does not collect data about retention. One might consider using the survey's data to estimate retention from the enrollment, degree, and new student data. For example, if all students are retained, then enrollment in year X minus degrees awarded in year X plus new students in year X should equal enrollment in year X+1. This calculation of retention, however, would yield gross estimates at best since (1) new student data is not available by gender and ethnicity, (2) not every department that participates in the survey in a given year also participates in the following year (though the vast majority do), and (3) as discussed above, retention can be strongly affected by when students declare their major, and there is no class rank information which can help account for this.

ACM NDC Study

Beginning with the 2012-13 academic year, ACM began surveying non-doctoral-granting departments in computing (NDCs) in the U.S. to provide a report that complements the CRA Taulbee Survey. This annual NDC Study (Tims, Zweben, and Timanovsky, 2017) collects enrollment and degree production data at the bachelor's and, as appropriate, master's levels for these departments' programs in CS, Computer Engineering, Information Systems, Information Technology, and Software Engineering. Bachelor's degree programs also report data about new majors. Degree production is broken down by gender and ethnicity, but neither enrollment nor new student data is disaggregated this way.

As is the case for the Taulbee Survey, the NDC Study does not collect data about retention. Furthermore,

unlike the Taulbee Survey, the NDC Study has a fairly low response rate (typically under 20%). The number of CS programs responding is similar to the Taulbee Survey; however, the population of such programs is much higher for departments that do not grant doctoral degrees in computing. Therefore, the NDC Study is not a good source from which to reliably estimate retention in CS.

CRA Generation CS

Since 2006, many universities and colleges have seen an enrollment surge in undergraduate CS courses and under-graduate CS programs (major and minor programs). The magnitude of the surge, the influence of non-CS majors on the surge, and the difficulties many CS departments ap-peared to have managing the surge caused the Computing Research Association (CRA) to create a committee in 2015 to investigate the situation. The committee's work led to a survey that was deployed with the CRA Taulbee Survey and ACM NDC Survey discussed previously. The goal of this survey was to "measure, assess, and better understand enrollment trends and their impact on computer science units, diversity, and more" (Computing Research Associa-tion, 2017). With regard to retention, the survey asked each unit's *perception* about trends in the unit's recruit-ment and retention of students from underrepresented groups. In addition, the survey requested enrollment data of four different courses (two intro-level courses, one of which was for non-majors, one mid-level course, and one upper-level course) at three different points in time (2005, 2010, and 2015). Approximately 50% of both doctoral and non-doctoral units perceive the percentage of women in their unit to be increasing, and enrollment data collected with the survey indicate this perception is likely accurate. In addition, approximately 20% of doctoral and 40% of non-doctoral units perceive the percentage of students from underrepresented groups to be increasing and, again, there are some data that indicate this perception may be reality. However, the one-time nature of the survey, and the nature and level of granularity in the data collected, precluded drawing any conclusions relative to retention. The CRA committee analyzing the responses to the survey stressed that retention of women and underrepresented groups requires further study because different hypoth-eses can explain the increased percentages of women and underrepresented students collected during the CRA Generation CS effort (Camp, Adrion, Bizot, Davidson, Hall, Hambrusch, Walker, and Zweben, 2017).

NCWIT

The National Center for Women and Information Technol-ogy (NCWIT) is a non-profit organization whose mission is to significantly increase girls' and women's meaningful participation in computing. NCWIT comprises a "change leader" network of more than 1,100 corporations,

academic institutions, government agencies, and outreach organizations that act in support of its mission. NCWIT is organized into several alliances, allowing organizations with similar challenges and interests to learn from each other. One of these is the Academic Alliance, made up of 540 institutions. NCWIT also has programs and campaigns that help members accomplish their goals of attracting and retaining women in the workforce and educational settings. One of these programs, NCWIT Extension Services for Undergraduate Programs (ES-UP), supports academic de-partments in changing the system experienced by students in ways that attract, retain, and graduate women.

One of the resources used by ES-UP clients is the NCWIT Tracking Tool, which allows users to input their data, then visualize it to better understand which of their efforts work to attract and retain women and which do not. Users are asked to select from a set of possible CIP codes and to input the actual name of their major(s). Data that relate to retention includes the count of declared majors at each of five levels (freshman, sophomore, junior, senior, fifth+ year senior) and the count of and reason for departures (graduation, switching major, or leaving the institution). Within a given class rank, declared majors in a given year are broken down by gender and ethnicity. New enrollees to the major are also distinguished by whether or not they transferred from another institution, and these students are also disaggregated by gender and ethnicity, but not by class rank. Departure data is disaggregated within a given class rank only by gender. The Tracking Tool allows clients to log in and view trends related to groups of students enrolled at different points in the major, year to year, and whether some groups take longer to graduate than others. Over the past ten years, NCWIT has served more than 100 ES-UP clients, each of which agrees to submit at least three years of data during the period when it is receiving consul-tation (1-2 years). In addition, the Tracking Tool is available to NCWIT Academic Alliance members who are not part of ES-UP, though use is voluntary. As of late 2017, about 200 departments of CS, Engineering, and other computing-related majors had submitted data.

The committee decided to explore this dataset to see what retention trends we could identify. The dataset is extremely heterogeneous. For some academic programs there is only one year of data while others have ten years. Also, the level of disaggregation of data available varies, even year to year for the same academic program, with some data consisting of only totals (e.g., all women) but not cross-tabulations (e.g., women by race/ethnicity). The names of majors also vary widely and CIP codes are used inconsistently, so it was sometimes hard to pinpoint the de-gree to which an academic program could be considered CS for the committee's project. In addition, the year of the data submitted for any given institution varies, depending on when it received consultation and whether it continued to update beyond the consulting period mentioned in the previous paragraph.

Another problematic aspect of this dataset for the committee's analysis of retention is rooted in institutional differences for when students declare a major. As discussed earlier, institutions may require students to declare a major upon enrollment or may not allow them to declare until the end of their freshman or sophomore year. Among the institutions, 43% reported that students typically declare upon enrollment, 15% at the end of their first year, 25% at the end of the second year, and 18% selected "other." These differences may account for why the committee found an overall significant increase in the number of students as class rank increased, as discussed in the "Data Analysis" section.

National Student Clearinghouse Research Center

In the latter stages of the committee's work, the committee became aware of a potentially rich source of data at the National Student Clearinghouse Research Center (NSC), which could be useful in studying retention. NSC is a nonprofit, non-governmental organization that obtains data from nearly all universities at the individual student level (National Student Clearinghouse, 2018). The data fields include both institutional and individual student enrollment information. At the individual student level, they provide gender, ethnicity, program of study, and student rank information and are updated regularly by the participating institution's central data office. Programs of study are identified using CIP codes, as defined in IPEDS.

The comprehensive nature of participation in this center by postsecondary institutions, and the nature of the data in the data fields, appears to provide all of the essential ingredients to study enrollment patterns, retention in an individual program of study, and even to track a student across different institutions. While certain high-level reports are available on the NSC website, more discipline-specific reports would be of value in studying CS retention. These reports would only be developed if purchased under an agreement with NSC. The committee had initial discussions with NSC regarding such an agreement, but cost and timing prohibited obtaining and analyzing the data for this project. The committee believes that such an undertaking in the future could provide valuable, data-based insights into retention in the computer science field.

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DATA ANALYSIS

Prior to learning about the NSC data, the committee decided to study the NCWIT data, as it appeared to offer the most comprehensive dataset available that allowed for some analysis of retention. Readers should be cautioned that the NCWIT data represents departments that were strategically recruiting and retaining women, supported by a small amount of funding and a consultant, and this undoubtedly could influence the results. Though the NCWIT data contains information about programs other than CS, the committee restricted its analysis to the data from CS programs. Even this restriction posed challenges in both identifying and analyzing the data. The committee employed a consultant experienced in data analysis methodology to identify the subset of data that could be analyzed effectively and to perform appropriate analyses. The committee provided the consultant with guidance about interpreting the fields in the NCWIT data and about the types of analyses desired.

Data Selected

Identifying Computer Science Programs

The six digits in the IPEDS CIP codes are in the form nn.xxxx, where nn is a broadly described discipline, and the xxxx are more finely defined areas (using the first two x's) and sub-areas (using the remaining two x's) within that broad discipline. For nn=11, the broadly defined area is entitled Computer and Information Sciences and Support Services. This broad category includes codes (in particular, "11.0101, Computer and Information Sciences, General" and "11.0701, Computer Science") under which CS programs report their data (Computing Research Association, 2017) and others under which programs that are distinct from CS (e.g., "11.0103, Information Technology") report their data. The distinction between using only 11.0101 and 11.0701 versus using all of 11.xxxx to represent CS can be appreciable, both in terms of total number of students included, as well as the gender and ethnicity demographics of these students (Zweben and Bizot, 2016).

Respondents providing data to NCWIT input several descriptors of their majors, including name of major and CIP code and title from a pull-down menu. However, the CIP code choices were carried to only two decimal places instead of the possible four. One of the choices was "Computer Science (11.07)." This obviously was an appropriate set of programs to include. In fact, there is only one CIP code under 11.07, and that is "11.0701, Computer Science." Another choice in the NCWIT survey

was "Computer and Information Science (11.01)" which was distinct in the survey by name from the other possible survey choices "Information Technology (11.01)" and "Informatics (11.01)." However, beyond the NCWIT survey there are a variety of other possible program areas within the IPEDS category 11.01, so the committee decided to include in its analysis programs that selected "Computer and Information Science (11.01)" only if those programs also had described their major as "Computer Science."

Identifying the Time Period to Study

Although the NCWIT database was populated by programs in academic years 2004-05 through 2015-16, the quantity and quality of the data varied widely. The committee desired to study retention differences by gender, ethnicity, student rank, and year. Unfortunately, ethnicity differences could not be studied in this dataset since the data input form did not require that respondents report key retention data by ethnicity; in particular, there was no way for respondents to report by ethnicity what happened at the end of the academic year to students who were majors in the program (whether they stayed in the program, graduated, changed majors, or left the university). This "outcomes" data was essential to studying retention, which was defined as the fraction of declared majors who either stayed in the program or graduated from the program.

The committee selected the academic years 2010-11 through 2014-15 for analysis in order to get a contiguous number of years of data that contained sufficient outcomes data disaggregated by gender and rank of student. This enabled the committee to study each of these factors over a period of at least five years. Even with this decision, the number of programs providing outcomes data for all of its majors varied from one year to the next, as did the number of programs providing breakdowns by gender and student rank. The committee analyzed only those programs that provided data for the desired statistical test. A program that did not provide outcomes data for all declared majors in a given year was discarded from the analysis for that year. This further limits the generalizability of the results. We will comment further on the number of programs providing data for our analyses in the next subsection.

Results

The data described in the previous subsection was analyzed in two ways. First, overall enrollment trends were analyzed for statistically significant differences in gender and ethnicity over time. (Even though the data wasn't useful to study

retention based on ethnicity, the committee could and did use it to analyze enrollment trends by ethnicity.) Second, retention was analyzed for statistically significant differences by gender, year, and class rank. Statistical significance is reported as either significant at alpha = 0.05, significant at alpha = 0.01, or not significant.

Enrollment Trends, By Gender and Ethnicity

The data used for analysis of enrollment trends included only those programs that provided gender and ethnicity enrollment breakdowns by class rank. The number of programs included in these analyses is shown in the "# Programs" column of Table 1; the rest of this table provides the percentage representation of women by class rank for each of the five years. For these programs, there was no statistically significant correlation with respect to time for the overall percentage representation of women over the five-year period. The data showed a dip in representation between 2010-11 and 2012-13, followed by a rise in each of the last two years of this period. The last column of Table 1 illustrates this.

However, if only seniors are considered, there is a clear increasing representation of women over time. This is consistent with observations about the increasing representation of women during this period among graduates of CS bachelor's programs (Computing Research Association, 2017), a phenomenon that may be due to differences in when students typically declare their majors, as mentioned above.

In Table 1, the diagonals across the various class ranks, moving downward and to the right, denote changes in the reported representation of women in freshman year n, sophomore women in year n+1, junior women in year n+2,

and senior women in year n+3. Unfortunately, various factors prevent these data points from representing a true "cohort" of students. For example, the number and set of programs is clearly not identical from one year to the next. Furthermore, the students accounted for are declared majors. As indicated earlier in the discussion of the NCWIT dataset, several programs do not permit declaration of major in the freshman year, and some require declaration after the sophomore year. Transfer students further complicate the treatment of these data as a cohort. Nevertheless, it is interesting to see that, for the diagonals beginning with Freshman in years 2011-12 and 2012-13, for which there are at least three years covered in the diagonal, the representation of women is increasing. This is not the case for the two other diagonals for which there are at least three years' worth of data (beginning with Freshman in year 2010-11 and beginning with Sophomore in year 2010-11).

Table 2 summarizes the representation by ethnicity for the same set of programs. Entries show, for each year and gender, the percentage of students of that gender that were of a given ethnicity. Thus, each column adds to 100%. The percentages are computed from the aggregated representation across all class ranks. The total number of students of each gender is shown in the last row of the table for each year.

Correlation analyses and one-way ANOVA was performed on each ethnicity. Both tests showed a significant increase over time in the percentage representation of both Asian men and women ($p < 0.01$). For Hispanic students, the ANOVA was not significant, but there was a significant negative correlation of percentage representation for both men and women over time ($p < 0.05$), though the effect size was small. The ANOVA

Table 1: Representation of Women by Rank and Year

Year	# Programs	Freshman	Sophomore	Junior	Senior	Overall
2010-11	59	12.65%	14.68%	13.83%	12.85%	13.42%
2011-12	61	11.72%	13.16%	13.86%	13.27%	13.08%
2012-13	64	11.33%	13.29%	12.94%	13.40%	12.81%
2013-14	57	13.56%	15.83%	14.84%	14.07%	14.52%
2014-15	67	15.37%	14.83%	16.90%	16.12%	15.95%

Table 2: Ethnicity Percentages by Gender and Year

	2010-11		2010-12		2012-13		2013-14		2014-15	
	F	M	F	M	F	M	F	M	F	M
Asian	15.5	12.4	19.4	15.9	17.2	14.8	23.7	18.7	30.5	23.4
Black	8.7	4.4	7.4	4.1	9.9	5.4	7.5	4.6	5.8	4.1
White	43.5	55.6	38.5	50.5	42.4	53.1	37.0	47.3	34.2	44.6
Hispanic	20.9	15.9	20.7	16.8	14.2	12.6	15.2	15.3	11.9	13.0
Pacific Islander	0.3	0.4	0.2	0.3	0.2	0.2	0.2	0.3	0.1	0.2
2 or more races	5.2	5.4	5.8	5.2	5.8	5.9	5.9	6.0	3.8	3.5
American Indian	0.3	0.4	0.4	0.3	0.6	0.2	0.1	0.3	0.1	0.2
None or unknown	5.4	5.5	7.7	6.9	9.8	7.8	10.4	7.7	13.5	11.0
Total # students	2,888	18,632	3,277	25,047	2,884	19,631	3,440	20,248	4,388	23,118

and correlation analysis also showed a significant decrease in representation of White men over time ($p < 0.01$), but no significant change in the representation of White women. A similar result was found among American Indian students, although the number of students involved is quite small. No statistical significance was found for either men or women among Black, Pacific Islander, or students of two or more races.

Retention by Gender, Year, and Class Rank

The ability to analyze the NCWIT data with respect to retention is dependent on a program having provided, for each of its declared CS majors of a given gender and class rank in a given year, whether a student graduated from the program or stayed in the program going into the next year (as indicated by student status at the end of the given year), versus whether the student left the program (either by leaving the institution or by moving to another program within the institution). The committee defined retention within a given year as:

Retention = (# declared majors who either graduated from the program in that year or for whom end-of-year status indicated they would stay in the program going into the following year) / (total # declared majors in the given year)

In the analyses that follow, the committee will report retention as a percentage, by multiplying this ratio by 100.

The number of programs that provided the data needed to compute retention varied from year to year and, within a given year, varied by class rank and gender combination. The number of programs responding includes those that contributed valid data specifically relevant to retention (i.e.,

they reported how many of their declared majors were still in the major at the end of the year). This value was provided "by cell," where a cell is a specific year-gender-class rank combination. So there was at least one such combination where only 45 programs provided data, and at least one other such combination where 69 programs provided data. Since the data included 5 years, 2 genders and 4 class ranks, there are a total of 40 such cells. And for most of these cells, the number of programs contributing data was in the upper 50s to low 60s. Despite these differences, the committee felt that the retention computed for each individual gender-year-class rank combination is valid and that it is meaningful to aggregate the individual retention computations along each of the dimensions (gender, year, class rank) of interest.

Table 3 shows the number of declared majors for whom the necessary data was reported to compute retention for each gender-year-class rank combination. As was noted earlier, the entries in this table are influenced by changes in the number of programs that reported outcomes for each of their majors in a given year. This precludes, for example, treating the diagonals within a given gender as a meaningful cohort. Table 4 shows the computed retention percentages for each of the individual gender-year-class rank combinations.

The retention data will be analyzed in turn with respect to each of the three dimensions of gender, year, and class rank.

Analyses for Differences by Gender

The committee began with the question of whether or not retention of men and women was significantly different when aggregated over all years and class ranks. Several statistical analyses were performed using independent sample t-tests for differences based on gender. In retro-

Table 3: Number of Declared Majors for NCWIT Retention Computations

Year	Freshman		Sophomore		Junior		Senior	
	F	M	F	M	F	M	F	M
2010-11	387	2,657	505	2,890	570	3,278	822	5,011
2011-12	500	3,490	602	3,438	715	4,155	1,012	5,741
2012-13	404	3,104	457	2,712	480	3,054	674	4,363
2013-14	492	3,011	647	3,190	645	3,724	773	4,149
2014-15	444	2,692	582	2,850	699	3,593	839	4,756
All Years	2,227	14,954	2,793	15,080	3,109	17,804	4,120	24,020

Table 4: Retention Percentages

Year	Freshman		Sophomore		Junior		Senior	
	F	M	F	M	F	M	F	M
2010-11	66.9%	7 0.5%	76.4%	77.6%	83.7%	84.6%	92.8%	92.0%
2011-12	69.0%	71.1%	73.8%	75.2%	84.3%	83.9%	90.9%	90.0%
2012-13	60.6%	59.7%	65.4%	63.8%	72.5%	71.4%	86.6%	86.1%
2013-14	71.7%	71.7%	73.0%	69.4%	79.5%	77.4%	87.2%	84.3%
2014-15	73.4%	71.5%	77.8%	75.3%	81.8%	82.9%	88.2%	89.1%
All Years	2,227	14,954	2,793	15,080	3,109	17,804	4,120	24,020

spect, since the committee was comparing population proportions (percentages) with large underlying sample sizes, a z-test would have been more appropriate to use. Given the large p-values from the t-tests (ranging from $p = 0.179$ to $p = 0.912$) and the fact that the sample sizes are quite large (making the t-statistic very similar to the z-statistic), it's unlikely that a z-test would yield statistical significance either. The overall retention percentages are in Table 5.

Table 5: Overall Retention of Men versus Women

	Total students retained	Total declared majors	Percent of students retained
Women	9,776	12,249	79.81%
Men	56,784	71,858	79.02%
Total	66,560	84,107	79.14%

The committee next investigated if there was any difference between retention for men and women when only considering freshman year, or when only considering sophomores. These are the two years of greatest interest overall to the committee, since they are when students typically take their first CS courses. For these tests, all years were aggregated. Neither of these tests was significant. See Tables 6 and 7.

Table 6: Retention of Freshman Men versus Freshman Women

	Total students retained	Total declared majors	Percent of students retained
Women	1,528	2,227	68.61%
Men	10,293	14,954	68.83%
Total	11,821	17,181	68.80%

Table 7: Retention of Sophomore Men versus Sophomore Women

	Total students retained	Total declared majors	Percent of students retained
Women	2,054	2,793	73.54%
Men	10,920	15,080	72.41%
Total	12,974	17,873	72.59%

Finally, the committee looked at overall retention of men versus women in just the earliest year (2010-11) and in the earliest two years (2010-12). Once again, no significant differences were observed. See Tables 8 and 9.

Though none of these tests proved significant, it is interesting to observe that the retention of women was slightly higher than that of men when aggregated over all five years and all class ranks, but the retention of men was slightly higher than that of women when aggregated over all class ranks at the beginning of this period and also when aggregated over all years for the earliest class rank. Table 4 shows that the largest differences in retention across genders occurred for freshman year in 2010-11, when retention of men was higher, and for sophomores in 2013-14, when retention

Table 8: Retention of Men versus Women in 2010-11

	Total students retained	Total declared majors	Percent of students retained
Women	1,885	2,284	82.53%
Men	11,501	13,836	83.12%
Total	13,386	16,120	83.04%

Table 9: Retention of Men versus Women in 2010-12

	Total students retained	Total declared majors	Percent of students retained
Women	4,197	5,113	82.08%
Men	25,223	30,660	82.27%
Total	29,420	35,773	82.24%

of women was higher. Each of these retention differences was 3.6%. Though the committee had no way to study the cause of these changes, the data suggests that the programs participating in the NCWIT survey during the five-year period were at least somewhat successful in increasing the retention of women in the early parts of their programs.

Analyses for Differences over Time

Table 10 shows the retention data by year, aggregated over gender and class rank. A one-way ANOVA showed that there is a significant difference across years ($p < 0.01$). However, there is no significant direction of change from the early to the later years; there was some decrease from 2010-11 through 2012-13, and then increases in the last two years.

Table 10: Retention by Year, Aggregating Gender and Class Rank

Year	# retained	Declared majors	Retention
2010-11	13,386	16,120	83.04%
2011-12	16,034	19,653	81.59%
2012-13	10,997	15,248	72.12%
2013-14	12,768	16,631	76.77%
2014-15	13,375	16,455	81.28%

Disaggregating these data only by gender yielded the same results. Table 11 shows the data from Table 10 disaggregated by gender.

The committee also looked specifically at the sophomore class rank and again found a significant difference across years ($p < 0.01$) with no directional pattern. Table 12 shows this data.

Finally, the committee looked at retention of freshman and sophomore women by year. While the same pattern of decreasing retention percentages between 2010-11 and 2012-13 followed by increasing percentages from 2012-13 through 2014-15 existed in the data for each of these sets of students, the ANOVA did not show statistical significance across years in either case.

Table 11: Retention by Year and Gender, Aggregating Class Rank

Year	Freshman		Sophomore		Junior	
	F	M	F	M	F	M
2010-11	1,885	11,501	2,284	13,836	82.53%	83.12%
2011-12	2,312	13,722	2,829	16,824	81.72%	81.56%
2012-13	1,476	9,521	2,015	13,233	73.25%	71.95%
2013-14	2,012	10,756	2,557	14,074	78.69%	76.42%
2014-15	2,091	11,284	2,564	13,891	81.55%	81.23%

Table 12: Retention of Sophomores by Year, Aggregating Gender

Year	# retained	Declared majors	Retention
2010-11	2,629	3,395	77.44%
2011-12	3,031	4,040	75.03%
2012-13	2,030	3,169	64.05%
2013-14	2,686	3,837	70.00%
2014-15	2,598	3,432	75.70%

Analyses for Differences by Class Rank

The committee's final set of analyses of the NCWIT data investigated the class rank dimension. Aggregated by gender and year, retention increased with the progression by class rank. Table 13 illustrates this.

Table 13: Overall Retention by Class Rank, Aggregating Gender and Year

	# retained	Declared majors	Retention
Freshman	11,821	17,181	68.80%
Sophomore	12,974	17,873	72.59%
Junior	16,816	20,913	80.41%
Senior	24,949	28,140	88.66%

If the data is disaggregated by gender, there is a similar relationship between retention and class rank for both men and women. Table 14 provides the disaggregated data.

Table 14: Retention by Class Rank by Gender, Aggregating Year

	# retained		Declared majors		Retention	
	F	M	F	M	F	M
Freshman	1,528	10,293	2,227	14,954	68.61%	68.83%
Sophomore	2,054	10,920	2,793	15,080	73.54%	72.41%
Junior	2,513	14,303	3,109	17,804	80.83%	80.34%
Senior	3,681	21,268	4,120	24,020	89.34%	88.54%

As students increase in class rank within their declared major, they are more vested in the program. Thus, the observed retention increases with class rank are not surprising.

References

Computing Research Association. (2017). *Generation CS: Computer Science Undergraduate Enrollments Surge Since 2006*, ed. CRA Enrollment Committee Subgroup. Retrieved June 5, 2018, from https://cra.org/data/Generation-CS/

Zweben, S. and Bizot, B. (2016). Representation of Women in Postsecondary Computing: Disciplinary, Institutional, and Individual Characteristics. *Computing in Science and Engineering*, 18(2): 40-56.

The data in the previous section offers a window into the broad retention patterns of men and women in CS. However, as already shown, there are several limitations to the available dataset including the inability to track individual students through their programs and the different ways and times students may enter into or leave CS programs at different schools. In addition, large datasets often do not contain enough information to examine intersectional retention patterns by race/ethnicity as well as gender.

The following case studies are intended to provide a more nuanced view of how students move through undergraduate CS programs at two specific institutions: University of California, San Diego, and Colorado School of Mines. For each of these case studies, the committee collected and analyzed detailed data on individual students in the appropriate institutional contexts. The research questions for these case studies included:

- What are the subtleties of defining retention at these particular institutions?
- What are the institutional processes and barriers to collecting data on an individual student level?
- What is the actual percentage of students from different genders and racial/ethnic groups and has this percentage changed over time? How do these percentages compare across different "streams" of students (e.g., students who enter CS directly from high school, students who switch their major after arriving at the institution)?
- What is the cohort retention in the major by gender and race/ethnicity and are there any differences between any groups?
- What is the average cohort time-to-degree by gender and race/ethnicity and are there differences between these groups?

The case studies follow and include the type of retention data committee members were able to obtain from their institutions.

Data from University of California, San Diego

Institutional Context and Retention Subtleties

The University of California, San Diego (UC San Diego) is a public research university. Table 15 provides the institution's demographics.

UC San Diego has a large undergraduate Computer Science and Engineering (CSE) program divided into four

Table 15: UC San Diego Student Demographics as of 2016

Female	Male	Asian	Black	Filipino	Latinx	White
48%	52%	46%	2%	5%	16%	20%

different majors, listed in decreasing order of size: Bachelor of Science in Computer Science (CS BS), Bachelor of Science in Computer Engineering (CE BS), Bachelor of Science in Computer Science with a Specialization in Bioinformatics (CS-Bioinf), and Bachelor of Arts in Computer Science. Because of the number of students who are interested in these programs, and the fixed number of resources, since fall 2013 for incoming first-years and fall 2015 for continuing students and transfer students, entry into these majors is by application only. Because students must apply to the major, we can more accurately infer they intend to stay in CS.

Students enter these majors via three streams:

1. They apply and are accepted into one of the CSE majors directly from high school, entering UC San Diego as CSE majors. We call these students "incoming first-year students" or simply "first-year students."
2. They apply and are accepted directly into one of the CSE majors from another two- or four-year college or university. These students also enter UC San Diego as CSE majors, but typically join the curricular program midway through the lower division. We call these students "transfer students."
3. They apply to transfer into one of the CSE majors after they are already at UC San Diego (either in a different major or undeclared). We call these students "continuing students."

UC San Diego Admissions controls admissions decisions (to UC San Diego as well as to the CSE major) for incoming first-year students and transfer students, while the CSE department controls CSE admissions for continuing students. Until fall 2017 (i.e., for all data contained in this study), continuing students were admitted solely based on their GPA in a set of "criteria courses" in CSE.

In our analysis of retention at UC San Diego, we examined each of the three student streams separately.

Obtaining Data

While data on the individual student level is stored in a central database, the number of people who have access to this database at scale is extremely restricted. Each division has a dedicated data analyst who is able to obtain and de-identify

the student data for that division only. Furthermore, the database is complicated, and even simple queries can require vast amounts of expertise to construct. Because of these limitations, we had to wait months to get our requested data. (We are now working with our data analyst to develop a system where we can obtain this data on an annual or even quarterly basis.)

The dataset we were able to obtain includes the following sets of students in each category:
- Incoming first-year students: All students who were admitted from high school directly into a CSE major that entered UC San Diego between fall 2009 and fall 2017
- Transfer students: All students who transferred from another college or university directly into a CSE major that entered UC San Diego between fall 2009 and fall 2017
- Continuing students: All students that entered UC San Diego between fall 2009 and fall 2017 in a non-CSE major, whose graduation major or current major as of May 2018 was a CSE major.

For each student in our dataset we have their:
- Gender,
- Race (where Latinx is included as a race),
- Incoming major (including undeclared),
- Incoming term,
- Graduating term (if any),
- Major of the degree received (i.e., the major they graduated with),
- Current GPA (as of fall/winter 2018, or their last GPA if they graduated), and
- Grades in all CSE courses they completed.

We used this data to answer the research questions posed above. In the next sections we present results responsive to some of these questions and discuss the ways in which they complement the broader results from the national datasets.

CSE Demographics

Table 16 shows the gender representation for our different streams of students over the years of our study. Generally, there are proportionally fewer women than men in the transfer student population and proportionally more women than men in the continuing student population.

It is not clear from the data whether enrollment restriction has affected the representation of women in the program or that it has had a negative effect for students coming directly into CSE from high school or as transfer students. For the incoming first-year students, the percentage of women shows slight signs of increasing in the past few years, while for the transfer students there is no clear trend. On the other hand, in the continuing student body, the percentage of women has dropped sharply in two of the last three years (2014-15 and 2016-17 cohorts).

Based on representation within the overall U.S. population, Asian students are over-represented generally in the UC San Diego CS student population, while Black, Latinx, Pacific Islander, Alaska Native, and American Indian students are all underrepresented, in most cases severely so. Women of all races are underrepresented compared to men of the same race; however, within Table 17, in most years (except for 2013-15) Latinas appear to be better represented (compared to Latinos) than women of other races.

Table 18 shows the severe underrepresentation of women in the transfer student population. Unlike the first-year students, the Latinas in the transfer population are very underrepresented, particularly recently. This data also shows that the transfer students do not bring racial or ethnic diversity to the program. The vast majority of transfer students are White and Asian.

From Table 19 it is clear that Asian students are much more prominently represented in the continuing student population than other races. In particular, in 2015-16 and 2016-17, when entrance to the major was application-only for all students, there was a drastic reduction in racial diversity and the representation of women from all races besides Asian dropped almost to zero.

Table 16: Gender Representation by Incoming Class Year and Stream (The percentages do not always sum to 100% because some students decline to state their gender.)

Year	First-year Students			Transfer Students			Continuing Students		
	% Men	% Women	Total #	% Men	% Women	Total #	% Men	% Women	Total #
2009-10	81.5%	18.5%	135	88.7%	11.3%	62	80.0%	20%	135
2010-11	80.4%	19.6%	153	82.3%	17.7%	62	77.6%	22.4%	174
2011-12	80.2%	19.8%	162	89.2%	10.8%	157	77.7%	22.3%	193
2012-13	81.0%	19.0%	405	90.8%	9.2%	142	75.8%	24.2%	264
2013-14	82.6%	17.4%	184	87.3%	12.7%	229	70.7%	28.8%	205
2014-15	81.0%	19.0%	258	86.5%	13.1%	260	83.1%	16.9%	195
2015-16	78.2%	21.8%	229	85.3%	14.7 %	116	74.2%	25.8%	124
2016-17	74.5%	25.5%	141	89.3%	9.8%	112	82.2%	16.9%	118
2017-18	81.2%	18.8%	225	79.7%	16.5%	133	N/A	N/A	N/A

Table 17: Ethnicity Percentages by Gender and Year for First-year Students ("Other" includes American Indians, Alaska Natives, Pacific Islanders, and students who selected "Other." Students could select only one race and were asked to choose the race with which they most closely identify.)

Year	%Asian		%Black		%Latinx		%White		%Other*		%Unknown		Total # Students
	F	M	F	M	F	M	F	M	F	M	F	M	(F/M)
2009-10	10.9	36.7	0	0.7	3.4	15.0	1.4	17.0	0	0	2.0	12.9	26/121
2010-11	13.1	50.3	1.3	0	3.3	10.5	2.0	9.8	0	0.7	0	9.2	20/123
2011-12	11.7	45.7	0	1.2	2.5	7.4	1.9	16.7	0	0.6	3.7	8.6	32/130
2012-13	12.1	50.9	0	1.0	2.5	6.4	1.0	13.3	0	0.5	3.5	8.9	77/328
2013-14	14.7	45.7	0.5	0.0	0.5	6.5	0.0	15.2	0	0	1.6	15.2	32/152
2014-15	16.3	43.4	0.4	0.8	0	4.7	1.2	16.3	0	0	1.2	15.5	49/209
2015-16	13.1	53.3	0	0.4	1.3	4.8	4.8	14.0	0.4	0	2.2	5.7	50/179
2016-17	15.6	48.9	0.7	0.7	2.1	5.0	5.7	15.6	0	0	1.4	4.3	36/105
2017-18	11.4	58.8	0	1.6	3.5	8.2	2.4	10.6	0	0	1.6	2.0	48/207

Table 18: Ethnicity Percentages by Gender and Year for Transfer Students ("Other" includes American Indians, Alaska Natives, Pacific Islanders, and students who selected "Other." Students could select only one race and were asked to choose the race with which they most closely identify.)

Year	%Asian		%Black		%Latinx		%White		%Other*		%Unknown		Total # Students
	F	M	F	M	F	M	F	M	F	M	F	M	(F/M)
2009-10	9.2	33.8	0	3.1	0	6.2	0	18.5	0	6.2	1.5	21.5	7/58
2010-11	3.2	38.7	0	1.6	0	8.1	9.7	21.0	0	0	4.8	12.9	11/51
2011-12	4.5	38.2	0	1.9	1.3	8.3	4.5	26.1	0	0	0.6	14.6	17/140
2012-13	4.2	45.8	0.7	0.7	1.4	7.0	1.4	26.8	0	0	1.4	10.6	13/129
2013-14	7.9	39.3	0.4	1.3	1.3	12.7	2.2	23.6	0	0	0.9	10.5	29/200
2014-15	5.8	45.2	0	1.9	0	10.0	5.8	22.4	0	0.4	1.5	6.9	34/225
2015-16	11.2	46.6	0	2.6	0.9	6.9	0.9	16.4	0	0.9	1.7	12.1	17/99
2016-17	5.4	65.8	0	0	0	2.7	4.5	18.9	0	0	0	2.7	11/100
2017-18	11.7	59.4	0.8	0.8	0	3.9	4.7	17.2	0	0	0	1.6	22/106

Table 19: Ethnicity Percentages by Gender and Year for Continuing Students ("Other" includes American Indians, Alaska Natives, Pacific Islanders, and students who selected "Other.")

Year	%Asian		%Black		%Latinx		%White		%Other*		%Unknown		Total # Students
	F	M	F	M	F	M	F	M	F	M	F	M	(F/M)
2009-10	12.5	48.5	0	0	2.2	6.6	2.2	13.2	0.7	0	2.2	11.8	27/109
2010-11	15.5	51.1	0	0	1.1	5.2	1.7	15.5	0	1.1	4.9	4.6	39/135
2011-12	15.5	50.8	0	1.0	3.1	9.3	3.1	13.0	0	0	0.5	3.6	43/150
2012-13	17.0	43.6	0	1.5	1.9	8.7	4.2	10.2	0	0.8	1.1	11.0	64/200
2013-14	21.1	42.2	0	0.5	0	4.9	2.9	9.3	0	0	4.9	14.2	59/145
2014-15	9.2	46.2	0	1.0	0	3.1	0.5	10.3	0	0.5	7.2	22.1	33/162
2015-16	23.4	61.3	0	0	0	0	1.6	2.4	0	0	0.8	10.5	32/92
2016-17	16.2	67.5	0	0	0	2.6	0	6.8	0	0	0.9	6.0	20/97

CSE Retention and Time to Degree

This section provides the retention data for each cohort and each stream. Because students at UC San Diego (and likely elsewhere) are often slow to change their declared majors even when they have decided to switch programs, tracking year-to-year retention using major codes is challenging. In addition, our dataset does not include when students switched their majors, only the majors in which they received their degrees. Thus, retention is defined here as graduation with a degree in a CSE major.

Table 20 shows the retention, by gender, of the three streams of students at UC San Diego. Entries with asterisks indicate a significant difference between retention rates for men versus women students. Overall (as might be expected), continuing students' retention rates are higher than the first-year and transfer students' retention rates. Students who decide after coming to UC San Diego to pursue CS are quite likely to complete their degrees in CS. It is also expected that transfer students' retention rates would be generally higher than first-year students' retention rates, as transfer students have fewer classes to complete to receive their degrees. For first-year and continuing students, retention rates are comparable (and not statistically significantly different). However, among transfer students, women's retention is much lower than men's retention, and lower even than retention of first-year women.

Table 21 details retention by race. The students are not separated here by gender for two reasons. First, retention rates between men and women in each race are not statistically significantly different. Second, the numbers in some categories become too low to report. It can be seen from the results that Asian and White students graduate at a higher rate than Black and Latinx students. A Chi-squared test indicates that the difference between the proportions are significant at the $p < 0.001$ level (Chi-squared statistic = 100.3).

Table 21: Percentage of All Students by Race in Incoming Classes 2009 through 2013 Who Graduated with a CSE Degree. (Numbers in parentheses show the total number in the group.)

Asian	Black	Latinx	White
65.8% (626)	40% (10)	38% (113)	65.8% (161)

Future Analysis

This dataset allows for the exploration of additional questions that have not been explored here. In particular, future work will be able to examine the following questions:

- Are there grade differences between men and women or by race in any of the courses in the CS major?
- When students leave the major, what is the last class they take before leaving?

These questions will help to determine whether there are any bottlenecks by race or gender in this program.

Data from Colorado School of Mines

Institutional Context and Retention Subtleties

Colorado School of Mines (Mines) is a small science and engineering university and has a much smaller CS degree program than UC San Diego. The CS major program at Mines (CS@Mines) has one degree, Computer Science, with the following tracks: business, computer engineering, data science, honors research, robotics and intelligence systems, and computer science (which offers students the opportunity to design their own "tracks" if desired). Many of these tracks are in collaboration with other departments on campus (i.e., CS+X). At Mines, students do not typically declare their major until spring of their sophomore year, though students can express interest in a major upon their arrival. Similar to Stanford's situation (which was discussed previously in the "Challenges to Collecting Retention Data" section), there are no barriers to entry for the CS major at Mines.

Approximately 40% of all first-year students take Mines' CS0 course (which maps to AP CS Principles). This course, called Introduction to Computer Science, attracts many students into Mines' CS major. Approximately 50% of all students at Mines take the CS1 course, which is a C++ programming course. Similar to other universities, Mines' CS1 course attracts students into CS. Data from Mines shows, however, that the CS1 course is also a main point of attrition, as some students use this course to decide

Table 20: Retention Rates by Incoming Class Year and Stream (Retention is defined as graduating with a degree in a CSE major. This data includes only cohorts through fall 2013, under the assumption that most students need at least 4 years to graduate.)

Year	First-year students		Transfer Students		Continuing Students	
	% Men retained (Total men)	% Women retained (Total women)	% Men retained (Total men)	% Women retained (Total women)	% Men retained (Total men)	% Women retained (Total women)
2009-10	63.6% (110)	56% (25)	80% (55)	57.1% (7)	86.1% (108)	81.5% (27)
2010-11	58.7% (121)	59.3% (27)	78.3% (46)*	45.5% (11)*	82.4% (131)	86.8% (38)
2011-12	70.9% (126)	55.1% (29)	76.7% (120)	62.5% (16)	79.7% (143)*	97.6% (41)*
2012-13	68.5% (316)	66.2% (74)	75.2% (117)	53.8% (13)	84.7% (189)	82.5% (63)
2013-14	68.0% (149)	68.8% (32)	80.6% (191)*	53.6% (28)*	82.2% (135)	79.3% (58)
Total	66.4% (822)	62.6% (187)	78.3% (529)*	54.7% (75)*	83.0% (706)	85.0% (227)

whether they want to major in CS. CS@Mines performs well in terms of recruitment and retention. For example, of the 32 students who started at Mines as CS majors in the fall of 2010, 29 stayed in CS, and only two students who started in CS switched to another major.

Obtaining Data

Similar to UC San Diego, the number of people who have access to student level data is limited at Mines. One person in the Institutional Research Office collects, analyzes, and interprets data on Mines students for a variety of stakeholders (e.g., the federal government, the Colorado Department of Higher Education, faculty). While this person is willing to provide data for various faculty projects, providing data for the government must take priority, which means answers to faculty questions can take weeks or even months. While the Mines Institutional Research Office has provided data for this project, that data is not included here because (1) undeclared students who join CS are not included in the dataset because cohorts are defined for students when they join Mines based on their major of interest and (2) the data in any given cohort often contains fewer than three students representing women and other underrepresented groups.

While data from the Mines Institutional Research Office provides some understanding of retention within CS@Mines, for this work we were also interested in students who arrived at Mines undeclared and later declared CS as their first major, and in particular, whether these students are retained in the degree program. We also were interested in where Mines is not retaining students in the degree program. Specifically, what are the main points of attrition in the CS course sequence at Mines? We were interested in both CS attrition to another major and attrition of CS@Mines students who leave Mines.

A staff member associated with CS@Mines who has access to student data was willing to help investigate retention/attrition questions. The dataset she collected on CS@Mines students included:
- Gender,
- Incoming major (including undeclared),
- Incoming term,
- Graduating term (if any),
- Major of the degree received (i.e., the major they graduated with), and
- CS courses completed.

The following section presents the results of the CS@Mines investigation into retention and attrition, using this dataset to answer as many of the committee's research questions as possible.

CS@Mines Outcomes

As mentioned, the CS@Mines dataset includes students who (1) arrived at Mines planning to major in CS and (2) arrived at Mines undeclared and subsequently declared CS as their first major. Tables 22 and 23 below show the total number of students who had CS as their "first major," including their graduation outcomes, by gender. Similar to the UC San Diego case study, Mines defines retention here as graduation with a degree in CS. It should be noted that between 2008-2014, only 24-27% of all students at Mines were women.

Table 22 shows that 536 students were registered with CS as their first major (i.e., students who (1) arrived at Mines with an interest in CS or (2) arrived at Mines undeclared and subsequently declared CS as their first major within the 2008-2014 time frame). By spring 2018, 73.88% (396 of the 536 students) graduated, 20.15% (108 of the 536 students) left the institution, and 5.97% (32 of the 536 students) are still students at Mines. Since the data includes students who started in 2014, many of these 32 students will likely complete their degree in their 5th or 6th year (after spring 2018 graduation).

Table 22: Total Number of Students with a CS First Major

Status	Number of Students	% of Students
Graduates	396	73.88%
Left Inst.	108	20.15%
Current	32	5.97%
Total	536	100%

Table 23 shows that, of the 396 students who were CS first majors and graduated from Mines between 2008-2014, 85.6% (339 students) graduated from CS while 14.4% (57 students) graduated from another major at Mines. Of the 339 students that graduated from the CS program in this period of time, 88.5% (300 students) were male and 11.5% (39 students) were female. Of the 57 students that graduated from another major in this period of time, 84.2% (48 students) were male and 15.6% (9 students) were female. Since a larger percentage of females graduated from another major than from CS, there is a concern about female retention in CS@Mines.

Table 23: Graduation Outcomes for Students with a CS First Major

	Number of Students	% of Students	% Men	% Women
Graduated in CS	339	85.61	88.50	11.50
Graduated in another major	57	14.39	84.21	15.79
Total Graduated Students	396	100		

Tables 24 and Table 25 show the time to graduate for the 396 students who were CS first majors and who graduated, for both the 339 students who graduated in CS and the 57 students who graduated in another major.

Table 24: Graduation Rates of CS Students Who Graduated from CS

CS Major	Men	Women
4 year	72.00%	71.79%
5 year	93.67%	87.18%
6 year	97.67%	97.44%

Table 25: Graduation Rates of Students Who Left CS to Graduate for Another Major

Other Major	Men	Women
4 year	70.83%	66.67%
5 year	91.67%	88.89%
6 year	97.92%	88.89%

Comparing the cohort in Table 24 to the one in Table 25, it is noteworthy that the graduation rates for male students are similar: approximately 71% of male students graduate in four years from another major while approximately 72% of male students graduate in four years from CS. For females, however, students who are retained in CS are more likely to graduate in four years (i.e., 71.8% for CS and 66.8% for other majors). Furthermore, females are much more likely to graduate in six years (i.e., 97.5% for CS and 88.9% for other majors). Again, it is important to note the small number of women overall. Specifically, only nine females had CS as their first major and then graduated from another major so if one of those nine students graduated in CS instead of another major, then the percent of females who graduated in another major would drop from 15.8% to 14.3%.

We also were interested in the main points of attrition in the CS course sequence at Mines. Figure 3 illustrates the most advanced CS course taken by a student who either (1) did not graduate or (2) graduated from another major.
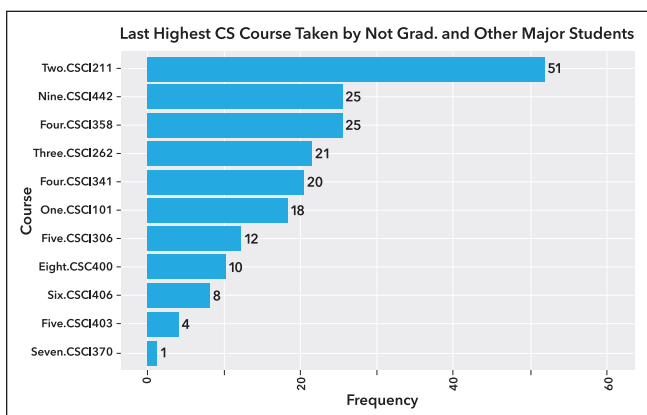

Figure 3. The highest CS course taken by a student who was not retained in CS at Colorado School of Mines.

As shown, most students that leave the CS degree program do so after taking CS1 (CSCI261). This result is not a surprise, as it is Mines' first programming course. It is, however, surprising that many students took operating systems (CSCI442) (OS) and did not graduate in CS (since OS is a senior-level course). Of the 25 who took OS, six students left the CS degree program and graduated with another major. Perhaps these students took CSCI442 and earned a minor in CS. The remaining 19 students had not graduated by spring 2018. Perhaps these 19 students started at Mines in 2014 and did not complete their degree in four years. More investigation is needed to fully understand the main points of attrition in the CS@Mines degree program.

Lessons Learned from Data Analysis Case Studies

The case studies at UC San Diego and Mines provide a richer perspective on retention at these two institutions. First, the case studies allowed researchers to treat different streams of students separately, as appropriate to each institution (e.g., transfer students versus first-year students at UC San Diego). This separate analysis allowed researchers to determine where aggregate results might have been hiding specific issues. Second, the case studies allowed researchers to track retention at a more granular level. For example, at Mines the researchers were able to see which courses were the "terminal" courses in a student's trajectory, allowing Mines to focus its attention on addressing issues that might exist in those courses. In future, both UC San Diego and Mines plan to conduct further analyses (e.g., grades earned by women versus men in different courses) with this data. Finally, the analyses allowed researchers to track individual students through to graduation and to distinguish between students who graduated from a different major as opposed to those who did not graduate at all.

Collecting and analyzing this data also provided some important lessons about gathering and analyzing fine-grained retention data specific to an institution. First, it is not always obvious how to obtain the data desired. The committee members had to talk to several people and groups within their institutions before they found people who had the time and ability to provide the desired data. Also, once the right contact was identified, explaining what data was wanted was not an easy task because there are so many ways to look at student data. Second, despite its richness, the data is still missing some information that would be useful in measuring retention. For example, at UC San Diego, changes to student majors are not tracked (only incoming major and current major are tracked), so students who switched into CS and then out again at some point in their university careers could not be included.

Given the importance and the complexities of collecting and analyzing student retention data, the committee encourages universities to consider hiring a staff member to look at student data. Much can be learned and improved from quantitative analysis, especially from a diversity standpoint.

A CROSS-SECTION OF PROMISING INTERVENTIONS

The previous sections discussed the challenges of collecting retention data and provided some preliminary results about retention. The good news from the data the committee analyzed is that in many cases women are being retained in computing programs in approximately equal proportion to men. Yet it remains critical that programs prioritize changes in their CS classes to improve the experiences of all students, and especially the experiences of women and other groups underrepresented in CS. This section provides an overview of some specific barriers to retention and some promising interventions to overcome these barriers.

Give Students a Better Understanding of CS

Many students come to college with misconceptions about computing and may hold invalid stereotypes of computer scientists. For example, many students and their influencers believe that CS is typified by antisocial geeks coding in iso-lated settings. CS, however, is a collaborative field with inter-esting applications and the need for diverse perspectives and participants. Perceptions of computing can have a dramatic impact on students' decisions, not only to pursue, but also to remain in CS (Margolis and Fisher, 2002). Fortunately, there are many ways to challenge misconceptions and stereotypes within the local context by promoting broader images of CS. Here are a few examples of possible interventions.

- *Use students as near-peer ambassadors in outreach:* College students who are passionate about computing can help offer outreach programs to younger students (Frieze and Treat, 2006). This near-peer approach provides younger students with a positive, inspiring experience to learning about computing from college near-peer mentors. Outreach also provides college students with teaching experiences which support their own learning and leadership development.
- *Hold an orientation session:* Connecting students' CS career goals with their interest in societal impact is a strong predictor of retention for all undergraduate computing students (Barker, Garvin-Doxas, and Jackson, 2014). When students attend recruitment or orientation sessions, CS programs can show off the variety of student team projects that their majors have completed. This highlights the wide range of applications of computing and also builds teamwork and interpersonal skills and encourages interaction.

- *Educate counselors, teachers, parents:* Many individuals perpetuate misconceptions about what CS is and who can study CS. Departments can do outreach to potential students and their influencers.
- *Develop curricular structures to encourage students to explore CS:* Technically-oriented schools, such as Harvey Mudd College, may require all students to take computing, while other schools allow computing to count toward a general education requirement. This encouraged (and preferably early) exposure to CS can help some students discover an interest they didn't know they had.
- *Build courses around compelling contexts:* Some schools connect CS1 with image processing or robotics (Bryn Mawr, Georgia Tech, and Grinnell) or with music (UMass at Lowell). In some cases, faculty from art or music attend some CS1 class sessions to provide insights about application themes. These types of experiences may resonate with students in the arts or other populations and help engage students outside STEM fields in CS.

Meet Students' Varied Backgrounds

Most introductory CS classrooms have students with varied levels of previous experience and some students might be intimidated by other students in the class who have more experience (Lewis, Yasuhara, and Anderson, 2011). This intimidation barrier can be overcome by curricular, programmatic, and cultural/behavioral interventions. Highlighted here are examples of such interventions.

- *Offer summer bridge programs for students from groups with historically higher attrition rates:* Summer bridge programs for incoming students (first-year or community college transfer students) help them make the best possible academic and social transition to a four-year college. These experiences help incoming students develop support networks, promote early student-faculty connections and mentoring opportunities, build community, and often include hands-on, project-based learning opportunities to excite students about CS.
- *Provide tutoring for introductory topics:* Tutoring centers across the disciplines may help students having difficulties in introductory courses. CS departments can also offer tutoring options, such as staffing laboratories with peer tutors who can help with a wide range of problems. These tutors should

be trained to ensure that the introductory students have a positive experience. Mt. Holyoke College, for example, has developed the MaGE program, which trains experienced students to become effective and inclusive technical mentors (Pon-Barry, St. John, Wai-Ling Packard, and Stephenson, 2017).

- *Provide various paths through the introductory sequence:* Several schools including Harvey Mudd College, UC San Diego, and Williams offer different versions of introductory courses and sequences—all with common core content, but different applications, contexts, and pacing. Ideally this structure allows those with less experience more time to learn the basics, while providing more advanced students a separate track on which to move more quickly without intimidating their less-experienced peers.
- *Offer elective courses to address gaps:* Some schools offer elective courses for modest credit to address preparation differences. Often, such courses utilize active student engagement, perhaps one-on-one between students and instructors or in small groups. For example, Stanford has a one-unit course accompanying the Mathematical Foundations of Computing course (CS103) to help students with less background get more practice with mathematics and proof techniques.
- *Encourage student groups to offer workshops for the student body:* Student groups, such as ACM and ACM-W student chapters, offer workshops on specific topics, build community, and provide students an opportunity to learn tools and problem-solving skills outside the classroom.
- *Set clear expectations for behavior in class:* Providing clear directives about students' behavior can help students understand what is and is not appropriate and avoid situations where more experienced students make less experienced students feel uncomfortable (intentionally or unintentionally). For example, requiring students to raise their hands to answer questions can provide students a chance to think before hearing an answer and can allow faculty to distribute opportunities to speak among students. Stating the goal that students will learn from and respect their peers can also help create an optimum learning environment (Cohen and Lotan, 1995).
- *Explain to students that even good intentions can lead to negative impact:* Often students who ask questions that are intimidating to other students are just excited about the material and do not realize the potential impact on other students. However, it is important that students understand that despite good intentions, some behaviors can have a negative impact (Utt, 2013). Faculty can talk to students privately to help them understand the potential impact of their behavior, or can address it directly in class by saying, "That's a great question, but isn't closely related to our course content. Let's chat about it after class. It might even be a little intimidating to other students, but I'm sure that wasn't your intention."
- *Practice how you will respond to biased comments:* How faculty frame their expectations for classroom behavior and how they respond to inappropriate behavior shapes classroom culture (Barker, O'Neill, and Kazim, 2014). Faculty can increase the impact of their interventions by consistently expressing their goals for the classroom community. Research has also shown that people who have practiced confronting bias are more likely to confront bias that they observe using questions such as, "What makes you say that?" (National Center for Women in Information Technology, 2018b). Making a statement such as "I'm not sure what to say, but your comment is important to talk about. Let's chat after class and we can follow up in the next class," can also be helpful.

Increase Helpful Collaboration

Helping students learn involves challenging them, but sometimes it is impossible to provide exactly the right level of challenge for all students. By integrating collaboration into classes and coursework, faculty can help students tackle challenges beyond their current level of ability and ultimately expand their skills (Vygotsky, 1980). Working in groups can also encourage students to recognize that getting stuck on a problem is normal. Helping students make connections to their peers is also important for students' feelings of belonging (Veilleux, Bates, Jones, Crawford, and Floyd Smith, 2013; Walton and Cohen, 2007).

Strategies to increase helpful collaboration range from course policies to classroom and out-of-classroom pedagogy. Several successful and widely used approaches, especially in CS1 and CS2, follow.

- *Use pair programming:* Exercises with pair programming engage students in a social learning environment. Pair programming has been shown to promote learning, improve code quality, and improve student retention (McDowell, Werner, Bullock, and Fernald, 2006). Since pair programming may be new to students, ongoing discussion may be needed to explain roles and suggest constructive behaviors. When pair programming is used, the person at the keyboard should change frequently to promote communication and shared responsibility, and partners should be changed often (perhaps weekly) to ensure one person does not become dependent upon another.
- *Integrate collaboration in class through active learning:* CS education research frequently finds positive outcomes, including increased exam scores and decreased failure rates, for integrating active learning (Freeman, et al.,Eddy, McDonough, Smith, Okoroafor, Jordt, and Wenderoth, 2014) and collaboration (Porter, Guzdial, McDowell, and Simon,

2013). Methods that promote active learning include peer instruction (Peer Instruction for Computer Science, 2017), Process-oriented Guided-Inquiry Learning (POGIL) (POGIL, 2017), and Team-based Learning (TBL) (Team-based Learning Collaborative, 2017).

- *Avoid competitive course policies:* Competitive enrollment in a major or grading on a curve can lead students to perceive the environment as competitive or the courses to be "weed-out" courses (Lewis, Yasuhara, and Anderson, 2011). These experiences of "weed-out" courses can discourage students and can lead to attrition (Seymour and Hewitt, 2000).
- *Tell students what collaboration is and is not allowed:* While collaboration can help dispel misconceptions about CS as solitary and help students know how to get started, it is important to set clear boundaries. Research has shown that providing clear instructions to students about what steps they should take to be successful collaborators is important for student learning and success (Winkelmes, 2016).

Increase Sense of Belonging and Build a Safe Learning Culture

One of the biggest barriers to retention is students' sense of belonging. Positive faculty-student interactions, teacher assistant-student interactions, and student-student interactions can all give rise to a sense of belonging in a community (Frieze and Quesenberry, 2015). Providing various opportunities to enhance the natural development of peer networks enables and encourages students to become part of a community of practice (Barker, O'Neill and Kazim, 2014). There are many things that faculty can do to help increase students' sense of belonging in CS:

- *Initiate contact with personal touches for underrepresented students:* Research has shown that personal encouragement is a major determinant of student interest and persistence in CS, especially students from underrepresented groups who may initially feel uncomfortable in the discipline (Google and Gallup, 2017). Personal encouragement can also help women recognize their own success and limit attrition, as women tend to leave the CS major with higher grades than their male peers (Babes-Vroman, Juniewicz, Nguyen, Lucarelli, and Tjang, 2017).
- *Encourage Women in Computing, other affinity groups, and mentoring programs:* Affinity groups or clubs allow students who share an identity—usually a marginalized or underrepresented identity—to gather, talk about issues related to that identity, and learn from each other in a safe space (Carter Andrews, 2012; Frieze and Quesenberry, 2015). Such student groups often offer leadership, professional development, and community engagement opportunities to members. Near-peer and corporate mentoring programs can also help students feel like

they belong in CS, especially if their mentors have backgrounds or experiences similar to their own.

- *Provide opportunities to learn outside the classroom:* Co-curricular programs provide activities and learning experiences that complement what students learn in their courses. These can include app jams, hackathons, coding and robotics competitions, internships, co-ops, and research experiences. Students' out-of-class engagement has many positive outcomes including improved learning, personal development, and social competence, which can lead to more feelings of belonging (Frieze and Quesenberry, 2015). Students who participate in co-curricular academic engagement activities also report higher levels of social integration (a sense of belonging) and on average had higher GPAs (Massi, 2012).
- *Send students to conferences/celebrations targeted to specific populations:* Conferences such as the Grace Hopper Celebration of Women in Computing (GHC) and the Richard Tapia Celebration of Diversity in Computing have been found to be very positive experiences for students early in their careers. Students who attended GHC, for example, took more CS courses and majored in CS at a higher rate than students who did not attend GHC (Alvarado and Judson, 2014).
- *Embrace all questions and admit personal mistakes:* Some faculty may find it embarrassing when a student asks a question that they cannot answer. However, instructors' negative reaction to their own mistakes can lead to the development of a defensive classroom climate, which is characterized by competitive behavior and a lack of empathy (Barker, Garvin-Doxas, and Jackson, 2002). When faculty embrace their mistakes, they model for students that mistakes are expected and are opportunities to learn.
- *Attribute success to effort and practice:* Encourage students to embrace challenge by helping them develop what psychologist Carol Dweck calls a "growth mindset"—the concept that mastery results from effort and practice, and not from a fixed innate ability (Dweck, 2006). This concept was also discussed in Twelve Tips for Creating a Culture that Supports All Students in Computing (Lewis, 2017).
- *Offer personal encouragement to students:* Faculty-student interaction is one of the most important predictors for retention (Barker, Hovey, and Thompson, 2014). Faculty can make an encouraging comment to a student after class, write a personal email, or comment on a returned assignment or exam. Such personal communications can address grade anxiety and also help students feel that they belong in the field (Lewis, 2017).
- *Recognize (and mitigate) bias:* While bias is typically seen as unconscious, efforts to mitigate bias need to be conscious because bias can have

impact regardless of intention (Kahneman, 2011). Specifically, subtle messages regarding difference make it harder for female and students from other underrepresented groups to develop their identity as computer scientists (Richardson, 2017). Faculty therefore need to identify places where they might make quick judgments or decisions and identify ways in which these decisions might be unintentionally biased. Bias can shape grading (Malouff and Thorsteinsson, 2016), expectations of students (Gershenson, Holt, and Papageorge, 2016), judgments of which students should be placed in a high track (Klapproth, Kärchner, and Glock, 2017), which students teachers pay attention to (Gilliam, Maupin, Reyes, Accavitti and Shic, 2016), and how teachers respond to students (Glock, 2016). EQUIP (Equity Quantified in Participation; Shah, Reinholz, Guzman, Bradfield, Beaudine and Low, 2016) is a classroom observation tool that measures equity in whole-class discussions. It can be helpful in documenting the unintentional impact of bias, such as calling on some students more frequently than others. Additional resources for educators include the Teaching Systems Lab at MIT (MIT Teaching Lab, 2018), resources on teaching tolerance (Southern Poverty Law Center, 2018), Tips for Reducing Bias (Lewis, 2018), and Carnegie Mellon's BiasBusters@ Campus program (Frieze, Marculescu, Quesenberry, Katilius, and Reynolds, 2018).

- *Remind students about resources available to them on campus:* Most campuses have resources to help students navigate their complex college environments and lives. Be sure that students are aware of these resources, especially counseling, advising, and other initiatives for specific student populations. UC Irvine, for instance, has its Student Success Initiatives which are "dedicated to serving and assisting with the transitions of low-income students, first-generation students, undocumented students, former foster youth, transfer students, adult-learners, students with dependents, and students with disabilities" (University of California, Irvine, 2018).

The Carnegie Mellon Experience

This section offers highlights of the practices that Carnegie Mellon University (CMU) employed to exceed national percentages of female CS majors in R1 (a U.S. university classification indicating significant research activity) schools for many years and, for the past two years, to enroll 50% women in the first year CS major. Retention rates (tracked individually) have stayed virtually the same for men and women (around 89%) over the past few years. The critical practices that have contributed to CMU's success in improving gender diversity and increasing the retention of women are as follows:

1. institutional commitment and multiple levels of support,
2. assessment of context and environment,
3. ongoing attention paid to the situation,
4. a community that is open to cultural change, and
5. assurance that women are central to the culture.

Without these initial conditions in place, successful interventions would have been difficult, if not impossible. Here is what is meant by these five critical conditions:

- *Institutional Commitment and Multiple Levels of Support:* Real change requires the involvement and endorsement of leaders, decision makers, and those with financial power. Diversity and inclusion efforts require long-term investment, financial support, and dedicated staffing to run programming. Faculty and staff who understand why diversity matters are more likely to be helpful and contribute to the efforts. Over the years CMU has developed a community of allies at different levels who are involved, enthusiastic, and proactive in achieving successful diversity and inclusion efforts.
- *Assessment of Context and Environment:* It is important to take the context of diversity efforts into account such that efforts fit the value system of the school and become part of the institutional fabric (Blum and Frieze, 2005). A successful diversity and inclusion program "reflects and embodies the philosophy that computer science thrives on the interaction of diverse perspectives and expertise" (Frieze and Quesenberry, 2015, 26). Diversity is an essential part of CMU's strategic plan and is seen as a *means* to better problem solving and higher innovation (Hazzan, 2006).
- *Attention Paid to Leveling the Playing Field:* Monitoring student attitudes and experiences offers data that can help guide retention efforts. Our ongoing interview and survey findings from sophomores through seniors show that men and women students feel they fit in academically and socially in the CS environment. Because there are fewer women than men and women can miss out on leadership, visibility, networking, mentoring, and advocacy experiences, CMU also works to ensure all students have similar opportunities for valuable social and professional development.
- *A Community That Is Open to Cultural Change:* CMU has focused on developing a culture that works well for all for many years and openness to change has been essential for success. For example, research studies found institutional bias in the CS admissions process which favored men while creating obstacles for women and for men who had little to no CS background (Margolis and Fisher, 2002). Removing the programming requirement dramatically increased the number of women and students (men and women) with a broad range of

personalities and perspectives. To ensure success for all, CMU also designed introductory courses to accommodate those students entering with little or no CS background.

- *Assurance That Women Are Central to the Culture:* By 2000, CMU's School of Computer Science (SCS) initiated strategies to ensure women had a central voice in shaping the culture and environment through a dedicated organization called Women@SCS (2018). Women's leadership has contributed to dramatic cultural change and benefited the entire community. Women@SCS activities tie in with CMU's holistic approach, recognizing that experiences inside and outside the classroom are closely interconnected in the lives of CMU students and in their academic success.

The Role of a Women's Organization: Women@SCS

CMU's Women@SCS organization has provided an excellent vehicle for successful interventions that take place mostly outside the classroom yet serve the social, academic, and professional lives of students by improving their sense of belonging, their commitment to the school and their peers, and their "social compatibility with the domain" (Steele, 1997; Veilleux, Bates, Jones, Crawford, and Smith, 2013; Walton and Cohen, 2007). The organization is not only endorsed by the school, but is also recognized as a great resource acting in an advisory capacity and as a sounding board for diversity and inclusion efforts.

Importantly, the organization has no membership applications; graduate and undergraduate students, post-docs, and faculty from all seven departments in SCS are automatically included. With women dispersed through seven departments and across all levels, it becomes particularly valuable for women to make connections (McCarthy, 2004). These connections can evolve naturally or may need to be formalized into mentoring and networking programs. CMU has paid particular attention to ensuring that faculty (male and female) and students have opportunities to get together in informal settings.

Women@SCS provides mentoring, networking, peer-to-peer advice and skills-building workshops, outreach activities, conference attendance, research experience, and much more. It also works to ensure the goals of the group are clear: that they are working for parity not privilege. Students are encouraged to understand some of the reasons for having a women's organization, and for all to see that working for gender balance can bring benefits to all. Efforts are made to ensure female students are integrated into the student body so they do not feel like a "separate species." Women@SCS provides opportunities for women to lead events and activities that are open to men and women. This gives women leadership, visibility, and professional growth and helps bridge the seven departments in SCS, showing their value to the school.

One of the major outcomes of Women@SCS is the development of a new organization, SCS4ALL, which recognizes that there is still much work to do in terms of broader diversity and inclusion. SCS4ALL has developed a variety of activities, many of them focused on building community but also on raising the visibility of under-represented groups in computing. For example, working with AccessComputing (University of Washington, 2018), SCS4ALL organized a capacity-building workshop to help raise awareness and acknowledge the contributions of people with disabilities in computing.

Importantly, for women to be successful in CS at CMU, the curriculum did not need to be changed to be "pink" in any way. But CMU did need to change the culture and environment and to develop and sustain programs that work to level the playing field. This is an ongoing process but CMU continues to see success in developing a culture that works well for both men and women.

Having a women's organization as a primary vehicle for retention interventions may seem counterintuitive to integrating women into the community. But CMU found that when the organization is endorsed by the school and when women work on behalf of themselves and the broader community, their efforts pay off, and their value is recognized and applauded. (For the full CMU story see Frieze and Quesenberry, 2015.)

Results Are Not Guaranteed or Persistent

A common fallacy is that there is one silver bullet that can transform an institution into an inclusive and equitable learning environment for all students. The frustrating fact is that there is no silver bullet. Even a single bad actor within a department can thwart efforts to improve the culture and community of the department. Rather than a set of predefined steps to follow in diversity and inclusion work, making improvements requires understanding the culture and community at an individual institution and the narratives and actors that work against an inclusive environment. Individual faculty may follow all of the "steps" that led to success at another institution without results because the specific challenges differ from institution to institution.

A second common fallacy is that the work to create an inclusive department is a temporary effort. Instead, continued success requires continued effort. The underrepresentation of women and people of color of all genders in CS arises from a broad range of systemic social constructs and issues which traditionally have defined some groups as more capable and/or more deserving than others. Because these constructs change very slowly, issues of equity will continue to be pressing in all fields including computing and therefore will require continued vigilance and determined effort. Through continued effort, faculty and administrators can create and sustain a welcoming and responsive environment.

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RECOMMENDATIONS FOR FUTURE RESEARCH AND INTERVENTIONS

There is a clear need for additional research around issues related to student retention in CS programs if meaningful improvements in retaining students through and beyond graduation are to be made. Such research needs to be scientifically rigorous, intentional, involve stakeholders at many levels, and, where possible, be coordinated across institutions.

Rigor is a central need in any research study, whether using qualitative, quantitative, or mixed methods. In quantitative research, rigor is usually defined as encompassing construct validity (the extent to which a concept is accurately measured and whether one can draw inferences from the data) and reliability (the consistency/replicability of the measure). As noted previously in this paper, rigor can be particularly challenging when looking at the issue of retention because there is not yet a standard for consistently collecting, storing, and representing student data. Moreover, differences among institutions can make analyzing and generalizing from such data extremely challenging. While daunting, these challenges must be addressed if a solid foundation is to be laid for future research on retention.

Being intentional with regard to gathering consistent and complete data is critical for both understanding retention in CS within an institution and for facilitating cross-institution collaboration leading to a more global view of retention dynamics. For example, individual units should plan data-gathering efforts that regularly capture information about student progressions through courses and programs rather than relying on existing data to try to piece together *ex post facto* analyses. When possible, data about student intent should be explicitly captured at particular points (e.g., start and end of introductory CS courses) to be able to identify where "leaks" are occurring in the program pipeline. And institutions should share data-gathering instruments (e.g., surveys) and best practices for how to collect data consistently. Where possible, institutions should hire data specialists with the expertise and time to provide complete datasets and assist faculty with analysis.

At a broader level, institutions should collaborate to determine the types of data that could be captured consistently across institutions and how this data might be regularly aggregated and evaluated. The data captured by each institution need not be exactly the same, as in reality it is unlikely that this would be possible, but should have some consistent "core" that can readily be aggregated in a semantically meaningful way. This requires deliberate data capture and cleaning to make sure that aggregate results are not corrupted by the inclusion of bad data.

Standardized data on a national scale is now being captured by the National Student Clearinghouse (2018). This includes gender and ethnicity demographics of students enrolled in programs leading to CS bachelor's degrees. With its ability to track individual students from year to year, the NSC data should be able to provide discipline-specific information about persistence in CS programs. The granularity of the data is not at the individual course level, so it would not provide the ability to accurately measure continuation in CS courses beyond CS1, as the committee earlier defined retention. Nevertheless, it offers a window into how persistence differs based on gender, ethnicity, and class rank, which can form the basis of other, more targeted studies based on specific research questions that arise from this data.

Furthermore, researching the complexities of student retention requires the engagement of a wide range of stakeholders. On the front end, instructors of introductory courses need to be involved in data collection. Administrators need to help enable data collection by marshaling the resources necessary to gather, clean, and analyze data. And some schools , like UC San Diego and Colorado School of Mines, may have an office supporting institutional research that can serve as an ally in the data gathering process.

On the back end, educators and administrators need to be open to changing teaching practices, program structures, and barriers to entry as leaks in the retention pipeline are identified. For example, rather than trying to encapsulate one perspective or a set of initial assumptions regarding incoming students, introductory courses may need to be broadened to connect with students of all backgrounds, perspectives, and interests as they first enter the classroom. Changes that are made to courses and programs should be monitored to measure the impact that they may have on increasing student retention, and successful efforts should be shared with the broader community to help develop best practices.

While additional research and institution-specific evaluation efforts are critical to providing a richer, more nuanced understanding of the dynamics of attrition and retention, students are already in CS programs and making critical decisions about their futures. For this reason, undergraduate CS programs cannot delay action while researchers seek more comprehensive and clearer data. There are multiple low- and no-cost initiatives (many detailed in the section entitled "A Cross Section of Current Interventions") that have compelling support in the form of empirical results or a robust theory of action. The committee encour-

ages institutions to continue with or launch new interventions and to use new insights produced through further research and evaluation to continuously refine and improve these interventions.

Based on the data examination, analysis, and case studies, this report makes a number of recommendations regarding data collection, successful interventions, and future research:

- Additional research is needed to provide a more nuanced understanding of the dynamics of attrition and retention, to identify the factors that decrease retention, and to find ways to address these factors.
- Individual programs should plan data gathering efforts that regularly capture information about student progressions through courses and programs.
- Where possible, institutions should hire data specialists with the expertise and time to provide complete datasets and assist faculty with analysis.
- Institutions should collaborate to determine the types of data that could consistently be captured across institutions and how this data might be regularly aggregated and evaluated.
- Instructors of introductory courses need to be involved in data collection.
- Administrators need to help enable data collection by marshaling the resources necessary to gather, clean, and analyze data.
- Data should be evaluated in different contexts, using different denominators to determine how women and other groups are represented in computing in the context of their participation in higher education and their representation in society.
- Educators and administrators need to be aware of barriers to entry as leaks in the retention pipeline are identified.
- Institutions should not wait for more research before launching new interventions and using new insights to continuously refine and improve these interventions.
- Educators should provide students with a well-rounded understanding of the discipline of CS and seek to overcome misconceptions.
- Institutions should provide funding and educators should adopt pedagogical strategies to ensure that all students perceive classrooms and labs as welcoming environments.
- Educators should adopt pedagogical strategies that incorporate collaboration and team-based learning.
- Institutions should provide programs, services, and pathways that enable students entering the institution with varying computational backgrounds to succeed in their intended major (especially with regard to computing and mathematics).
- Educators need resources to help them incorporate real life problems into courses so students have early exposure to the positive societal role of CS.

- Educators need funding for undergraduate research programs (especially at MSIs) because many students cannot afford to participate in summer programs unless they are compensated at a level equal to what they would earn in a summer job.
- Institutions need support to investigate and adopt the ACM Committee for Computing Education in Community Colleges (CCECC) transfer guidelines (ACM, 2018) to encourage and facilitate transfer from two-year and community colleges to four-year institutions.
- Institutions need to provide proactive advising to ensure that students are exposed to career opportunities and pathways early in their undergraduate experience and are able to complete their intended major on time.

The ultimate goal of any work in this area should be to increase the retention rate for students considering programs in computing. Additional research is certainly needed to make that happen by identifying the factors that decrease retention and finding ways to address them. In addition, undergraduate CS education programs need to change their pedagogy, courses, and programs to accommodate students of all backgrounds, rather than expecting students to change themselves to fit into a possibly narrow, existing expectation. That requires a better understanding of students, their intentions, and the ways in which educational structures impact both.

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