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The Determinants of Women and Racial Minority High School Students' Willingness to Pursue an IT Major

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Completed Research Paper

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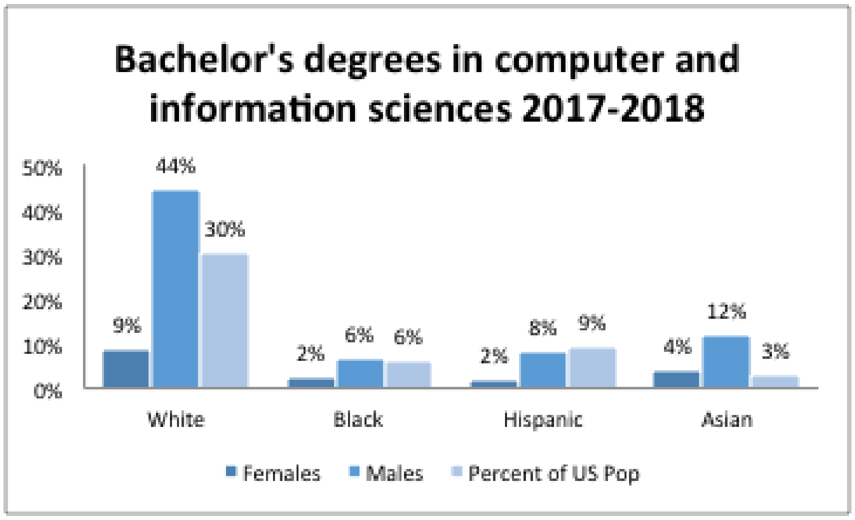
Abstract

Women and racial minorities are underrepresented in IT careers. One reason for this is that women and racial minorities choose to major in IT subjects in college at a lower rate than overrepresented groups in IT careers do. Thus, it is important to better understand how high school students make decisions about whether to major in IT subjects in college. We report on a racially diverse, nationwide sample of college-bound high school seniors and their intentions to major in IT subjects in college. Using expectancy-value theory, we add the construct of outside opportunities (i.e., how many options one has for a major) with cumulative high school GPA as a proxy. We find that higher GPAs actually tend to increase the intention to major in IT for several underrepresented groups but decrease the intention to major in IT for some overrepresented groups. Policy implications include including IT training in high schools.

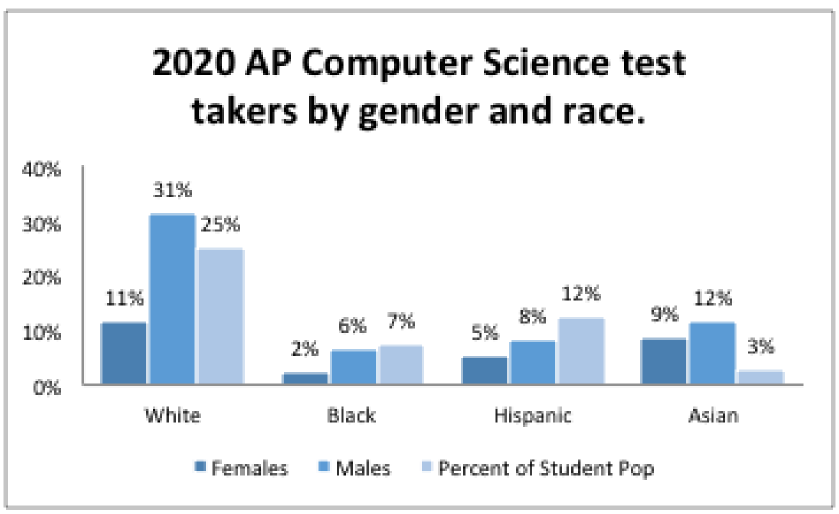
Keywords: Gender, racial minorities, expectancy-value theory, high school students, conference publications

Introduction

Women and minorities are underrepresented in information technology (IT) careers. In 2019, the computing workforce was only 26% women, 3% Black women, and 2% Hispanic women (Department of Labor Bureau of Labor Statistics 2019). One main driver of this is that women and non-Asian minorities are underrepresented in college degrees that prepare students for IT careers. This is represented in the graph below showing bachelor's degrees awarded in Computer and Information Sciences in the United States (US) in 2017-2018. The data come from the US Department of Education. Next to the percentage of degrees awarded by gender is the proportion of the US population that is in each racial/gender category. For example, White non-Hispanics make up about 60% of the US population, so 30% of the US population is White female and 30% is White male. As the graph shows, White males and Asians of both genders are overrepresented. White, Hispanic, and Black females are underrepresented.



Just as the lack of college degrees in Computer and Information Sciences is a major issue for the eventual diversity of the IT workforce, the lack of diversity among high school students planning to pursue these degrees in college may be a major cause of the lack of diversity. The graph below shows the gender and race of high school students taking AP (advanced placement) Computer Science tests. As the graph illustrates, the diversity issue is actually worse than it appears because Black and Hispanic populations in the US skew younger, so they make up a larger proportion of the high school age population than the general population. Of course, not all students taking the AP Computer Science courses intend to major in Computer and Information Sciences, nor do all people majoring in Computer and Information Sciences take the AP Computer Science exam. Nonetheless, the same pattern holds for the IT workforce, bachelor's degrees awarded in Computer and Information Sciences, and the AP Computer Science test.



Before corporations and colleges can take actions on diversity, there is already an aversion by women and (non-Asian) racial minority high school students to following an IT career path. Moreover, nothing that colleges or corporations have done to date has changed that fundamental aversion.[1] The corporate IT workforce and college classrooms mirror the preferences of high school students. Therefore, to increase diversity it is necessary to understand college-bound high school students' perceptions of IT career choice.

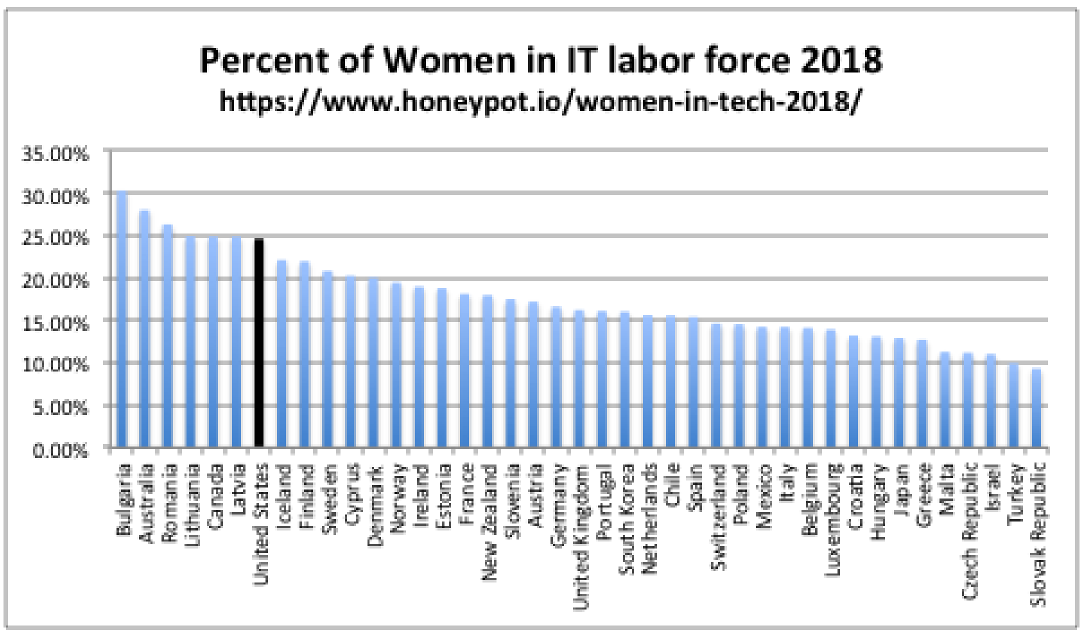
[1] Some organizations have had success increasing diversity. Carnegie Mellon in particular has done excellent work (Frieze and Quesenberry 2019). Nonetheless, in aggregate neither universities nor corporations have had a positive effect on IT diversity for several decades.

Although there have been valuable studies on obstacles women and minorities face in the IT industry and why they leave the field (Armstrong et al. 2007, 2012; Riemenschneider et al. 2006; Trauth et al. 2009), we place our study at the beginning of the pipeline: before people decide to major in an IT field in college: Our focus is on career choice rather than career continuance.

In this work, we develop a model of high school students' preferences for an IT career and test it using a panel of 842 high school students in the US. Our model is novel in that it uses expectancy-value theory but adds a construct: outside opportunities. However, our main contribution is examining a racially diverse panel of high school students from across the US. This is particularly important because many engineering degrees like computer science have a four-year curriculum, which means that there are significant barriers to entry for students who do not arrive at college with the intention of majoring in these degrees.

Because our data set is unique, we are more exploratory in our analysis than is typical in an information systems (IS) paper. Although we use an empirically supported theory of career choice, our addition of the outside opportunities construct and comparisons between genders and races becomes more exploratory. Thus, we caution the reader to interpret these results as such—a place to begin understanding rather than confirmation of theory. However, exploratory research plays an important role in open-science for stimulating hypotheses (Munafò et al. 2017). Our findings may serve as the beginning stages of theorizing—leading to further work that advances our theoretical understanding of the phenomenon (Avison and Malaurent 2014; Hambrick 2007)

We note our study has a US perspective, as that is where our data come from. Nonetheless, the diversity problem in IT, particularly concerning women, applies to most of the world. Although minorities differ by country, women are present in all countries. As dismal as IT diversity is in the US, it is actually among the best in the world as shown below. The diversity problem applies worldwide.



Theory

There have been calls in IS and management for more problem-based, exploratory research on important issues (Avison and Malaurent 2014; Dennis 2019; Hambrick 2007; Hirschheim 2019)—especially that which studies new phenomena with great societal impact—(Dennis 2019). The diversity problem in IT is not new but taking it seriously as a field is—as of 2019 only 16 articles had been published in Senior Scholars' Basket of Eight journals on the topic. Studies that examine both gender and racial diversity in IT are even rarer.[2] The societal impact of studying the diversity problem in IT is evident: understanding the problem could bring a more diverse IT workforce and with it more diverse thinking in how to improve systems.

In this paper, we study the diversity issue in IT from a problem-based approach grounded in strong theory. The goal of problem-based research to is to understand new or important phenomena through the lens of well-established theory (Dennis 2019). Expectancy-value theory is our theoretical grounding. This theory is robust at explaining how people make education or career choices (Eccles 2009; Wang and Degol 2013). Grounded in expectancy-value theory, we study the IT diversity problem by exploring whether the model differs between genders and races.

This approach to studying the IT diversity problem is appropriate for two reasons. First, we must understand *what* is occurring in a phenomenon before we can explain *why* (Avison and Malaurent 2014; Hambrick 2007). In the management literature, there is a distinction between two types of studies of gender composition: studies of whether differences exist and studies of why differences exist. (Ely and Padavic 2007). Though both are important, our work focuses on whether high school students from different demographic groups hold different perceptions of IT careers rather than why they hold different perceptions. Second, our research can act as a starting point for advancing our theoretical understanding of high school students' decisions about IT careers. In addition to a grounding in expectancy-value theory, our approach allows us to make a contribution to knowledge and stimulate further work in IS practice and theory development (Avison and Malaurent 2014). Using an empirical, exploratory approach, we can report facts about all of the data that could stimulate future theorizing (Hambrick 2007).

Research Model

We use a slight modification of Expectancy-Value theory (Eccles et al. 1998) to examine career choice. Expectancy-value theory proposes two primary determinants of career choice: expectancy of success and value placed on each career option. The research model can be seen in Figure 1.

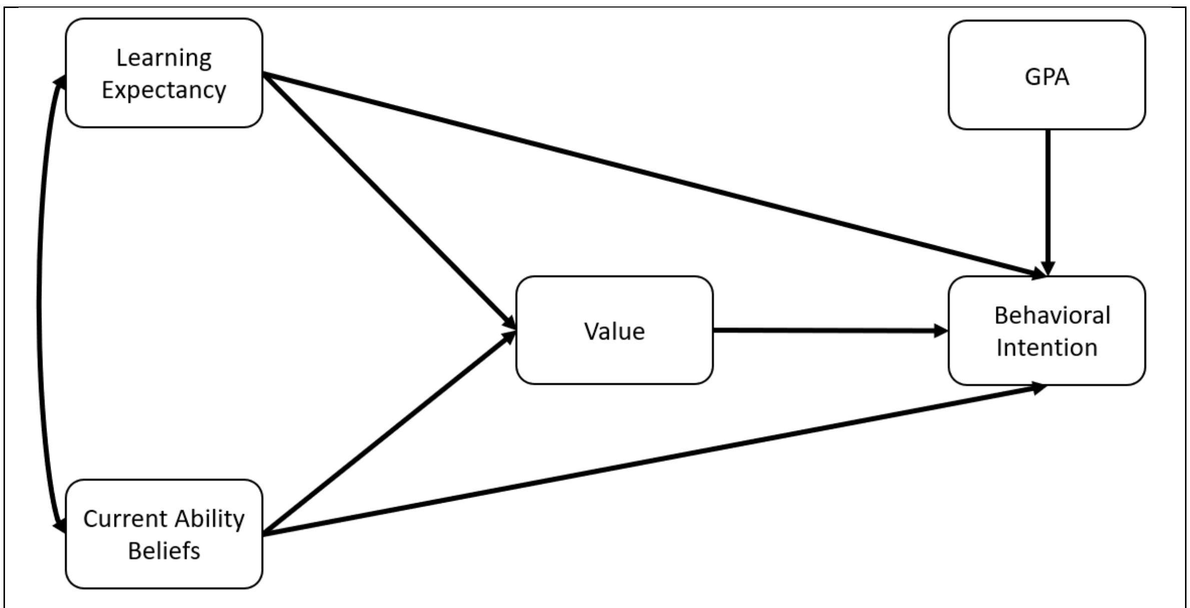


Figure 1. Research Model

Expectancy is summed up with the question, "Can I do the task?" (Eccles et al. 1998). This is divided into expectations of success and ability beliefs (Eccles and Wigfield 2002). Expectations of success refer to whether people think they can learn to succeed if they follow a given path. In this study, we refer to this as **learning expectancy**. Ability beliefs refer to the perception of current abilities in a subject. For our study,

[2] Notable exceptions include (Kvasny 2006; Kvasny et al. 2009; Trauth et al. 2016).

we refer to this as **current ability beliefs** to emphasize it answers the question "Can I do it now?" rather than the "Can I learn to do it?" question that learning expectancy answers. For a college major to be considered, one must believe that they could be successful in it. If someone thinks that they would be successful in a subject, this subject may be considered an option. However, these expectancy beliefs are necessary but not sufficient for someone to consider and choose a particular college major (Eccles 2009).

If someone believes they can succeed in a major but does not value the subject, it will not be considered an option. Thus, someone must value a subject as well to consider it. Value is summed up with the question, "Do I want to do the task?" (Eccles et al. 1998). If someone believes they can succeed in a career and they value it, they may select that option. Value can be broken into subcomponents. Three types of value that have been considered to explain career choice are interest value, utility value, and attainment value (Eccles 2009; Wang and Degol 2013). **Interest value** refers to how enjoyable or interesting a subject is perceived to be. **Utility value** refers to how relevant a subject is to fulfilling personal goals. **Attainment** value refers to how important a subject is to one's identity. The three of these can combine to form an overall **subjective value** for a subject.

In addition to learning expectancy and current ability beliefs affecting career decisions directly, they may also do so indirectly through value. We are more likely to value things we are good at (Bandura et al. 2001) and believing we could succeed in a career could make the career seem less costly and therefore valuable. Therefore, we include both direct and indirect effects via value for the impacts of learning expectancy and current ability beliefs on intention to major in IT. Moreover, these beliefs are correlated with one another.

To the basic expectancy-value model we add **outside opportunities**. The more opportunities an individual has, the less likely they are to pursue a given opportunity. This can be an important explanatory variable in career choice for women in particular (Stoet and Geary 2018; Wang and Degol 2017). A person may believe that they have the skills necessary to be in career A and that they would derive value from being in career A, but they are less likely to choose career A if they also have the skills and anticipate value from career B, whereas someone with no alternatives is more likely to choose career A.

The final construct in our research model is behavioral **intention to major in IT** in college. This is the current behavioral intention of college bound high school seniors to choose an IT major in college including majors such as IS or computer science.

The general hypotheses are that learning expectancy, current ability beliefs, and value have positive effects on intention to major in IT in college, whereas opportunities has a negative effect. Moreover, both expectancies—learning expectancy and current ability beliefs are expected to have indirect effects on intention to major in IT via value. However, the main purpose of our paper is to see if there are differences in the size of these effect for different race and gender groups. However, we do not have *a priori* hypotheses for these differences.

Method

One contribution of this work is the use of a nationwide sample of college-bound high school students. Before detailing the data, we explain why this is important and difficult. Although college students are an easy population to access, it must be assumed that during the college registration and enrollment process students must have contemplated many details about careers and college degrees and solidified many opinions as well. It is not uncommon for students majoring in computer science to make that declaration *before* professors have access to them as research participants. Moreover, college students in those career paths would answer from an insider's point of view, which is likely to be more fully informed than the view of the high school student who chose that major in the first place.

Unfortunately, there are roadblocks to getting a nationwide sample of high school students including federal regulations on privacy and the fact that most high school students are not legally adults. These protections extend to many communities where one might expect to find high school students, such as Instagram, Reddit, or Twitch.

Our solution was to partner with a company that already had a panel of high school students recruited. After we created the survey, it was administered by this company. This study was approved by the IRB at our university. Our sample includes 842 respondents from 49 of 50 US states. See Table 1 for demographic information. Because gender is of such importance to this study, those who selected "Prefer not to answer" for gender were not included in analyses.

	Frequency	**Proportion**
Age		
17	280	33.3%
18	380	45.1%
19	133	15.8%
20 or older	49	5.8%
Gender		
Women	602	71.5%
Men	240	28.5%
Race/Ethnicity		
White/European American	295	35.0%
African/African American/Black	224	26.6%
Biracial/Multiracial	129	15.3%
Hispanic/Latino(a)	99	11.8%
Asian/Asian American	49	5.8%
Asian Indian	10	1.2%
American Indian/Native American	8	1.0%
Arab American/Middle Eastern	7	0.8%
Pacific Islander	7	0.8%
Other	4	0.5%
Preferred not to answer	10	1.2%

Table 1. Participant Demographics (*N* = 842)

This partnering lead to an issue that should be discussed. Because human subjects research relies on volunteers, samples are unrepresentative of the underlying population in unknown ways. Our sample has disproportionately more Black and female respondents than the high school population of the US. We are also underrepresenting people who are not electronically connected, as the survey was filled out online. Thus, like all human subjects research, our results are a starting point for exploration and may not generalize to the population of the US or the world.

Measures

All items (see Table 2) were assessed on 7-point Likert scales.

Construct	**Item**	**Standardized Loading**
Learning Expectancy (adapted from Midgley et al., 2000)	1. I'm certain I can master the skills taught in information technology classes in college.	.77

	2. I'm certain I can figure out how to do the most difficult information technology class work.	.74
	3. I can do almost all the work in college information technology classes if I don't give up.	.76
	4. Even if the work is hard in information technology classes, I can learn it.	.77
	5. I can do even the hardest work in information technology classes if I try.	.75
Value – (adapted from Conley, 2012)		
Interest Value		.93*
	1. How much do you like working with computers?	.78
	2. I like computers.	.87
	3. Computers are exciting to me.	.88
	4. I am fascinated by computers.	.87
	5. I enjoy working with computers.	.88
	6. I enjoy the subject of computer skills.	.86
Utility Value		.91*
	1. How useful is learning computer skills for what you want to do after you graduate and go to work?	.82
	2. Computer skills will be useful for me later in life.	.84
	3. Computer concepts are valuable because they will help me in the future.	.85
	4. Being good at computers will be important when I get a job or go to college	.82
Attainment Value		.97*
	1. Being someone who is good at computers is important to me.	.84
	2. I feel that, to me, being good at solving problems which involve computers is (*not at all important… very important*).	.81
	3. Being good at computers is an important part of who I am.	.82

	4. It is important for me to be someone who is good at solving problems that involve computers.	.83
Current Ability Beliefs (adapted from Eccles & Wigfield, 1995)		
	1. How good with information technology are you? (*not at all… very good*)	.90
	2. If you were to list all the students in your class from the worst to the best in information technology skills, where would you put yourself? (*one of the worst… one of the best*)	.80
	3. Some students are better in one subject than in another. For example, you might be better in information technology skills than in English. Compared to most of your school subjects, how good are you in information technology skills? (*a lot worse in information technology skills than in other subjects… a lot better in information technology skills than in other subjects*)	.81
Intention to Major in IT – (adapted from Sia et al., 2009)		
	1. I am considering majoring in information technology in college.	.90
	2. I would seriously contemplate majoring in information technology in college.	.89
	3. It is likely that I am going to major in information technology in college.	.90
	4. I intend to major in information technology in college.	.90

Table 2. Construct Items and Factor Loadings

Learning Expectancy

Learning expectancy was measured using an adaptation for an IT context of the Academic Efficacy scale of the Patterns of Adaptive Learning Scales (Midgley et al. 2000). This scale has been used to measure expectancy in an expectancy-value framework (Conley 2012).

Current Ability Beliefs

To measure current ability beliefs, we adapted items used to measure ability beliefs for math in an expectancy-value framework (Eccles and Wigfield 1995) to an IT context.

Value

To measure value for IT, we adapted items developed by Conley (2012) to an IT context. The original items were used for value for math. Subscales include interest, utility, and attainment.

Outside Opportunities

Because we could not directly measure outside opportunities, we used a proxy: cumulative high school GPA. GPA is a cumulative measure of all of the different classes that a person has taken. Thus, not only is it a necessary input to college admissions, but it is also a measure of how broad one's skills are. One cannot get a high GPA without language, science, and humanities skills. Participants self-reported this information.

Intention to Major in IT

To measure intention to major in IT, we adapted items from the IS literature measuring intention to buy (Sia et al. 2009). We added an additional item ("I intend to major in information technology in college") that used similar wording to behavioral intention items used in other IS research (Malhotra and Galletta 2005; Taylor and Todd 1995). Participants were told that information technology majors included majors like information systems or computer science.

Results

Means, standard deviations, and internal consistency reliability estimates are presented in Table 3.

Variable	***M***	***SD***	**Cronbach's α**
Major Intention	3.92	1.87	.94
Learning Expectancy	5.02	1.29	.87
Interest Value	4.51	1.56	.94
Utility Value	4.82	1.50	.90
Attainment Value	4.53	1.55	.89
Current Ability Beliefs	4.60	1.39	.87
GPA	3.69	0.48	-

Table 3. Means, Standard Deviations, and Internal Consistency Estimates

We conducted primary analyses using structural equation modeling (SEM) with reflective latent variables. We used Mplus version 8.2 (Muthén and Muthén 2017) and used maximum likelihood with robust standard errors (MLR) estimation which is appropriate with continuous manifest variables and corrects for skewness allowing distributional assumptions to be relaxed (Li 2016).

Measurement Model

Besides GPA—used as a proxy for outside opportunities—all variables were modeled as latent variables. In addition to first-order variables, we modeled a second-order latent variable for *value* with interest, utility, and attainment value as its first-order variables. Variances of latent variables were fixed to 1.

Our proposed model fit the data well, $\chi^2(290) = 742.91$, $p < .001$, RMSEA = .043, CFI = .963, SRMR = .043. We compared the fit of this model to a model with no second-order value factor which also fit the data well, $\chi^2(284) = 641.88$, $p < .001$, RMSEA = .039, CFI = .971, SRMR = .038. We compared the fit of these two models using change in RMSEA (ΔRMSEA) change in CFI (ΔCFI), and change in SRMR (ΔSRMR) (Chen 2007). When comparing models, ΔRMSEA > .015, ΔCFI > .01, and ΔSRMR > .01 suggest a difference in model fit. Comparing our second-order model to the first-order model showed the models' fit did not differ significantly, ΔRMSEA = .004, ΔCFI = -.008, and ΔSRMR = .005. Therefore, we retained the model with a second-order factor for value, because it allowed greater parsimony in structural models.

We then evaluated factor loadings, composite reliability, convergent validity, and discriminant validity for this measurement model. All factor loadings were significant and greater than .70 (see Table 2). All composite reliability values were acceptable (See Table 4). Convergent and discriminant validity were assessed using average variance extracted (AVE) (Gefen et al. 2000). As seen in Table 4, convergent validity was supported for each construct. Discriminant validity was supported for each construct except for current ability beliefs which had one correlation with another factor (value) that was slightly greater than its square root of the AVE. To investigate this, we ran another model in which the current ability beliefs items loaded onto the value factor instead of a current ability beliefs factor. If this model performed worse than the original model it would provide evidence of discriminant validity (Gefen et al. 2000) This model did not fit as well as the original model, $\chi^2(294) = 957.99$, $p < .001$, RMSEA = .052, CFI = .946, SRMR = .081. This new model fit worse than the original model on two metrics, ΔRMSEA = .009, ΔCFI = -.017, and ΔSRMR = .038. This provided evidence of discriminant validity for the current ability beliefs factor. Because of this, and the other strong properties found for this factor, we proceeded with it in the model.

	Variable	**1**	**2**	**3**	**4**
1	Major Intention	**.90**			
2	Learning Expectancy	.48	**.76**		
3	Value	.85	.69	**.94**	
4	Current Ability Beliefs	.80	.55	.86	**.84**
Composite Reliability		.94	.87	.96	.88
AVE		.80	.58	.88	.70

Table 4. Interfactor Correlations, Average Variance Extracted, and Composite Reliability

Notes: Bolded values in the diagonal are the square root of the average variance extracted. AVE = average variance extracted.

Structural Analyses

We next evaluated our structural models. For each group comparison between genders and races, we examined mean differences on variables using structural regression. We used multigroup models to examine gender or racial differences in our research model (i.e., differences in parameter slope estimates).

We first examined male and female differences mean differences. We see several significant differences (see Table 5). Men scored higher than women in value, current ability beliefs, and intention to major in IT. On the other hand, women had significantly higher GPAs than men.

Dependent Variable	**β**	**z**	***p***
Learning Expectancy	.04	1.13	.26
Value	.16	4.41	< .001
Current Ability Beliefs	.15	4.32	< .001
GPA	-.08	-2.18	.03
Intention to Major in IT	.20	5.75	< .001

Table 5. Standardized Mean Differences: Gender

Notes: 602 women; 240 men. Gender is dummy coded (1 = Men, 0 = Women).

We then ran the multigroup structural model to examine male and female differences in slopes. The findings (see Figure 2) suggest that there are no differences in the relative importance of the variables between men and women. Moreover, there was no significant effect for GPA.

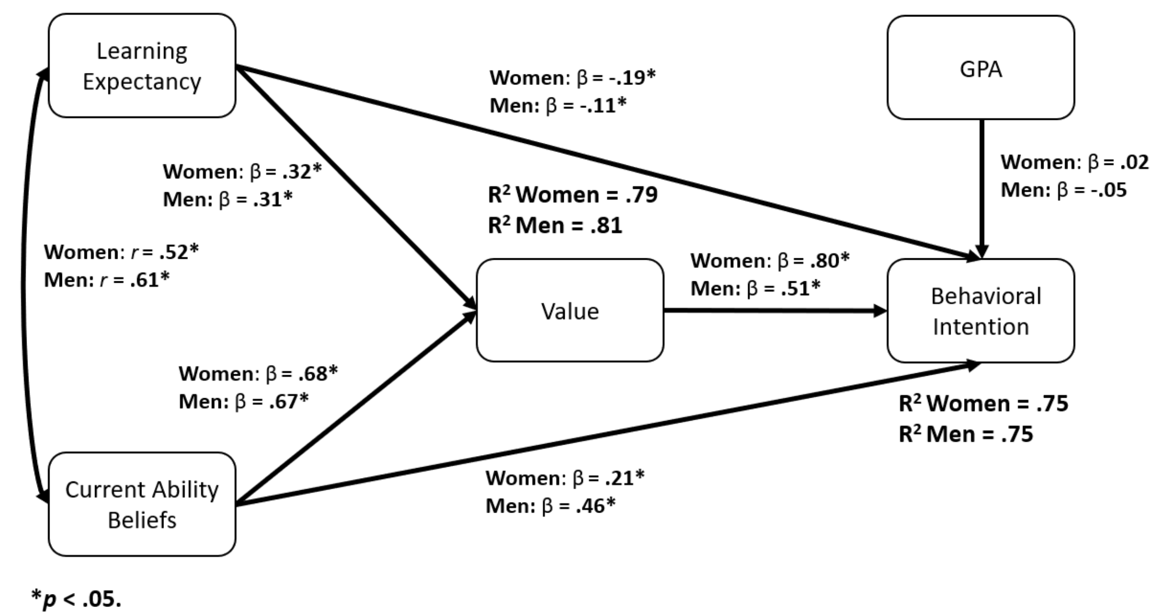


Figure 2. Multigroup Model – Men and Women (*N* = 842; 602 women; 240 men)

Things change when considering race. First, we compared Black and White respondents because those were our two largest groups. Here we see fewer mean differences, but a parameter slope difference emerges. In Table 6, we see the only mean difference between Black and White students is in intention to major in IT with Black students scoring higher.

Dependent Variable	β	z	*p*
Learning Expectancy	-.04	-0.93	.35
Value	-.01	-0.17	.86
Current Ability Beliefs	.09	1.93	.05
GPA	-.04	-0.81	.42
Intention to Major in IT	.12	2.73	< .01

Table 6. Standardized Mean Differences: Black and White Students

Notes: n = 519 (295 White; 224 Black). Race is dummy coded (1 = Black, 0 = White).

In the multigroup model (see Figure 3), there are no significant differences in the relative importance of either expectancy construct nor value between Black and White respondents. However, there is a significant difference in the importance of GPA for each group's intention to major in IT, $z = -3.33$, $p < .01$. More importantly, the signs are opposite, and each is significantly different than zero. Thus, a higher GPA implies a low intention to major in IT for White students, but a higher intention to major in IT for Black students.

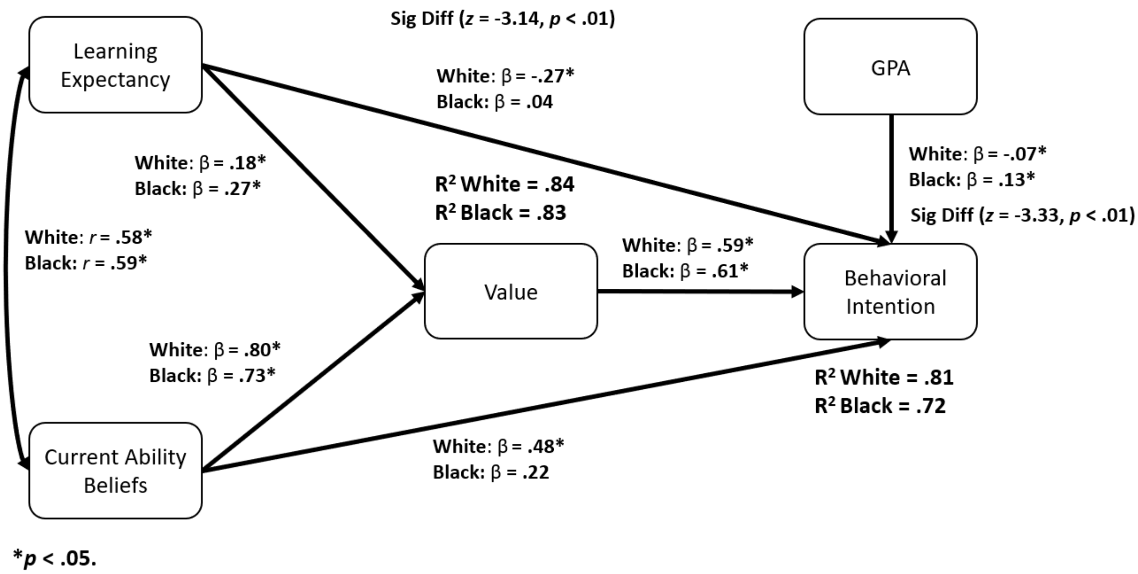


Figure 3. Multigroup Model – Black and White Students (*n* = 519; 295 White; 224 Black)

When we look at only female Black and White respondents, we get similar results. In addition to the significant difference in intention to major in IT, Black women scored higher than White women in current ability beliefs (See Table 7).

Dependent Variable	**β**	**z**	***p***
Learning Expectancy	.02	0.28	.78
Value	.03	0.60	.86
Current Ability Beliefs	.13	2.28	.02
GPA	.01	0.25	.80
Intention to Major in IT	.15	2.89	< .01

Table 7. Standardized Mean Differences: Black and White Women

Notes: n = 376 (218 White; 158 Black). Race is dummy coded (1 = Black, 0 = White).

In the multigroup model (see Figure 4), the same result from above holds, and the difference in the effects of GPA grows larger, z = -3.59, p < .01.

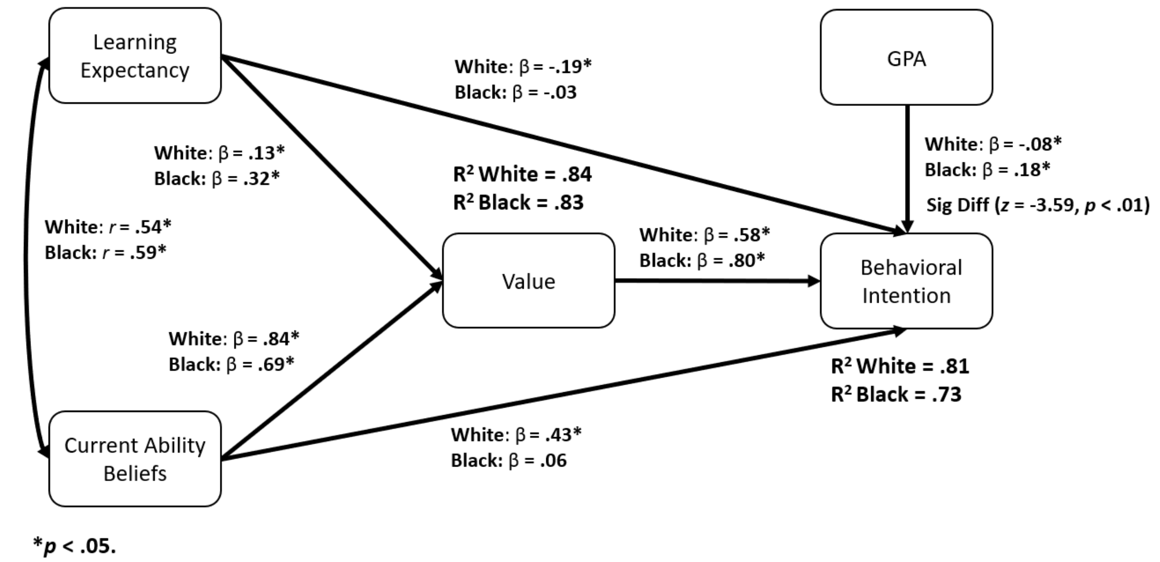


Figure 4. Multigroup Model – Black and White Students who are Women (n = 376; 218 White; 158 Black)

We also include Asian and Hispanic students of both genders (there are not enough Asian respondents to generate a model for just one gender). In terms of mean differences, the only new effects to emerge (the Black and White differences were already seen), were Hispanic students scoring significantly higher than White students on current ability beliefs. and intention to major in IT (see Table 8). Thus, we see two underrepresented groups (Black and Hispanic students) score higher than White students on current ability beliefs and intention to major in IT.

Dependent Variable	**Race**	**β**	**z**	***p***
Learning Expectancy	Black	-.04	-0.92	.36
	Hispanic	-.06	-1.26	.21
	Asian	-.03	-0.94	.35
Value	Black	-.01	-0.15	.89
	Hispanic	.02	0.38	.71
	Asian	-.01	-0.24	.81
Current Ability Beliefs	Black	.09	1.91	.06
	Hispanic	.11	2.43	.02
	Asian	-.001	-0.038	.97
GPA	Black	-.04	-0.81	.42
	Hispanic	.02	0.40	.69

	Asian	.07	1.82	.07
Intention to Major in IT	Black	.12	2.76	< .01
	Hispanic	.09	2.19	.03
	Asian	.03	0.66	.51

Table 8. Standardized Mean Differences: Black, White, Asian, And Hispanic Students Differences From White Students

Notes: n = 667 (295 White; 224 Black; 99 Hispanic; 49 Asian). Race was entered into the model as three dummy codes with White as the reference group.

For the multigroup model (see Figure 5), we find the same general result—GPA has a positive effect for Black respondents and a positive but non-significant effect for Hispanics, while GPA is negative and significant for both Asian and White students. In other words, the overrepresented groups in IT careers—Asian and White respondents—tend to show a negative effect for GPA. In addition to the significant difference in these parameters between Black and White students reported above, the difference in parameters is significant between Asian and Black students, $z = -3.79$, $p < .01$, and Asian Hispanic students, $z = -2.47$, $p < .01$, as well.

Two more significant differences in parameter slopes emerged in this model. Although both large and significant, the relative importance of current ability beliefs in explaining value was greater in White students than Hispanic Students, $z = 2.73$, $p < .01$. In addition, the direct effect of learning expectancy on intention to major in IT was significantly different between Hispanic and Black students, $z = 2.29$, $p < .05$.

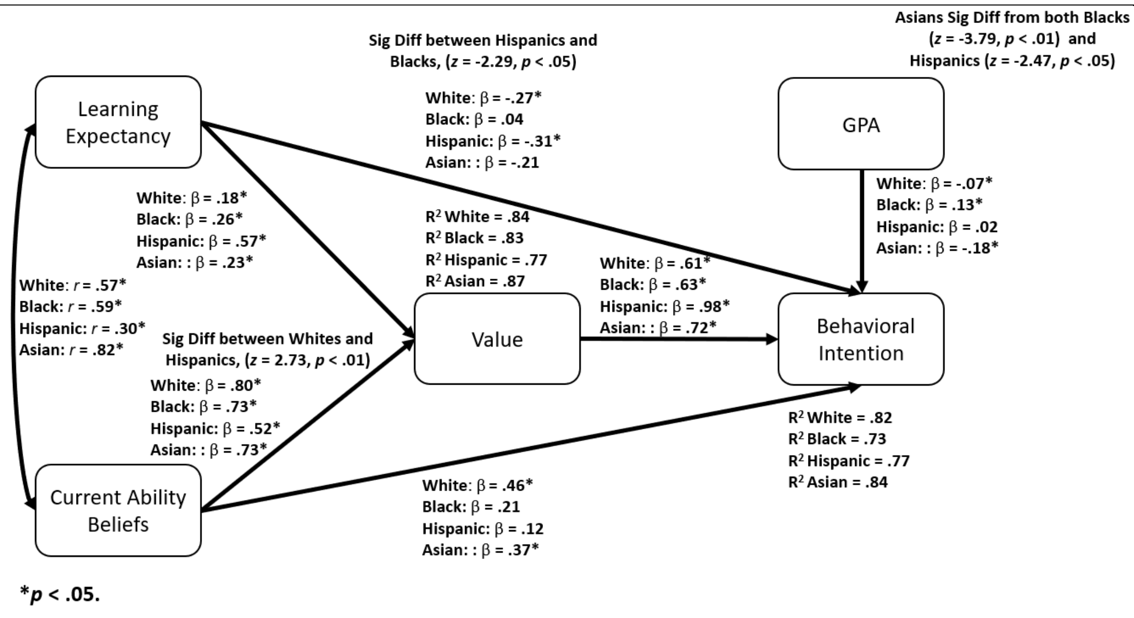


Figure 5. Multigroup Model – Black, White, Asian, Hispanic Students (n = 667; 295 White; 224 Black; 99 Hispanic; 49 Asian)

Next, we group White and Asian respondents together (the two overrepresented racial groups in IT) and group everyone else together (this group includes: Black, Hispanic, Asian Indian, American Indian, Middle Eastern, and Pacific Islander. We did not include Biracial, Other, or Prefer not to Answer in this group because it was unclear which would be appropriate, so they were not included in these analyses). Again, the same pattern holds. First, as seen in Table 9, the White and Asian students scored lower than the other group on current ability beliefs and intention to major in IT. Second, in the multigroup model (see Figure 6), the effect of GPA on intention to major in IT is significant and negative for White and Asian students but positive and significant for all others. This difference in parameters was significant, $z = 3.43$, $p < .01$. There was also a significant parameter difference for the direct effect of learning expectancy on intention to major in IT, $z = 2.94$, $p < .01$.

Dependent Variable	**β**	**z**	***p***
Learning Expectancy	.05	1.33	.18
Value	-.002	-0.06	.95
Current Ability Beliefs	-.10	-2.46	.01
GPA	.04	0.93	.35
Intention to Major in IT	-.11	-2.85	< .01

Table 9. Standardized Mean Differences: White/Asian and Everyone Else

Notes: n = 701 (344 White or Asian; 357 Other). Race is dummy coded (1 = White or Asian, 0 = Everyone else).

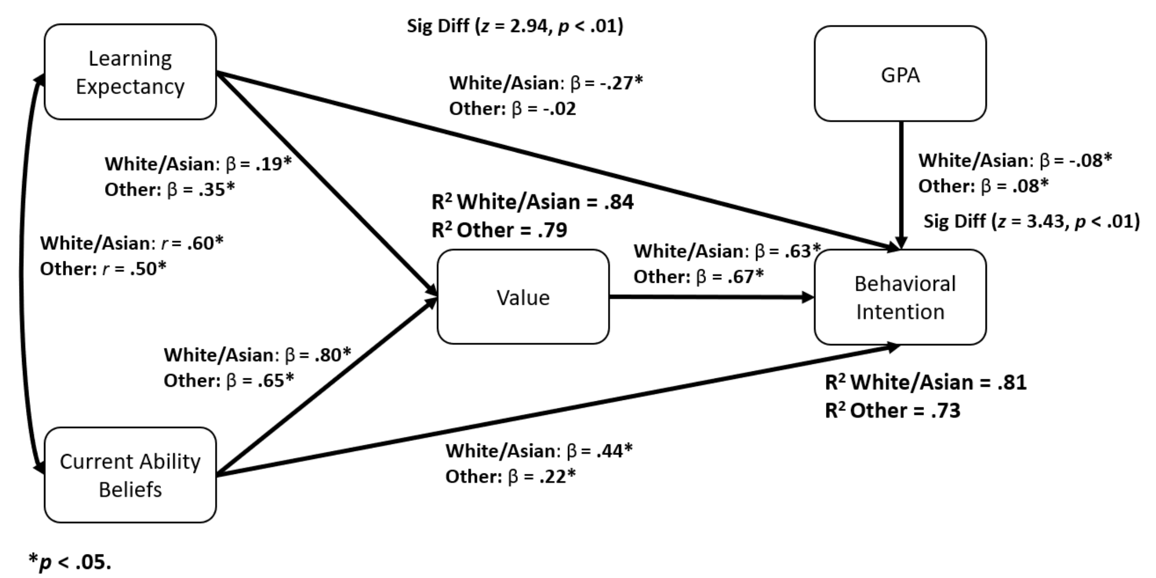


Figure 6. Multigroup Model – White and Asian Students Compared to All Others (*n* = 701; 344 White or Asian; 357 Other)

Finally, we compare the White and Asian students as a group and everyone else for just those who are female. In terms of mean differences, the same pattern emerges. White/Asian women score lower on current ability beliefs and intention to major in IT than other women (see Table 10).

Dependent Variable	**β**	**z**	***p***
Learning Expectancy	-.004	-0.09	.93
Value	-.03	-0.73	.47
Current Ability Beliefs	-.12	-2.49	.01

GPA	-.001	-0.02	.99
Intention to Major in IT	-.13	-2.93	< .01

Table 10. Standardized Mean Differences: White/Asian Women and Other Women

Notes: *n* = 494 (248 White or Asian; 246 Other). Race is dummy coded (1 = White or Asian, 0 = Everyone else).

For the multigroup model (see Figure 7), the difference in the effect of GPA is larger than for the analysis with male respondents included, $z = 4.06$, $p < .01$. In addition, White/Asian students have significantly lower beta scores for the effect of learning expectancy on value, $z = 2.68$, $p < .01$, but significantly higher for current ability beliefs, $z = -2.13$, $p < .05$. Thus, for White/Asian women it seems to be more important if they believe they can do IT work now and less important if they think they have the ability to learn how to do it in college.

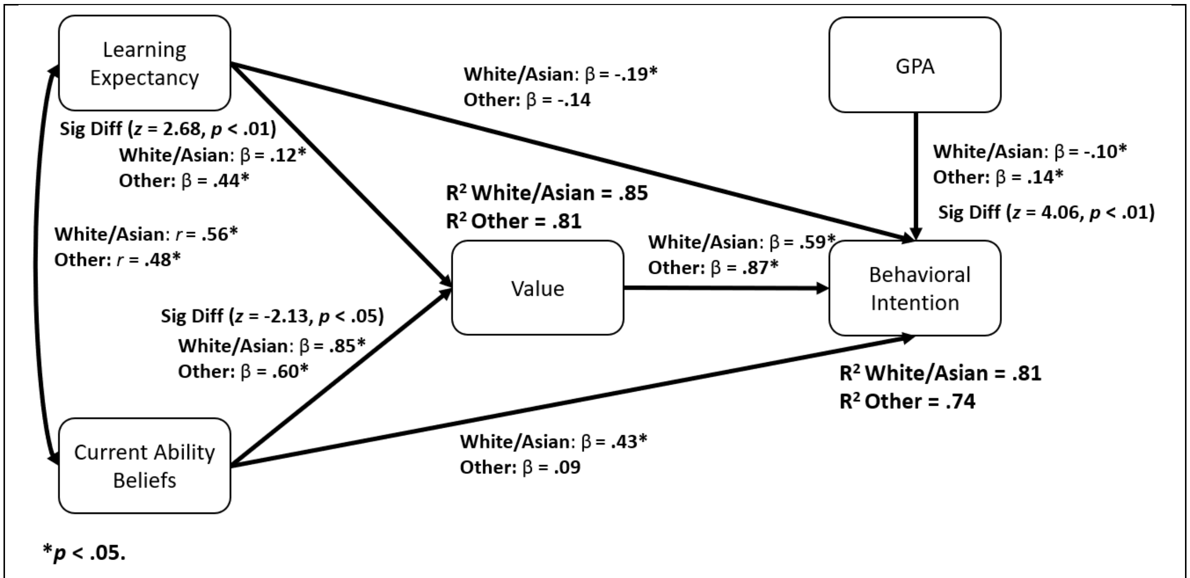


Figure 7. Multigroup Model – White and Asian Students Compared to All Others – Only Women (*n* = 494; 248 White or Asian; 246 Other)

Discussion

The IT workforce has a diversity problem. IT is dominated by White and Asian males. This is due partly to a lack of women and non-Asian minorities pursuing college degrees aimed at training students for the IT workforce. This underrepresentation is present nationally in college-bound high school students who go on to not major in IT related degrees. So, an explanation of the lack of diversity in the IT workplace must include an understanding of high school students.

Unfortunately for IT diversity, high school students are a difficult population to study, but we were able to obtain a nationwide panel of 842 college-bound high school students and ask about their choice of majors. To the best of our knowledge, this is the only high school panel that focuses on IT college majors. Moreover, it is one of the largest and most diverse studies of IT major preferences. We examined race on a scale that other IT studies have not yet done.

We find that men have a greater average intention to major in IT, greater current ability beliefs (but not greater expectations of being able to learn IT skills) and report greater perceived value from an IT career than women. Things become more complicated when we consider race. Based on mean difference comparisons, non-Asian racial minorities may actually have greater average intention to major in IT and current ability beliefs than White and Asian students. However, each of these comparisons includes mostly women, and in this sample White women tend to be particularly averse to going into IT and have low current ability beliefs.

Regardless, the importance of each of these variables is similar across races and genders (i.e. the beta weights tend to be similar). This suggests that one way to increase the representation of women and non-Asian minorities in IT is to offer IT training in high school. This echoes others' suggestions of eary access to STEM experiences for women and minorities (Hernandez et al. 2013). If we do not expose women and non-Asian minorities to IT skills at that point, then it is too late when they are in college. The skills and perceptions of success need to be developed *before* they choose college majors.

The second interesting thing we found was that White and Asian students are *less* likely to pursue IT majors as their GPA's increase, whereas Black students are *more* likely, and there is no significant effect for Hispanic students. We use GPA as a proxy for other opportunities because it is made up of the sum of a student's performance in multiple subjects ranging from language to math to history to health. It is unsurprising that more opportunities would reduce the probability of pursuing any one opportunity. But it is surprising that there is no effect for Hispanic students and a positive effect for Black students. One explanation for this is that there is a continuum of prestige of careers that might have fast food worker on one end and medical doctor on the other end. Students may rate themselves along this continuum based on their current resources and academic potential. Some majors will consume more time and resources to obtain success. For example, to become a medical doctor requires four years of undergraduate study, four years of medical school, and several more years of residency. On the other hand, one could start an IT career in just four years of undergraduate work. Even within four-year degrees some are perceived rightly or wrongly to require more time resources. This generates opportunity cost in lost earnings. Students from traditionally well-resourced groups could, potentially, rely on parental financial support for years to pursue these degrees, whereas those from groups traditionally with fewer resources might have to support themselves and even help their own families. This makes these more financially rewarding, but more time-consuming degrees less desirable. Therefore, the individual's place on the continuum could be a combination of their financial situation and GPA. If IT careers lie around the midpoint of the continuum, people starting with fewer resources may need higher GPAs to achieve that point on the continuum, whereas people with more resources may move past the IT careers if they have a high GPA.

Of course, this is conjecture based on this sample, but it is a direction worth considering in future research. Moreover, it offers implications to increase diversity in IT majors and the workforce. The simple solution is more financial support for people who have few resources to pursue IT majors. If companies are serious about increasing diversity, then this is the best way they can help (e.g., offer money for living expenses). The issue may not be that under-resourced people with high GPA's cannot do the work, but that they cannot spare the time if they need to work outside school. If these high GPA students with low resources are given money to satisfy basic needs so they can focus on studies as much as high-resource students, then they could choose more time intensive majors, like IT.

Even if our conjecture is wrong, many high GPA non-Asian racial minorities including women may want to pursue IT majors. Thus, there is a great opportunity for companies and universities to increase diversity *and* hire high performing people. Our responsibility as a discipline is to figure out how to help these high school students achieve their college goals. This benefits the students, colleges, the companies who hire them, and presumably the entire IT discipline through increased diversity.

Conclusion

The diversity problem in IT careers is arguably the biggest problem our field faces. Although it is valuable to understand the experiences of women and minorities who are currently in the workforce or in college, it is essential that we also understand their experiences where the pipeline begins: in high school. Our study is the first study in our field of a large, nationwide, diverse sample of college-bound high school seniors and their intention to major in IT in college. Given the novelty of our data set, we took an exploratory approach within a strong theoretical framework (i.e., expectancy-value theory) to learn all we could. We hope our work will stimulate future research and theory development in how high school seniors make choices about IT majors and careers.

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