A Statewide Survey on Computing Education Pathways and Influences: Factors in Broadening Participation in Computing

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ABSTRACT

In computing education, we have only just started developing methods for accurately measuring a student's understanding of introductory computing, let alone characterizing a whole classroom, school, or university system. As part of evaluating the impact of "Georgia Computes!" we sought an understanding the factors influencing undergraduate enrollment in introductory computing for an entire state in the United States of America. We gathered surveys from over 1400 undergraduate students in introductory computing classes from 19 higher-education institutions in a single state. The analysis provided insight into the impact of "Georgia Computes!", into the connections between stages of the computing education pathways, and how factors that influence students' pursuit of computing differ between genders and majority/minority group students.

Categories and Subject Descriptors

K.3.2 [**Computers and Education**]: Computer and Information Science Education — computer science education

Keywords

Assessment,statewide assessment,education pipeline,education pathways,broadening participation, women, under-represented minorities

1. MEASURING THE COMPUTING STATUS OF A STATE

"Georgia Computes!" (GaComputes) was a National Science Foundation funded alliance whose goal was to improve the state of computing education across the entire state of Georgia, and in so doing, improve the diversity of students pursuing computing-intensive degree programs [6]. It was funded 2006–2012 by the Broadening Participation in Computing (BPC) program in NSF. Our focus extended from motivating the learning of computing starting in Grade 4 (about 10 years old), through the creation of weekend workshops and summer camps for students in later primary and secondary school years, to professional development for secondary school and even higher education faculty.

All the public institutions of higher-education in the state belong to the University System of Georgia (USG), which is a partner in the GaComputes Alliance. When we originally started GaComputes, we planned to tap into data from the University System of Georgia to help us understand enrollment of computing education in the state and to measure the impact of our interventions. While they gather enrollment and demographic data from all the 35 institutions, including the 29 institutions that offer some form of computing (e.g., computer science, information technology, or information systems), the data are not aggregated. For our evaluation purposes, there was no systemwide data store.

Measuring across 358 high schools and 29 higher education institutions is an unusual challenge for computing education. We have been developing measures of the computing understanding of individuals [13, 14], and some on the progress of a whole class (typically, focusing on demographics and retention) [12]. We know of only one effort to measure progress on computing education goals (e.g., diversity, retention, and transfer from two-year to four-year programs) of a whole state, in Massachusetts through the Commonwealth Alliance for IT Education (CAITE) [1]. The CAITE effort focused on higher education, including community colleges. In our effort, we aimed to get some measure of the pipeline or formal education pathway from secondary school into higher education studies in computing education.

In 2009, we started a process of trying to measure the status of computing education across the entire state ourselves. All Georgia institutions offering introductory computer science courses were asked to administer a survey to their introductory computing students in Spring, 2010. Of the 35 colleges and universities in Georgia, 29 offer computer science coursework, and 19 participated in the survey. In total, 1,434 introductory computer science students (in either a first or second semester course, but all in the same semester without duplication of students) completed the survey[1]. In addition, we surveyed the instructors as well, but we are not presenting that in this paper. Georgia Tech is unique from other institutions in Georgia in that introductory computer science courses are required. Of the total number of introductory CS students completing the survey (1,434), 673 were identified as attending Georgia Tech (GT). At several points in the analysis, we separated Georgia Tech from the pool.

The survey was ten pages long. We gathered demographic data, and asked students about their middle school and high school experiences. We asked students for their major and about their college and university experience. We asked them about their interest in computer science, using the factors identified in studies like the ACM-WGBH teen survey[2]. We asked them about the factors influencing their engagement and how much support they felt that they had in studying computing. Finally, we asked them about their career aspirations.

In this paper, we look at these data to address three questions:

- Who takes computing in our state, and how computing experiences in middle school and high school influenced their choices?
- What impact has GaComputes' work in middle and high schools had on computing enrollment in Georgia?
- What influences the decisions of women and minorities to pursue computing?

2. DESCRIPTION OF POOL: DEMOGRAPHICS AND INFLUENCES

Overall, the pool was 31% female and 69% male (Table 2); 59% of the students reported their race/ethnic group as White, 15% Asian, 15% Black, 5% Hispanic, less than 1% Native American, and 5% Multiracial. 41% of the respondents were first year students, 29% were second year students. Perhaps surprising, given that the survey was given in the introductory course, 18% were third year students, 7% fourth year, and 2% fifth year, and 3% Other (e.g., graduate, or non-traditional/special students).

The majority of our respondents were at the beginning of their higher-education career. 40% had never taken a college or university computer science course, and 34% had taken only a singe one, and 12% had taken two.

Less than a third of students engaged in any computing activities in middle school. Only 28% of students said that they participated in middle school (grades 6–8, typically ages 12–14) computing activities (18% chose not to participate, and 57% were not aware of any being available). Only 14% engaged in computing activities out-of-school during middle school grades. GaComputes activities had little impact at the middle school level. Only 1% of respondents engaged in our Boys and Girls Club Activities, and 1% did Girl Scouts workshops, and those were the only categories with any respondents at all. 34% of the students said that they were not interested in computing in middle school, 26% slightly interested, 25% somewhat interested, and 15% very interested. Some students did study computing in middle school classes, with 14% taking HTML basics, 13% web design, 10% database, 12% programming, and 13% robotics.

There was slightly more engagement with computing at high school. 32% of respondents said that they participating in computing activities or clubs in high school (37% chose not to participate in any, and 32% were not aware of any). 16% engaged in out-of-school computing activities or clubs. Only 21% of the students said that they were *not* interested in computing in high school, 22% were slightly interested, 28% were somewhat interested, and 29% were very interested – a big shift from middle school.

57% of our respondents said that they took computing courses in high school. 28% of those were "computing applications" courses, but the other 69% had courses whose learning objectives include significant programming. The Georgia high school computer science curriculum defines four courses [8]:

- Computing in the Modern World, which 9% of students had taken.
- Beginning Programming, 15%.
- Intermediate Programming, 4%.
- AP Computer Science, 5%.

In addition, 11% of the students had taken IT and systems management courses, 3% had taken game and animation classes, 3% had taken HCI design classes, and 17% had taken others, not-specified.

Because of the Georgia Tech (GT) effect, most of our respondents were not majors in computing, 52%. 31% were computer science (CS) majors, 3% were CS minors, 10% were in computing but not CS, 4% were undeclared. Table 1[3] describes students attitudes about factors that might influence a choice to pursue computing. Other than the factors related to programming, there is surprisingly strong sentiment about many of these factors.

We asked students, "If you are NOT a computing major/minor, indicate your reason(s) for not selecting computing." Below are the choices for that question, in the order that they appeared. These responses are valuable because of the large number of informed respondents, since they were currently enrolled in a computing course.

- Computing major/minor courses are too difficult, 12%.
- I don't want to do the kind of work that a computing major/minor leads to, 30%.
- I don't enjoy computing courses, 20%.
- I am not sure what jobs are available for students with a computing degree, 8%.
- I don't have confidence that I could succeed in computing, 16%.
- I have little interest in computing subject matter, 25%.
- It is too expensive to switch majors, 5%.
- My academic performance in computing to date is poor, 9%.
- The computing assignments require too much time, 8%.
- Computing is only about programming, 5%.

[1] A copy of the survey can be found on the Publications page at `http://www.gacomputes.org`.

[2] `http://www.acm.org/press-room/news-releases/2009/nic-interim-report/`

[3] The scale is Strongly Disagree, Disagree, Agree, to Strongly Agree.

Table 1: Student attitudes about factors influencing a choice to pursue computing

Statement	SD	D	A	SA
I have always wanted to be in computer science	25%	42%	23%	10%
I like to program in my spare time	31%	36%	25%	8%
I like solving complex logic puzzles	9%	18%	51%	22%
I would like to build cutting edge tools and applications that help people	10%	22%	35%	23%
I like talking with my friends about programming	27%	33%	28%	12%
To what extent do these apply to you?	Not at all	A little	Some	A lot
I am good at math or science.	5%	13 %	39%	43%
CS provides good financial opportunities after graduation.	4%	17%	35%	43%
CS allows me to be creative.	7%	15%	39%	40%
I am interested in helping people or society.	5%	18%	36%	40%
I have an interest in computer games.	10%	19%	25%	46%
Computing offers diverse and broad opportunities.	5%	13%	33%	49%
I am interested in solving problems with computing.	7%	17%	34%	43%
I like to program computers.	14%	22%	29%	35%
I enjoy working with computers.	4%	7%	24%	66%
I am interested in creating computer animation/movies.	17%	26%	26%	31%

- I don't think I belong in computing (don't fit the stereotype), 13%.
- Family, friends, etc. recommend that I not major in computing, 4%.
- Other (not specified), 13%.

2.1 Summarizing the Georgia Tech Effect

Georgia Tech *requires* computer science of all students, which leads to several interesting impacts on our results. Without Georgia Tech (GT), our pool is only 25% female (compared to 31% when GT is included Table 2). Without Georgia Tech, most students take the first course in CS in their second year, and are more likely to have taken a "bridge" course. More non-GT students report not having the option of out-of-school-time middle school computing experiences. 56% (vs. 57% with GT) of non-GT students took a high school computer science course. GT is a prestigious school, so students who go to GT may have had more enrichment opportunities and computer classes available.

Non-GT students were *more* interested in computer science in middle and high school. For example, 21% of students in the overall pool say that they had no interest in computer science in high school, but only 11% when GT is removed. Students from non-GT institutions were more likely to have engaged in middle and high school computing activities, when they were available (e.g., in high school, 32% of the overall pool, 38% of the non-GT pool). Likely, these results are due to students being forced to take computer science. The middle school to high school gap in interest is *more* pronounced without GT. In the overall pool, 15% of students say that they were "very interested" in CS in middle school, and 29% in high school. Without GT, 15% of students say that they were "very interested" in CS in middle school, and a whopping 41% in high school.

3. INFLUENCES OF GACOMPUTES ON PATHWAYS

One question that we pursued in this survey was an understanding of how students progressed from secondary school into higher education studies in computing, and if GaComputes professional development had any impact on that progression. GaComputes funds the Institute for Computing Education at Georgia Tech[4] which provides professional development for high school CS teachers. We asked all of the participants in our study about their high school experience. Of 2,244 schools in Georgia as of 8 February 2010, 422 offer 10th, 11th, and 12th grade classes (typically, students in the range of 15–18 years old). Most of these (358) are traditional high schools offering grades 9–12, and 16 offer grades 1–12.

Traditional introductory computer science students in our Spring 2010 study are most likely freshmen who attended high school during the 2005–2006, 2006–2007, 2007–2008, and 2008–2009 school years. Non-traditional students may have attended high school earlier, and the Institute for Computing Education (ICE) started training teachers in 2004. Therefore, any influence from the program would be from teachers who attended between 2004 and 2009 which was a population of 258 teachers from 53 public school districts in Georgia. Overall, these 258 teachers represent 152 public schools in Georgia. This group of teachers represents almost 36% (152 out of 422) of all schools in Georgia offering high school grade levels.

Overall, the introductory CS students surveyed came from 252 public schools in Georgia, and 107 of those schools had sent teachers for ICE training. While GaComputes had trained teachers at fewer than half of the schools sending students to introductory CS programs in Georgia, GaComputes schools are responsible for 60% of all Georgia students attending introductory computing courses. That is, of the 1,434 students taking the survey, 932 (64.99%) report that they attended a public high school in Georgia, and 531 (56.97%) of Georgia students attended a school that has sent a teacher to ICE training between 2004 and 2009. So, the 36% of schools with an ICE teacher produced 56.97% of introductory computing students in our survey who came from Georgia high schools. We did not have the data to track at a finer grain of detail, e.g., did those students have an ICE teacher in a class, talk to an ICE teacher, take a course from someone that an ICE teacher influenced, etc.

We conducted a separate analysis without Georgia Tech. 761 non-GT introductory CS students took the survey. Overall, the 761 introductory CS students surveyed come from 211 public schools in Georgia, and 98 of those schools have sent teachers for ICE training. Of the 761 students, 553 (72.67%) report that they attended a public high school in Georgia, and 291 (52.62%) of Georgia students attended a school that has sent a teacher to ICE training between 2004 and 2009, which is still disproportionate to the 36% of Georgia high schools that had an ICE teacher.

Gender Comparison: ICE schools produce more female introductory computing students than non-ICE schools, but

[4] http://coweb.cc.gatech.edu/ice-gt

Table 2: Number and percentage of male and female students in an introductory computing class from ICE and Non-ICE high schools

	Non-ICE Schools		ICE Schools	
	n	%	n	%
Female	120	29.92%	169	31.83%
Male	281	70.07%	362	68.1%
Total	**401**	100%	**531**	100%

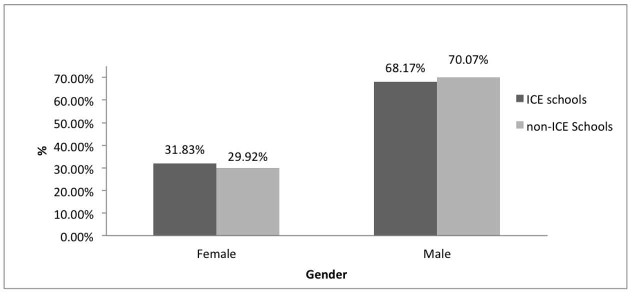

Figure 1: Bar chart of percentage of male and female students in an introductory computing class from ICE and Non-ICE high schools.

the differences between the production of female and male introductory CS students is *not* significantly different between ICE and non-ICE schools (Figure 1). We looked at the number and ratio of female and male students produced by each school (Table 2), and used a Chi-square analysis to compare ICE schools and non-ICE schools and gender, $\chi^2(df = 1) = 0.39$, $p = 0.534$.

Race/Ethnicity Comparison: ICE schools produced more minority students, both cumulatively and specifically for Black, Hispanic, and Multiracial categories, but not significantly, $\chi^2(df = 1) = 0.49$, $p = 0.534$ (Figure 2). More Asian introductory CS students come from ICE schools than non-ICE schools, and more White introductory CS students come from non-ICE schools than ICE schools. No differences were statistically significant.

4. INFLUENCING THE DECISION TO PURSUE COMPUTING

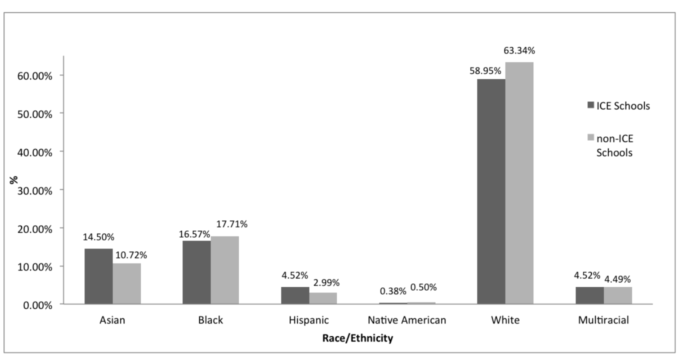

Figure 2: Barchart of percentage of students by race/ethnicity in an introductory computing class from ICE and non-ICE high schools.

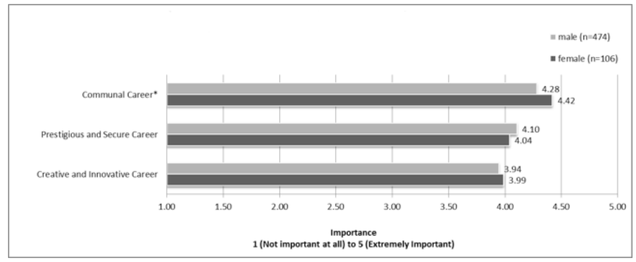

Figure 3: Important career characteristics, gender comparison (*$p < .05$, **$p < .01$).

We asked students about the characteristics of careers that were of interest to them. In the analysis in this section, we only look at participants who declared computing as their major or minor. Female respondents are significantly more likely than male respondents to place importance on communal career characteristics (Figure 3). That is, females are more likely to place importance on "being able to spend time with your family" and "having the power to do good and doing work that makes a difference" than males. Asian, Black, and Hispanic respondents are significantly more likely than White respondents to place importance on having a creative and innovative career and for achieving job security and prestige in their chosen professions (Figure 4).

As mentioned in the earlier section, we asked students about the factors for choosing a computing major or minor, and here we analyze those in terms of gender and race/ethnicity. Female respondents were more likely than male respondents to say that they chose a computing major/minor because of their "interest in helping people or society" (Figure 5). Male respondents were significantly more likely than female respondents to cite "interest in computer games," "interest in solving problems with computing," and "liking to program computers" as reasons for choosing a computing major/minor. Black respondents were significantly more likely than White respondents to cite "interest in helping people or society" as a reason for choosing a computing major/minor (Table 3). Asian and Black respondents were significantly more likely than White respondents (and multiracial respondents) to report "interest in creating computer animation/movies" as a reason for choosing a computing major/minor.

Perceptions of Ability and Relation to Encouragement in Predicting Success: We know that perception of ability plays an important role in students' decision to continue in computing (e.g., [9]). Recall that this survey was given to students who were mostly in their first or second computing course, and 69% of the students had taken a course involving computer programming in high school. So, when they tell us what they think about computer science courses and their abilities, they have experiences that inform their perceptions.

Female respondents rated their programming skills as significantly lower than male respondents did. On average, females rated their programming skills as average to slightly below average, whereas males rated their skills as average to slightly above average. Likewise, there was a significant difference between Black and White respondents in self-reported programming skills: Black respondents rated

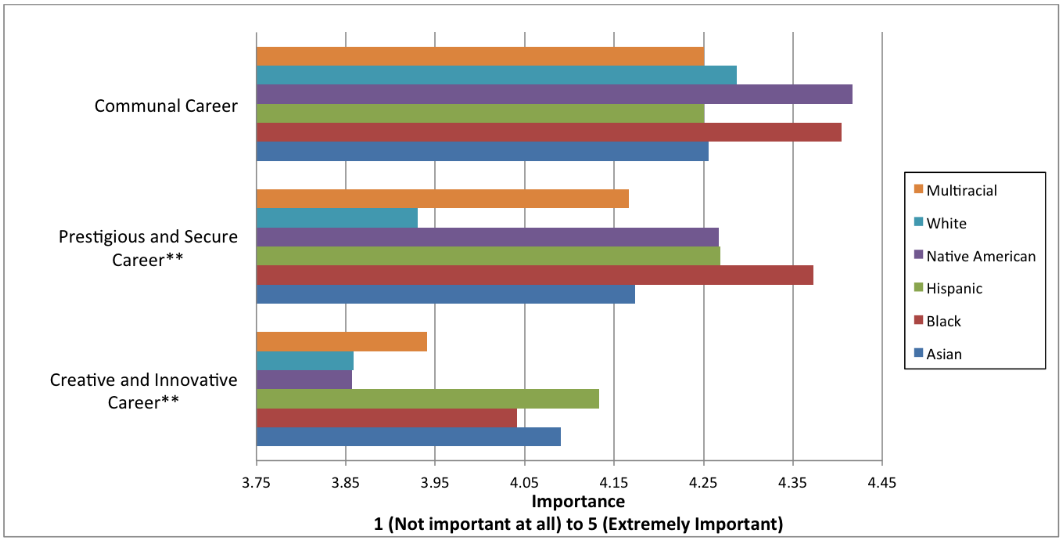

Figure 4: Important career characteristics, race/ethnicity comparison (*$p < .05$, **$p < .01$).

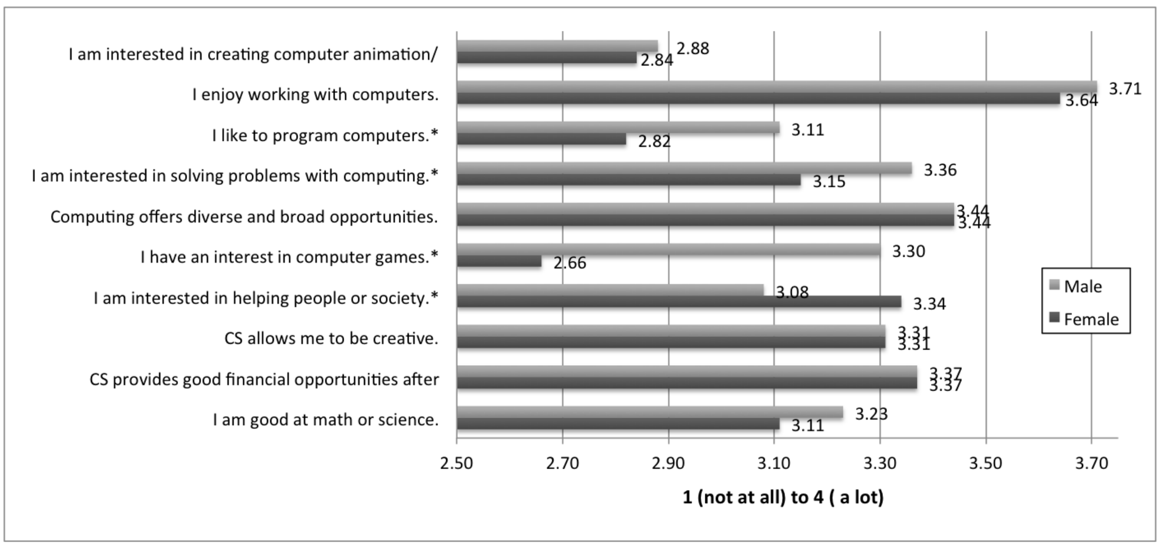

Figure 5: Reasons for choosing a computing career, gender comparison (*$p < .05$).

Table 3: 10 reasons for choosing a computing major/minor, race/ethnicity comparison. Numbers indicate mean responses, from 1 (not at all) to 4 (a lot). (*$p < .05$)

	I am good at math or science.	CS provides good financial opportunities after graduation.	CS allows me to be creative.	**I am interested in helping people or society.***	I have an interest in computer games.	Computing offers diverse and broad opportunities.	I am interested in solving problems with computing.	I like to program computers.	I enjoy working with computers.	**I am interested in creating computing animation/ movies.***
Asian	3.18	3.33	3.22	3.18	3.23	3.43	3.27	3.04	3.53	3.07*
Black	3.30	3.49	3.35	3.39*	3.15	3.52	3.30	2.93	3.74	3.04*
Hispanic	3.37	3.56	3.46	3.12	3.26	3.63	3.52	3.11	3.78	2.77
Native American	4.00	3.50	3.00	3.50	2.50	3.00	4.00	3.50	4.00	2.79
White	3.17	3.31	3.30	3.00*	3.18	3.38	3.33	3.12	3.71	2.79
Multi-racial	3.17	3.46	3.38	3.04	3.42	3.50	3.38	3.08	3.83	2.68

their programming skills as significantly lower than White respondents did.

We conducted a regression analysis [2] to assess the nature of the relationship among survey factors[5]. We hypothesized that self-reported *ability* (how students rated their programming skills) will directly predict (a) satisfaction in choosing to study computing, (b) likelihood in completing a computing major/minor, and (c) likelihood of pursuing a career in computing[6]. As perceived ability in computing increases, satisfaction and likelihood in completing and pursuing a career in computing will increase. However, we hypothesized that *encouragement* to belong and persist (e.g., construct includes responses to "Computing professors have offered me personal advice on how to succeed in computing" and "My parents/guardians encouraged me to take computing courses") will play a more important role than self-reported ability in predicting female and underrepresented minorities' outcomes. That is, we hypothesized that *encouragement* will statistically trump *ability* in predicting outcomes for female and minority respondents.

This hypothesis is based on previous research that investigated gender and racial differences in computer science (e.g., [5]). Previous research has repeatedly found that low affiliation and low interest in computer science assignments significantly accounts for the small number of women and underrepresented minorities in computer science majors and careers [3, 4]. In fact, Cohoon and Baylor [7] contend that increasing affiliation, confidence and interest in computing course work is equally, if not more, important as increasing ability in computing for females. Cohoon and colleagues [7] find that grades do not adequately explain why women and minorities leave CS at higher rates than men and majority group members. Strenta and colleagues [11] found that differences in introductory course grades did not adequately explain the effect of gender on willingness to persist in computer science.

To investigate the hypothesized meditational relationship, we conducted a series of regression analyses according to the guidelines stipulated by Baron & Kenny [2]. The numbers below reflect standardized Beta weights. The standardized Beta value indicates the number of standard deviations that the outcome will change as a result of one standard deviation change in the predictor variable. The standardized Beta-value also provides information regarding the importance of a predictor in the model.

For females, encouragement fully mediates the relationship between ability and satisfaction, likelihood to complete computing major/minor, and likelihood to pursue a career in computing (Figure 6). When the outcome variables are regressed on both encouragement and ability, the direct effect of ability becomes insignificant. This suggests that while ability enhances female's satisfaction and likelihood to pursue computing, encouragement is driving this effect. For every one standard deviation increase in encouragement, there was a .598 standard deviation increase in satisfaction, a .458 standard deviation increase in likelihood to complete computing, and a .320 standard deviation increase in likelihood to pursue a career in computing.

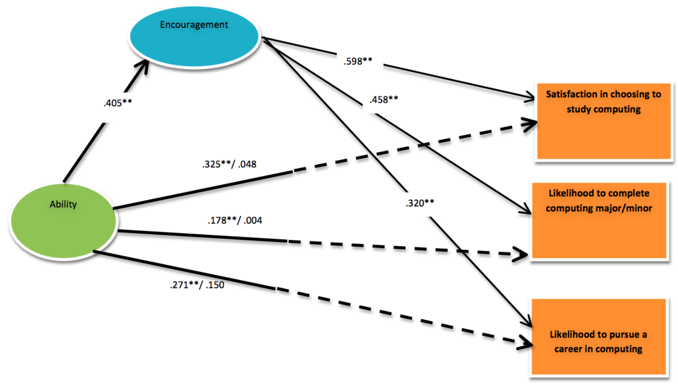

Figure 6: Mediation analysis for females (*$p < .05$, **$p < .01$).

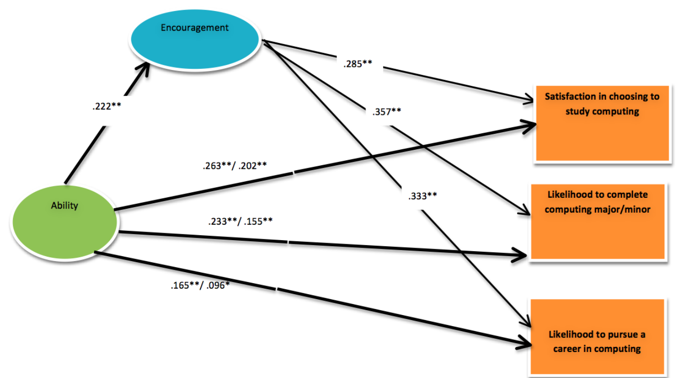

Figure 7: Mediation analysis for males (*$p < .05$, **$p < .01$).

For males, both ability and encouragement equally predict satisfaction, likelihood to complete a computing major/minor, and likelihood to pursue a career in computing (Figure 7). When the outcome variables are regressed on both encouragement and ability, the direct effect of ability remains significant; thus, encouragement does not mediate the relationship between ability and the outcome variables for males.

Overall, for females, encouragement matters more than ability in terms of how satisfied they are with computing, how likely they are to complete their computing major/minor, and how likely they are to pursue a career in computing. For males, encouragement and ability were equally important in predicting their outcomes. These results indicate that improving outcomes for females entails improving their affiliation with the computing department and enhancing the relationship between computing assignments and female interests and career goals.

For underrepresented minorities (Blacks, Hispanics, native Americans), encouragement, once again, fully mediates the relationship between ability and satisfaction, likelihood to complete computing major/minor, and likelihood to pursue a career in computing. When the outcome variables are regressed on both encouragement and ability, the direct effect of ability becomes insignificant. This suggests that

[5]Due to space constraints, we have removed our the regression analysis tables and the analysis of correlations between the factors and the outcome variables. These are available in a technical report at `http://www.gacomputes.org`.

[6]Statistical tests revealed no significant differences by gender or race on these three outcome variables.

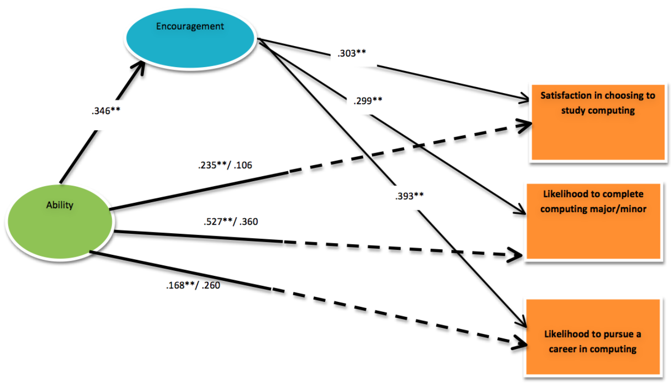

Figure 8: Mediation analysis for under-represented minorities (*$p < .05$, **$p < .01$).

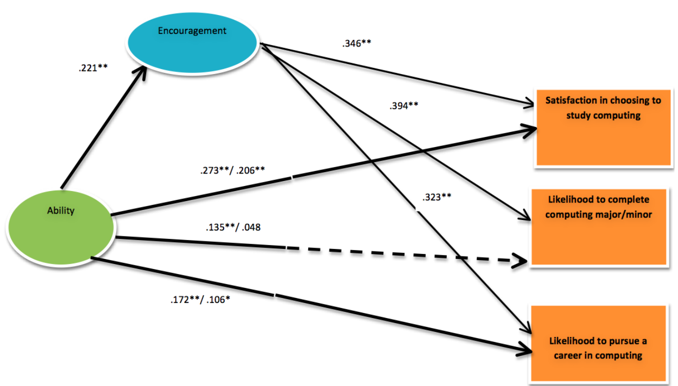

Figure 9: Mediation analysis for majority White and Asian (*$p < .05$, **$p < .01$).

while ability enhances underrepresented minorities' satisfaction and likelihood to pursue computing, encouragement is driving this effect. For every one standard deviation increase in encouragement, there was a .303 standard deviation increase in satisfaction, a .299 standard deviation increase in likelihood to complete computing, and a .393 standard deviation increase in likelihood to pursue a career in computing.

For White and Asian respondents, both ability and encouragement equally predict satisfaction in choosing to study computing and the likelihood to pursue a career in computing (Figure 9). When the outcome variables are regressed on both encouragement and ability, the direct effect of ability remains significant; thus, encouragement does not mediate the relationship between ability and the outcome variables. However, the relationship between ability and the likelihood to complete a computing major/minor was fully mediated by encouragement for White respondents. Interestingly, there was no difference between White and Asian respondents in their regression analyses, thus, for purposes of parsimony, they were combined.

Overall, for underrepresented minorities, encouragement matters more than ability in terms of how satisfied they are with computing, how likely they are to complete their computing major/minor, and how likely they are to pursue a career in computing. For majority group members in computing, encouragement and ability were equally important in predicting their outcomes. These results indicate that improving outcomes for underrepresented minorities entails improving their affiliation with the computing department and enhancing the relationship between computing assignments and minority student's interests and career goals.

5. DISCUSSION

Recall that the majority of respondents did not engage in middle school computing experiences and did not report interest in computing in middle school, yet they are responding in an introductory computing course. Students in middle school already have been thinking about careers and have negative attitudes about computing [15]. What changed for our respondents, between middle school and higher education? It may be that there was a lack of *access* to middle school computing, and if there was more, we might see more interest and participation in computing experiences.

The fact that a majority (57%) of the student respondents had taken some computing in high school has several possible interpretations. Since all the respondents were in introductory computing, having *some* high school computing may have played a role in the decision to take that course. We do not have comparison data to see if university students *not* in introductory computing had much high school computing, to see if there was a causal impact. Other indications suggest that relatively few high schools in Georgia offer high school computer science [8]. Thus, these results are *consistent* with a belief that high school computer science had an impact in drawing students into computing, despite a disinterest in middle school, but the results are not definitive.

The greater proportion of women and under-represented minorities from ICE-affiliated ("institute") schools than non-ICE schools is trending in the right direction, but isn't yet significant. This result might suggest that ICE professional development has had an impact. There could be other factors other than ICE causing this effect, e.g., perhaps the schools that were most interested in promoting women and under-represented minorities in computing *then* sought ICE professional development. We also do not have a more detailed explanation of how the teachers who received the ICE professional development might have influenced those students, e.g., we do not know the names of student respondents' teachers. Nonetheless, the results described are consistent with GaComputes and ICE professional development having an impact on undergraduate enrollment of women and under-represented minorities in computing courses in Georgia.

The results on the factors that influence women and under-represented minorities in pursuing computing careers are not surprising. What is notable here is the scale of the study, and replication of previous findings (e.g., [10]). Women and men, and majority and minority students have had different experiences, and these lead to different values. Understanding these facts can help us understand how to serve those interests and how to recruit students into the major.

Particularly notable in this paper is the mediation analysis. Issues of student self-perception of ability are not new in computer science, but noting differences in gender and race/ethnicity is new, when supported with such a large study. The results are also promising for interventions. Changing students' self-perception of ability is challenging. Encouraging them is not. The mediation analysis suggests that encouragement has a larger effect on women and underrepresented minorities than it does on male and majority group students.

6. CONCLUSION

Taking a pulse on what influences the computing education formal pathways in an entire state is challenging. This paper describes one such effort, involving over 1400 students and 19 higher education institutions. In so doing, we increase our understanding on what interventions along the pathways might be having an effect, and where they might not be. We also gain a better understanding of where we should put further work, and what kind of work is most likely to succeed.

7. ACKNOWLEDGMENTS

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