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RESEARCH ARTICLE

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Comparing Three Theories of the Gender Gap in Information Technology Careers: The Role of Salience Differences

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Abstract

The information technology (IT) field faces a skills shortage. Only 17% of a projected 3.5 million computing job openings are expected to be filled by 2026 (National Association for Women & Information Technology, 2018). Yet the number of women pursuing IT careers continues to decrease—only 19% of IT bachelor's degrees in 2016 were awarded to women compared to 57% of bachelor's degrees overall. We compared three theories that could explain this gender gap in the pursuit of IT careers: expectancy-value theory, role congruity theory, and field-specific ability beliefs theory. We find that women and men are similar in their levels of important factors related to career interest, but that two of these factors—technical learning self-efficacy and agentic goals—have increased salience for women. This suggests that some of the gender gap in the IT field could be addressed by placing more focus on developing technical learning self-efficacy in both men and women. While this could help both women and men, it would likely have an outsized effect on the IT career pursuit of women.

Keywords: Gender, Gender Gap, Information Technology, Career, Field-Specific Ability Beliefs, Expectancy-Value Theory, Role Congruity Theory

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1 Introduction

One of the perennial problems faced by IT managers is the shortage of skilled employees (Bessen, 2014; Kappelman et al., 2016, 2017, 2018; Korsakienė et al., 2015; Weitzel et al., 2009). Each year since 2013, IT managers have ranked skills shortage as one of the top three issues that worry them and "keep them up at night" in the Society of Information Management's annual report (Kappelman et al., 2018). The supply of skilled IT workers is lagging and it is likely to be exacerbated by the increased retirement of IT workers (Kappelman et al., 2018). The problem is so dire that only 17% of a projected 3.5 million computing job openings are expected to be filled by 2026 (National Association for Women & Information Technology, 2018)!

Concurrently, there is a large disparity in the gender composition of the IT workforce, such that women continue to be underrepresented in the IT field (Frieze & Quesenberry, 2019). Moreover, the IT worker pipeline shows the same or greater disparity in gender composition. In 2016, only 19% of IT college degrees in the United States went to women compared to about 57% of college degrees going to women overall (National Center for Education Statistics, 2016). Worse still, the problem is increasing—in 1985, only 37% of IT college degrees in the United States went to women (National Center for Women & Information Technology, 2018). The number of women seeking degrees in IT is declining in many other countries around the world as well (Trauth et al., 2003). Indeed, this number is under 10% in Switzerland, Belgium and Israel, and is above 30% only in Columbia, Mexico and Greece (Organisation for Economic Co-operation and Development, 2015).

In addition to the shortage of skilled IT labor, there are two other reasons to be concerned about the gender composition of the IT workforce and pipeline. First, although roughly half of all users of IT are women, most IT designers are men. Fewer than 20% of technical jobs at large technology companies such as Google, Facebook, and Twitter are held by women (Loiacono et al., 2016). Thus, because most IT is designed for the preferences of men and the preferences of women users are neglected, a blind spot emerges in our design processes (Loiacono et al., 2016). An infamous example of gender bias in IT design is voice recognition systems that fail to recognize women's voices (Loiacono et al., 2016).

Second, we are not fully engaging the available talent that could strengthen the IT field (Frieze & Quesenberry, 2015; Rosenbloom et al., 2008). This has ramifications for the world economy as well. The key driver of economic growth in the world is information technology (Jorgenson & Vu, 2009; Li, 2013). By not fully leveraging available talent, a primary driver of economic growth is undermined. If IT continues to drive economic growth, how we address the skills shortage could affect the world economy for years to come. Regardless, our response to the gender gap and skills shortage in IT will affect the composition of our workforce for the foreseeable future.

Unfortunately, we do not currently have a good explanation of why this disparity in gender composition exists (Gorbacheva et al., 2019). Thus, a coherent understanding of this issue should be a primary direction for gender research in information systems, and one way to accomplish this is to conduct research that compares different models that may explain the gender imbalance in IT (Gorbacheva et al., 2019).

2 Theory

Women's IT careers have three phases: career choice, career persistence, and career development (Ahuja 2002). We focus on the first phase by comparing three theories of career choice, expectancy-value theory (Eccles et al., 1998), role congruity theory (Diekman & Eagly, 2008), and field-specific ability beliefs theory (Leslie et al., 2015; Storage et al., 2016). Expectancy-value theory suggests that people choose careers based on the expectancy of their ability to complete the necessary behaviors needed for the career (often conceptualized as self-efficacy) and how much they value the career. Role congruity theory suggests that people pursue careers that can fulfill life goals that are important to them and that people tend to be motivated by stereotypical gendered goals. Field-specific ability beliefs theory suggests that women are underrepresented in fields that are perceived to require special, innate abilities to succeed.

We chose these three theories for the current study for the following reasons. First, we chose theories that were designed to explain gender differences in career choice rather than career choice in general. Second, because our focus is career choice rather than continuance, we chose theories that are appropriate for people who have not yet made career choices. Finally, we chose theories that have been explored extensively in other settings.

2.1 Mean Differences versus Salience Differences

There are two ways that gender could play a role in these theories. The first is through mean differences: Men and women could have different mean levels of important factors. This is the approach traditionally applied in research of gender differences in career choices (e.g., Bian et al., 2017; Cheryan et al., 2017; Diekman et al., 2010, 2011; Rosson et al., 2011). In this case, the causal model is that gender influences important antecedents of IT career choice. For example, gender might lead to differences in self-efficacy for learning IT skills, which would then lead to differences in IT career choice (Beyer, 2014; Rosson et al., 2011).

We propose a second way that gender may play a role in these theories: salience differences. In the salience differences approach, the same factor may be more (or less) important to members of one gender, so that changes in that factor have a greater (or lesser) impact on IT career choice for people of that gender. In this case, the causal model is that gender moderates the effect of a factor on IT career choice. For example, Venkatesh and Morris (2000) found that perceived ease of use is a stronger predictor of intention to use a technology for women than for men. Thus, perceived ease of use tends to be more salient for women. Note that this salience difference does not necessarily require that women find computers more difficult to use. Rather, it means that women tend to place greater importance on this factor when making decisions about technology use.

The theories we examine have been used to explain gender differences by invoking differences in the mean values of constructs. In other words, gender differences are predicted to arise because, on average, women and men have different levels of some construct (Bian et al., 2017; Cheryan et al., 2017; Diekman et al., 2010, 2011; Rosson et al., 2011). We add to each of these theories by proposing that gender differences in IT career choice may arise even if men and women have similar levels of some construct if that construct is more salient for one group than for the other (Venkatesh & Morris, 2000). Thus, our overarching theory is that men and women may value attributes that influence the desire to pursue an IT career in different ways and the difference in the salience of these attributes for men and women can be seen in gender as a moderator in the proposed theories.

Below, we explain the three models we use to test our theory that it is salience differences rather than mean differences of attributes that help explain the gender differences in IT career choice. Because our main contribution is the salience differences approach to these theories, we devote more space to developing the salience differences hypotheses. For completeness, we state and test the mean differences approach hypotheses so that we can compare them to the proposed salience differences approach.

2.2 Expectancy-Value Theory

Expectancy-value theory (Eccles et al., 1998) asserts that two factors influence career choices: expectations of success (expectancy) and the value placed on each available option. Expectancy is often operationalized as self-efficacy. Self-efficacy (Bandura, 1977) is people's belief that they have the skills necessary to perform specific behaviors. Self-efficacy for behaviors needed for success in a career partially determines what career path is pursued (Bandura et al., 2001). Individuals tend to eliminate attractive career paths from potential career options if their self-efficacy for that occupation is low (Bandura et al., 2001).

According to expectancy-value theory, self-efficacy is necessary but not sufficient to explain why people choose a certain career path—they must value the career field as well (Wang & Degol, 2013). Specifically, interest value—i.e., how interesting a field is perceived to be—is a strong predictor of career choice (Wang & Degol, 2013). The more interest value a person has for a field, the more likely the person is to pursue a career in it (Eccles, 2009). Together, self-efficacy and interest value predict what career is selected (Eccles, 2009; Wang & Degol, 2013). For this study, we will refer to IT interest value as IT career value.

In addition, people are more often interested in careers for which they believe they are capable (Bandura et al., 2001). A career may not be considered an option if individuals do not think they are capable of it and thus do not form an interest in it. Therefore, we conjecture that expectancy leads to interest value, which then leads to career choice.

2.3 Role Congruity Theory

Role congruity theory (Diekman & Eagly, 2008) suggests that people pursue careers that provide opportunities to meet important life goals. Specifically, career seekers might wish to fulfill agentic goals, which focus on personal gain in terms of power, money, and individual achievement; or they might wish to fulfill communal goals, which focus on community in terms of altruism, interaction, and belonging (Eagly et al., 2000). It is proposed that "broader gender roles in a society influence the goals of individuals in that society" (Diekman et al., 2010, p. 1052). Research suggests that these broader societal gender roles typically lead women to endorse greater importance of communal life goals than men (Diekman et al., 2010, 2011). Moreover, STEM fields in general are perceived to fulfill agentic goals but may be perceived as deficient in communal goals, which may lead to an uneven gender composition (Diekman et al., 2010, 2011; Eccles, 2007). Specifically, IT is often perceived as having greater fulfillment of agentic goals and being more deficient in communal goals (Joshi et al., 2013; Joshi & Kuhn, 2005; Joshi & Schmidt, 2006).

2.4 Field-Specific Ability Beliefs Theory

Field-specific ability beliefs theory suggests another explanation for the underrepresentation of women in some fields. Some authors have reported that women and men are stereotyped for having different innate abilities (Bian et al., 2017; Stephens-Davidowitz, 2014). Because of these stereotypes, some researchers have suggested that women are underrepresented in fields where a perception exists that one must have innate field- specific ability to succeed (Leslie et al., 2015; Meyer et al., 2015; Storage et al., 2016). This is referred to as field-specific ability beliefs. This theory proposes that it is not necessarily STEM fields that separate women and men: women are well represented in STEM fields like molecular biology and neuroscience and are underrepresented in some arts and humanities fields such as music composition and philosophy (Leslie et al., 2015). Rather it is the perceived innateness of the needed skills. Fields that are perceived to require innate abilities, as opposed to learned skills, tend to be underrepresented by women (Leslie et al., 2015; Meyer et al., 2015; Storage et al., 2016). One study asked professors and doctoral students in 30 fields how much their fields required some innate ability (Leslie et al., 2015). Results showed that fields with the highest perceived field-specific ability beliefs had the fewest women in them. Other studies found that undergraduates also perceive the same fields as requiring innate abilities (Storage et al., 2016) and that laypeople hold similar perceptions regarding which fields require innate abilities (Meyer et al., 2015). These studies show that field-specific ability beliefs are held not only by scholars in a field but also by students and laypeople.

3 Hypothesis Development

For our hypotheses and results, we refer to the desire to pursue an IT career as IT career pursuit. Our first hypothesis is a foundational hypothesis based on the gender imbalance in IT careers as well as other research indicating that women go into IT at lower rates than men. Thus, in accordance with this knowledge, we make the following hypothesis.

H1: Men score higher than women on IT career pursuit.

3.1 Expectancy-Value Theory Hypotheses

Many IS studies operationalize self-efficacy as computer self-efficacy—i.e., belief in one's ability to use a computer (Compeau & Higgins, 1995)—including studies of the gender imbalance in computing professions (Beyer, 2014; Rosson et al., 2011). However, computer self-efficacy has limitations for studying IT career choice. Computer self-efficacy is focused on current skills and on system use. The issue for people choosing a career in college is whether they can learn skills necessary to build, implement, and maintain systems, rather than how well they can use an existing system. Thus, we developed a new type of self-efficacy and measure called IT learning self-efficacy, which measures people's self-efficacy for learning the skills needed to become IT professionals. Details of the development of the scale are provided in Appendix A.

In the development of this instrument, we discovered that IT professional skills are divided into technical and business skills. This is consistent with prior research on IT skills self-efficacy (Joshi et al., 2010). Technical skills include programming and building systems, whereas business skills include communication, training, and the economic evaluation of systems. Across all business fields, business skills should be required but other business fields do not have the same gender disparity as IT. So, we expect that men and women may be similar in their perceptions of business learning self-efficacy. However, technical learning self-efficacy—unique to the IT portion of business—could be an important factor in the unequal gender composition of the IT field.

The operationalizations of expectancy in the hypotheses below are computer self-efficacy and technical learning self-efficacy. This allows us to compare the predictive validity of our new measure (technical learning self-efficacy) in explaining IT career pursuit compared to computer self-efficacy. Because business learning self-efficacy is relevant for all business fields, we did not expect any differences for this variable but report analyses with it for the sake of completeness.

3.1.1 Mean Difference Hypotheses

The mean difference approach to this theory is that women tend to score lower on expectancy and value, which predict IT career pursuit. We suspect this is not currently true in the United States because of the ubiquity of computing in young people's lives. Although it is true that in the 1980's computers were marketed primarily to boys (Natale, 2002), that is not the case today when 99% of Americans under the age of 49 own a cellphone (Pew Research Center, 2019). Computers are a part of everyday life for both women and men now. Thus, it is possible that in the past—because of socialization processes and a lack of opportunity—women may have felt less comfortable on average than men with the thought of working with computers, but we do not think that is likely the case now. So, we do not endorse this mean difference approach but test it for comparison with the salience difference approach. This yields the following three hypotheses:

H2: Men score higher than women on IT career value.

H3: Men score higher on expectancy than women.

H4a: IT career value is positively related to IT career pursuit.

Expectancy-value theory suggests that both self-efficacy and interest value predict interest in pursuing a particular career (Eccles, 2009; Wang & Degol, 2013). In the present study, this would be represented by our measures of self-efficacy and IT career value being significantly related to IT career pursuit. This yields the following hypotheses:

H5a: Expectancy is positively related to IT career pursuit.

H5b: Expectancy is positively related to IT career value.

H5c: The relationship between gender and IT career pursuit is mediated by expectancy and IT career value.

3.1.2 Salience Difference Hypotheses

In contrast to standard expectancy-value theory models in which gender causes mean differences in expectancy and value, we propose that gender is a moderating variable that impacts the salience of each attribute differently for men and women. As in traditional expectancy-value theory, expectancy and value lead to IT career pursuit, and expectancy influences IT career value, but we expect different effects for men and women.

Recent evidence on STEM career choices points to the importance of the relative cognitive strengths of the individual (Stoet & Geary, 2018; Wang & Degol, 2017). People have an array of cognitive abilities that may help them excel in a variety of careers. People will tend to choose careers that make use of their strongest abilities. However, for reasons yet unknown, an individual woman is more likely to have similar levels of cognitive abilities across a range of abilities and an individual man is more likely to have one or few dominant cognitive abilities (Stoet & Geary, 2018; Wang & Degol, 2017). For instance, on the Programme for International Student Assessment (PISA) the difference between verbal and quantitative scores was much more pronounced for boys than girls. Furthermore, "individuals with more symmetrical cognitive profiles in verbal and math domains are more likely to choose non-STEM professions as a result of the greater number of career options available to them, and because symmetrical profiles are more often found in women, they are also more likely to pursue other occupations" (Wang & Degol, 2017, p. 122).

Conversely, results from the PISA suggest that STEM areas are more likely to be a personal academic strength for men than women (Stoet & Geary, 2013). The comparison here is within-subject, so that men are more likely than women to have their internal relative best in STEM despite similar overall absolute scores between genders. Relative to their personal mean, men tend to be stronger in STEM than women. Because of this, men should be less impacted by changes in their expectancy than women whose STEM skills are, on average, closer to their mean score on all abilities.

Thus, some women are equally or close to equally self-efficacious in IT relevant skills and the skills necessary for other careers, meaning that small changes in expectancy for IT skills will have bigger impacts on IT career pursuit. Conversely, men tend to have STEM skills that are considerably higher than their personal mean, and it thus would take larger reductions in expectancy for IT skills for them to decrease their IT career pursuit. The overall effect of this different distribution of skills is that women could have a wider range of career options (Wang et al., 2013), which should also make the career value of any choice more salient. Thus, we hypothesize:

H4b: Gender moderates the relationship between IT career value and IT career pursuit such that the positive relationship is stronger for men than for women.

H5d: Gender moderates the relationship between expectancy and IT career pursuit such that the positive relationship is stronger for women than men.

H5e: Gender moderates the relationship between expectancy and IT career value such that the relationship is stronger for women than men.

3.2 Role Congruity Theory Hypotheses

3.2.1 Mean Difference Hypotheses

Role congruity theory suggests that women tend to have more communal goals than men, whereas men tend to have more agentic goals than women, and suggests that individuals seek careers that meet these life goals (Diekman et al., 2010; Diekman & Eagly, 2008). This theory and a mean difference approach yield the following hypotheses:

H6: Women have greater communal goal endorsement than men.

H7: Men have greater agentic goal endorsement than women.

H8a: Communal goal endorsement is negatively associated with IT career pursuit.

H8b: Agentic goal endorsement is positively associated with IT career pursuit.

H8c: Communal goal endorsement mediates the relationship between gender and IT career pursuit.

H8d: Agentic goal endorsement mediates the relationship between gender and IT career pursuit.

3.2.2 Salience Difference Hypotheses

Studies suggest that women now tend to endorse agentic goals as strongly as men (Twenge, 2001, 2009). It is now more common for women to incorporate the satisfaction of agentic goals into career choices (Croft et al., 2015; Twenge & Campbell, 2008). Many women are motivated by both agentic and communal goals, which could make both goal types salient in career choice (Diekman et al., 2011).

On the other hand, the endorsement of communal goals in men has grown more modestly (Twenge, 2009). Furthermore, the salience of communal goals in men's career choices appears less common, shown by the lack of increase in the representation of men in traditionally communal careers over the past few decades (Croft et al., 2015). This could be caused by the gender role socialization that men experience. The theory of precarious manhood suggests that manhood is a "social status that is hard won and easily lost" (Vandello & Bosson, 2013, p. 101). Men are often expected to constantly prove their manhood by acting masculine and avoiding anything perceived as feminine. They tend to be socialized from a young age that breaking gender stereotypes will be punished (Vandello & Bosson, 2013).

Although it has become more socially acceptable for women to take on traditionally male characteristics like agentic goals over the past few decades (Diekman et al., 2010; Twenge, 2001, 2009), acting on communal goals continues to be less socially acceptable for men (Croft et al., 2015; Vandello & Bosson, 2013).[1] Men are less likely than women to internalize communal goals into their self-concept (Croft et al., 2015), and men who enter traditionally female careers often expect to experience backlash and prejudice. (Croft et al., 2015). These factors could result in many men avoiding communal

[1] Consider, for instance, the increase in the number of women in traditionally male-dominated fields (e.g, physicians, lawyers) but the lack of a reciprocal increase of men in traditionally female-dominated fields (e.g., nurses, elementary school teachers (Croft et al., 2015).

careers that they would enjoy (Croft et al., 2015; Vandello & Bosson, 2013).

Because of the need to embrace masculinity and avoid femininity, careers that meet agentic goals and avoid communal goals could serve as default options for men. If this is the case, a small increase in agentic goals may do little to further enhance pursuit of careers meeting agentic goals. Furthermore, because men who pursue communal goals are often punished (Twenge, 2009; Vandello & Bosson, 2013), men would likely tend to not be very responsive to small increases in communal goals in terms of reducing the pursuit of careers expected to meet agentic goals and inhibit communal goals such as IT.

Conversely, women tend to be punished less than men for breaking gender roles (Twenge, 2009; Vandello & Bosson, 2013). Additionally, because society tends to place higher status on agentic goals than communal goals (Croft et al., 2015; Twenge, 2009), the pursuit of careers that fulfill agentic goals could provide women with enhanced social status. These factors may make it safer for women to pursue careers meeting either goal type, depending on personal motivations. This would allow women to be more responsive to changes in either communal or agentic goals compared to men, making each a more salient factor in IT career pursuit for women compared to men. Thus, we hypothesize:

H8e: The relationship between communal goals and IT career pursuit is moderated by gender such that the negative relationship is stronger for women than men.

H8f: The relationship between agentic goals and IT career pursuit is moderated by gender such that the positive relationship is stronger for women than men.

3.3 Field-Specific Ability Beliefs Theory Hypotheses

3.3.1 Mean Difference Hypotheses

Research has examined undergraduates' perceptions of field-specific ability beliefs and found that women are underrepresented in fields perceived to require some innate ability (Storage et al., 2016). The mean difference explanation for this suggests that women have more field-specific ability beliefs than men. These field-specific ability beliefs for IT would then decrease IT career pursuit. Thus, for the mean difference model, we predict that

H9a: Women have greater field-specific ability beliefs than men.

H9b: Field-specific ability beliefs are negatively related to IT career pursuit.

H9c: The relationship between gender and IT career pursuit is mediated by field-specific ability beliefs.

3.3.2 Salience Difference Hypotheses

The salience difference explanation suggests that if women internalize cultural stereotypes, they may be less likely than men to pursue a career that is perceived to require innate ability. If women internalize stereotypes about ability, there should be a negative relationship between field-specific ability beliefs and interest in pursuing an IT career for women. Conversely, men should not be affected by these stereotypes, and field-specific ability beliefs should not affect their IT career pursuit.

In addition, as argued above, if many women perceive that they have skills that are conducive to several career options, field-specific ability beliefs may help them decide between careers. If some women believe that IT requires innate abilities, some will likely believe they possess those abilities whereas others will not. For those who do not believe they have these abilities—but believe they possess the skills needed for several other career options—IT careers become less attractive. They would instead likely pursue one of several careers for which they believe they have the skills.

Conversely, if many men believe that IT skills are a relative personal strength compared to other fields, field-specific beliefs may not discourage IT career pursuit as strongly. If these men believe that IT requires innate talent, they may interpret their relative personal strength in the field as evidence that they have the innate ability required. Conversely, for men who do not believe they have the innate ability required, they may pursue an IT career anyway because of a perceived lack of other options.

In other words, the salience difference approach suggests that if people perceive a need for field-specific abilities, then people with more symmetrical perceived ability profiles will find field-specific ability beliefs to be a more salient factor. Thus, we hypothesize:

H9d: The relationship between field-specific ability beliefs and IT career pursuit will be moderated by gender such that the negative relationship will be stronger for women than men.

4 Method

4.1 Participants and Procedure

We sampled people who were either college students or soon would be, and limited our sample to people who were either first-year students, sophomores, juniors, or were not in college but planned on attending, based on the logic that seniors and graduate students are more likely to be firmer in their career decisions than those earlier in their academic career. Since we wanted a heterogeneous sample that would be more representative of this population in the United States than could be obtained from sampling from a single university, we sampled through Amazon's Mechanical Turk. (MTurk).

The survey included three "attention check" questions that helped us avoid analyzing the data of respondents who were not attentive. Our final sample included 209 participants from 40 different states and the District of Columbia. Demographic characteristics are presented in Table 1. For those in college, we asked for their cumulative GPA. For women (n = 71), the mean GPA was 3.45 (SD = 0.52); for men (n = 77), the mean GPA was 3.17 (SD = 0.56).

Participants first provided informed consent and then completed a demographics questionnaire. Participants then completed the measures described below. These measures were presented in random order. Each participant received $2.00 for participating.

4.2 Measures

For this study, we provided participants with the following definition for information technology: "the use of computers to store, retrieve, transmit, and manipulate data or information, often in the context of a business or other enterprise" (Wikipedia, 2019). The questions for each measure can be seen in Appendix B. For all measures, items were averaged to create composite scores.

4.2.1 Computer Self-Efficacy

Computer self-efficacy was measured using the Computer Self-efficacy Measure (Compeau & Higgins, 1995). We used the directions for the measure found in Holden & Rada (2011). For each item, participants completed the following statement: "In general, I could complete any desired task using any computer/Internet application if…" on a scale ranging from 1 (*not at all confident*) to 10 (*totally confident*).

4.2.2 IT Learning Self-Efficacy

We used the scale developed for this study to measure IT learning self-efficacy (see Appendix A). Items 1 through 8 measure technical learning self-efficacy and items 9 through 18 items measure business learning self-efficacy. For each item, respondents answer how confident they are that they could learn the listed skill. Responses range from 1 (*not at all confident*) to 7 (*completely confident*).

4.2.3 IT Career Value

We adapted the STEM Career Interest Questionnaire subscale used in Tyler-Wood et al. (2010) for IT careers. This subscale has five bipolar items on a scale from 1 to 7. Each item completes the phrase: "To me, a career in information technology (is)." Three items (3, 4, and 5) were reverse-coded. Cronbach's α improved from 0.88 to 0.91 when removing Item 1, so, we dropped this item.

4.2.4 Communal Goals

We used the 10-item rating scale used in Diekman et al. (2010) to measure communal goals. Participants rated how important 10 different communal goals were to them on a scale from 1 (*not at all important*) to 7 (*extremely important*). Items were averaged to create a composite communal goal score.

4.2.5 Agentic Goals

We used the 14-item rating scale used in Diekman et al. (2010) to measure agentic goals. Participants rated how important 14 different agentic goals were to them on a scale from 1 (*not at all important*) to 7 (*extremely important*).

4.2.6 Field-Specific Ability Beliefs

We adapted six questions from Leslie et al. (2015) and Meyer et al. (2015) to measure field-specific ability beliefs for IT. Response options ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). Two questions were reverse-coded (3 and 4). Cronbach's α improved from 0.79 to 0.88 when dropping Items 3 and 4, so these two items were dropped.

4.2.7 IT Career Pursuit

We adapted an item from Diekman et al. (2010) to measure IT career pursuit. Participants responded to the following statement: "Please rate your level of interest in pursuing a career in information technology on a scale from 1 (not at all interested) to 7 (extremely interested)."

4.2.8 Barriers

We asked four questions about participant's perceptions of barriers to pursuing IT careers placed on them by society. Specifically, we asked the degree to which they felt that society places barriers upon the ability of "people like you," "people of your gender," "people of your race," and "people of your social class" to pursue IT careers. Participants responded to each statement on a scale ranging from 1 (*not at all*) to 7 (*a great deal*).[2]

5 Results

Correlations and descriptive statistics for all variables are presented in Table 2. We conducted t-tests to examine any gender differences in variables. Results of these *t*-tests and effect size estimates (Cohen's d) can be seen in Table 3. We report first on hypotheses that were tested with *t*-tests for each theory before moving into modeling results for each theory.

[2] Supplemental analyses for each barrier question are presented in Appendix B.

Table 1. Study Participants Demographics (N = 209)

	Mean	Standard deviation	Median	Min	Max
Age	29.13	8.00	27	18	66
	Frequency	**Proportion**			
Gender					
Women	99	47.4%			
Men	110	56.6%			
Race/ethnicity					
White/European American	124	59.3%			
Hispanic/Latino(a)	10	4.8%			
Biracial/Multiracial	21	9.9%			
African/African American/Black	38	18.2%			
Asian/Asian American	11	5.3%			
Asian Indian	1	0.5%			
American Indian/Native American	1	0.5%			
Other	1	0.5%			
Preferred not to answer	2	1.0%			
Year in School					
First-year	27	12.8%			
Sophomore	65	30.8%			
Junior	57	27.0%			
Not in college but plan to go	62	29.4%			

Table 2. Description Statistics, Correlations, and Internal Consistency Reliability Estimates

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Career pursuit	-											
2	IT career value	.55**	-										
3	CSE	.36**	.21**	-									
4	TLSE	.53**	.36**	.48**	-								
5	BLSE	.47**	.36**	.64**	.74**	-							
6	CG	.19**	.09	.26**	.26**	.33**	-						
7	AG	.36**	.24**	.39**	.31**	.42**	.49**	-					
8	FAB	.23**	-.13†	-.02	.20**	.02	.15*	.29**	-				
9	Barriers – Like me	.12	-.15	.05	.14	.05	.24**	.26	.38	-			
10	Barriers - Gender	.09	-.18	.04	.05	.04	.14*	.23	.40	.67	-		
11	Barriers - Race	.15	-.26	.07	.15	.06	.15*	.26	.39	.62	.63	-	
12	Barriers - SES	.16	-.16	-.02	.17	.08	.18*	.15	.30	.64	.56	.67	-
13	Gender	-.17*	-.08	.01	-.10	-.01	.14*	.08	.15*	.14	.34	.06	.02
	M	4.58	4.77	7.49	4.64	5.38	4.99	4.86	3.61	3.53	3.43	2.99	3.49
	SD	1.82	1.61	1.48	1.58	1.23	1.29	1.03	1.37	1.88	2.06	2.09	1.98
	Cronbach's α	-	.88	.89	.97	.94	.92	.89	.88	-	-	-	-

Note: Career pursuit = Interest in pursuing a career in information technology; IT career value = Interest in the field of information technology; CSE = Computer self-efficacy; TLSE = Technical learning self-efficacy; BLSE = Business learning self-efficacy; CG = Communal goals; AG = Agentic goals; FAB = Field-specific ability beliefs; SES = socioeconomic status. Barriers items represent the perception that society places barriers on people ("like me", "of my gender," "of my race," of my socioeconomic status") from going into IT careers. Cronbach's α IT career value was calculated without item 1 because removal of this item improved the internal consistency reliability estimate. The same is true for item 9 for communal goals and items 3 and 4 for field-specific ability beliefs. Gender was dummy coded with men as 0 and women as 1.
†*p* < .10. **p* < .05. ***p* < .01.

Table 3. Means, Mean Differences, *T*-Tests, and Effect Size Estimates

Variable	*M* (Women)	*M* (Men)	Difference	*t*	*p*	*d* (95% C.I.)
Career pursuit	4.25	4.87	-0.62*	-2.49	.01	-0.34 (-0.62, -0.07)
IT career value	4.65	4.89	-0.24	-1.08	.28	-0.15 (-0.42, 0.12)
CSE	7.51	7.48	0.03	0.15	.88	0.02 (-0.25, 0.29)
TLSE	4.47	4.80	-0.33	-1.50	.14	-0.21 (-0.48, 0.07)
BLSE	5.37	5.39	-0.02	-0.11	.92	-0.01 (-0.29, 0.26)
CG	5.18	4.82	0.36*	1.98	.049	0.27 (0.01, 0.55)
AG	4.95	4.78	0.17	1.13	.26	0.16 (-0.12, 0.43)
FAB	3.83	3.41	0.42*	2.23	.03	0.31 (0.03, 0.58)
Barriers – Like me	3.81	3.28	0.53*	2.03	.04	0.28 (0.01, 0.56)
Barriers - Gender	4.16	2.77	1.39**	5.16	<.001	0.72 (0.43, 1.00)
Barriers - Race	3.13	2.86	0.27	0.92	.36	0.13 (-0.15, 0.40)
Barriers - SES	3.54	3.45	0.09	0.33	.74	0.05 (-0.23, 0.32)

Note: Career pursuit = Interest in pursuing a career in information technology; IT career value = Interest in the field of information technology; CSE = Computer self-efficacy; TLSE = Technical learning self-efficacy; BLSE = Business learning self-efficacy; CG = Communal goals; AG = Agentic goals; FAB = Field-specific ability beliefs; ; SES = socioeconomic status. Barriers items represent the perception that society places barriers on people ("like me", "of my gender," "of my race," of my socioeconomic status") from going into IT careers. Difference represents the mean difference between women and men. Degrees of freedom equaled 207 for all *t*-tests.
$^*p < .05$. $^{**}p < .01$.

We found gender differences in IT career pursuit to be statistically significant with a small effect size estimate. Men in our sample expressed, on average, greater IT career pursuit than women. This provided support for H1. Contrary to H2, there was not a significant gender difference for IT career value. Contrary to H3, there was not a significant gender difference for computer self-efficacy or technical learning self-efficacy. In support of H6, there was a significant gender difference in communal goals with a small effect size estimate. As hypothesized, women tended to rate communal goals as more important than men. Contrary to H7, there was not a significant gender difference for agentic goals. Finally, in support of H9a, there was a significant gender difference in field-specific ability beliefs with a small effect size estimate: Women tended to have greater field-specific ability beliefs than men.

5.1 Modeling Results

To test our research models, we conducted path analyses using Mplus version 8 (Muthén & Muthén, 2017). For all analyses, gender was dummy coded, with men coded as 0 and women coded as 1. For mediation analyses, we used the product of coefficients method of calculating indirect effects (MacKinnon, 2008). Bootstrap standard errors were also used for mediation models. The statistical significance of indirect effects was assessed using percentile bootstrap confidence intervals.

For salience difference analyses, we conducted multigroup path analyses—which are useful for testing moderation with nominal moderator variables (Ahuja & Thatcher, 2005). These multigroup models allowed parameter estimates to vary freely for each gender and demonstrated what the model would look like if ran separately for each gender and the amount of variance explained in the outcome for each gender while still examining between-group differences. Thus, for salience analyses, we provide parameter estimates for each gender as well as *z*-tests of gender differences in the estimates.

Because our primary contributions are given through our salience differences results, we briefly discuss our means differences results for each theory and present the salience differences results in more detail. For greater detail on the means differences results, see Appendix D.

5.2 Expectancy-Value Theory Models

For expectancy-value models, we present results for both measures of expectancy used—computer self-efficacy and the technical learning self-efficacy portion of IT learning self-efficacy. Again, although we did not hypothesize gender differences in models with business learning self-efficacy, we present analyses that also include it in the expectancy portion of the model.

5.2.1 Mean Difference

Direct effect analyses showed that IT career value was significantly related to IT career pursuit, providing support for H4. Each measure of expectancy was significantly related to IT career pursuit and IT career value, providing evidence for H5a and H5b, respectively.

Next, we tested the hypothesis that the relationship between gender and IT career pursuit would be mediated by expectancy and IT career value (H5c). None of the indirect effects were significant, contrary to H5c. These general results held after controlling for the various barriers people might face (see Appendix B).

5.2.2 Salience Difference

To assess salience differences, we used multigroup analysis to examine gender differences in slopes. Path coefficients and R^2 values for each gender for the salience difference expectancy-value models are given in Figure 1. When comparing the models using computer self-efficacy and technical self-efficacy for expectancy, there are notable differences. The model that uses computer self-efficacy seems to have few meaningful differences between women and men, albeit R^2 values that are a bit higher for women for both IT career pursuit and IT career value. However, more differences exist in the model that uses technical learning self-efficacy. The most striking difference in this model is that 51% of the variance in IT career pursuit is explained for women whereas only 32% is explained for men. Similarly, technical learning self-efficacy explains 16% of the variance in IT career value for women but 5% for men. In addition, this model shows potential differences in path coefficients for women and men, whereas the model with computer self-efficacy has similar slopes.

Because the expectancy-value model we propose includes a mediation effect between the constructs, our multigroup models for this theory take the form of moderated mediation with gender moderating the relationship between expectancy and IT career pursuit via IT career value. Table 4 shows the indirect effects, total effects, direct effects, and the a and b paths for each gender. It also includes bootstrap percentile confidence intervals for each parameter estimate and tests for differences in estimates between women and men.

The expectancy-value mediation model analysis shows that, although men and women have similar mean levels of IT learning self-efficacy, this construct is more salient for women than for men, providing support for H5d. However, we failed to find evidence for different slopes for the relationship between IT career value and IT career pursuit (H4b) and the relationship between expectancy and IT career value (H5a). These general results held after controlling for the various barriers people might face (see Appendix B).

5.3 Role Congruity Theory Models

5.3.1 Mean Difference

In the mean difference model for role congruity theory, gender is indirectly related to IT career pursuit through both communal and agentic goals. We found that communal goals are not significantly related to IT career pursuit, contrary to H8a. We found agentic goals, on the other hand, to be significantly positively related to IT career pursuit, providing support for H8b. After considering communal and agentic goals, gender was still significantly related to IT career pursuit, $\beta = -0.21$, $z = -3.20$, $p < 0.01$.

Neither the indirect effect through communal goals nor agentic goals was statistically significant, contrary to H8c and H8d. These general results held after controlling for the various barriers people might face (see Appendix B).

5.3.2 Salience Difference

To evaluate whether there were gender differences in slopes between communal goals and IT career pursuit and agentic goals and IT career pursuit, we conducted a multigroup path analysis. The results of this model can be seen in Figure 2. The R^2 of IT career pursuit for women was 0.22, whereas it was 0.10 for men. We also see potential differences in path coefficients between women and men that we explored further.

Path coefficients, along with their confidence intervals, are presented in Table 5, which also includes tests for differences in path coefficients between genders for both communal goals and agentic goals. The difference in coefficients for communal goals was not statistically significant, contrary to H8e. However, the difference in coefficients was significant for agentic goals, providing support for H8f. Specifically, the positive relationship between agentic goals and IT career pursuit was stronger for women than for men.

Overall, the role congruity theory models seem to indicate that, although women have higher mean levels of communal goals, communal goals are not good predictors of IT career pursuit. On the other hand, men and women have similar mean levels of agentic goals and those do seem to be good predictors of IT career pursuit. Moreover, agentic goals seem to have higher salience for women than men. This general result held after controlling for the various barriers people might face (see Appendix B).

5.4 Field-Specific Ability Beliefs Theory Models

5.4.1 Mean Difference

In the mean difference model for field-specific ability beliefs, gender is indirectly related to IT career pursuit through field-specific ability beliefs. The relationship between gender and field-specific ability beliefs was statistically significant, $\beta = 0.15$ $z = 2.32$, $p = 0.02$. This provides support for H9a. Field-specific ability beliefs was significantly related to IT career pursuit, $\beta = 0.26$, $z = 3.91$, $p < 0.01$, but in the opposite direction from that hypothesized in H9b.

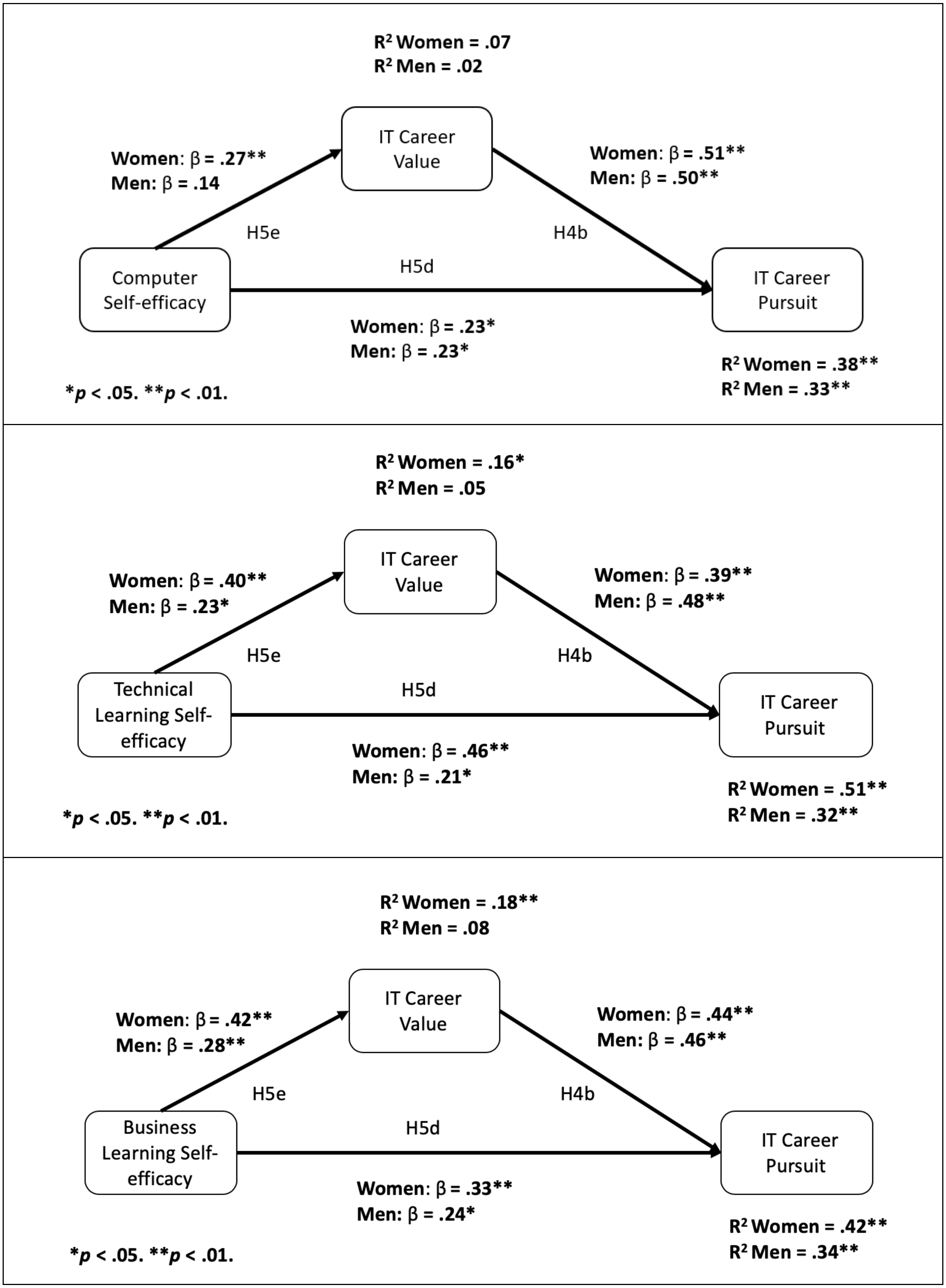

Figure 1. Salience Difference Expectancy-Value Models

**Table 4. Multigroup Mediation Analysis:
The Relationship Between Expectancy and Career Pursuit Mediated by IT Career Value**

	Women	Men	Difference tests	
Parameter	**Estimate (95% C.I.)**	**Estimate (95% C.I.)**	***z***	***p***
CSE				
a	.27 (.08, .47)	.14 (-.04, .32)	0.98	.33
b	.51 (.32, .68)	.50 (.29, .66)	0.38	.71
c	.37 (.15, .60)	.30 (.10, .48)	0.74	.46
ab	.14 (.03, .27)	.07 (-.02, .16)	1.00	.32
c'	.23 (.04, .46)	.23 (.05, .41)	0.27	.79
TLSE				
a	.40 (.18, .50)	.23 (.02, .43)	0.95	.35
b	.39 (.22, .58)	.48 (.28, .65)	-0.44	.66
c	.62 (.39, .69)	.32 (.12, .52)	2.03	.04
ab	.16 (.06, .24)	.11 (.01, .22)	0.53	.60
c'	.46 (.24, .57)	.21 (.05, .40)	1.79	.07
BLSE				
a	.42 (.22, .53)	.28 (.10, .45)	0.90	.37
b	.44 (.23, .62)	.46 (.26, .64)	0.05	.96
c	.51 (.28, .63)	.37 (.18, .54)	1.07	.29
ab	.18 (.07, .27)	.13 (.01, .22)	0.70	.48
c'	.33 (.12, .50)	.25 (.04, .44)	0.62	.54

Note: CSE = computer self-efficacy; TLSE = technical learning self-efficacy; BLSE = business learning self-efficacy; a = path from computer self-efficacy to IT career value; b = path from IT career value to IT career pursuit; c = the total effect from expectancy to IT career pursuit; ab = the indirect effect from expectancy to IT career pursuit via IT career value; c' = the direct effect from expectancy to IT career pursuit (after the indirect effect is accounted for). All estimates are standardized. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.

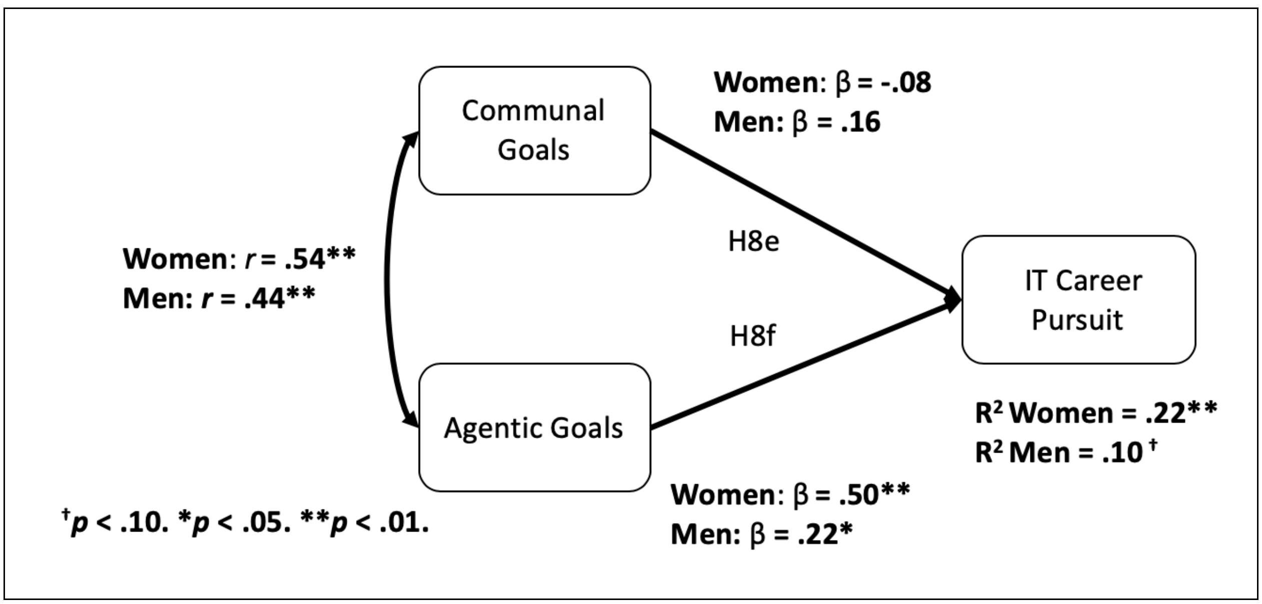

Figure 2. Salience Difference Model for Role Congruity Theory

Table 5. Explaining IT Career Pursuit using Role Congruity Theroy: Tests for Gender Differences in Slopes

	Women	Men	Difference tests	
Predictor	**Estimate (95% C.I.)**	**Estimate (95% C.I.)**	***z***	***p***
Communal goals	-.08 (-.28, .13)	.16 (-.03, .36)	-1.58	.11
Agentic goals	.50 (.32, .69)	.22 (.02, .41)	2.23	.03
Notes: All estimates are standardized.				

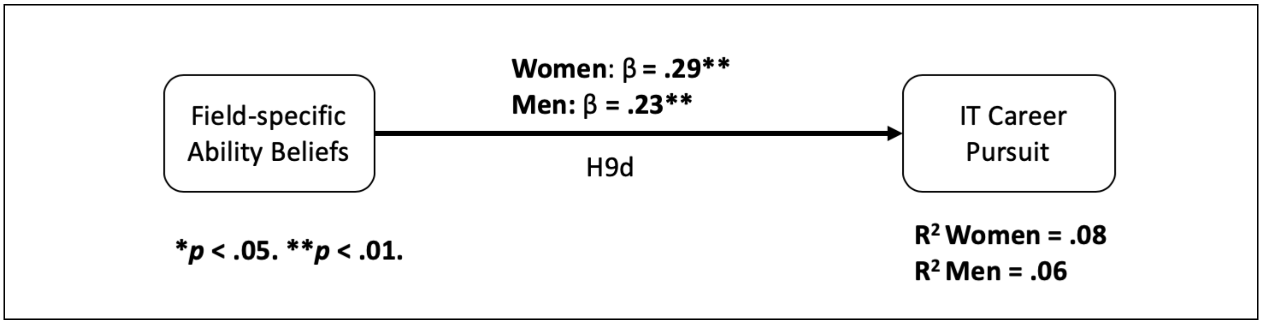

Figure 3. Salience Difference Model for Field-Specific Ability Beliefs Theory

After considering field-specific ability beliefs, gender was still significantly related to IT career pursuit, $\beta = -0.21$, $z = -3.16$, $p < 0.01$. We then tested whether field-specific ability beliefs mediated the relationship between gender and IT career pursuit. The indirect effect was statistically significant, but again in the opposite direction as that hypothesized in H9c. This general result held after controlling for the various barriers people might face (see Appendix B).

5.4.2 Salience Difference

To evaluate whether there were gender differences in the relationship between field-specific ability beliefs and IT career pursuit, we conducted a multigroup path analysis. The results of this model can be seen in Figure 3. The R^2 of IT career pursuit for women was 0.08, whereas it was 0.06 for men. The relationship between the two variables was positive and significant for both women and men.

We tested whether these slopes were different between women and men. The results of this difference test as well as parameter estimates for both genders and their confidence intervals are presented in Table 6. Parameter estimates were not significantly different, contrary to H9d.

Our findings suggest that women and men do seem to have different levels of field-specific ability, with women having higher average levels of field-specific ability beliefs. However, these field-specific ability beliefs were associated with an increased preference for an IT career. Thus, women's higher average level of field-specific ability beliefs would tend to lead them to be more interested in an IT career rather than less interested. There did not seem to be any salience differences between men and women, and this same general pattern held even after controlling for various barriers that people may face (see Appendix B).

6 Discussion

In this study, we examined three competing theories to explain women's underrepresentation in IT careers. Furthermore, we proposed that salience rather than mean levels of attributes would better explain differences in IT career choice between men and women. Overall, this proposal was supported (see Table 7). Specifically, a salience approach to expectancy-value and role congruity theories provided the best explanation for these gender differences. Men and women did not differ significantly on important drivers of career choice, with the exception of communal goals and field-specific ability beliefs, but communal goals did not have a significant impact on IT career pursuit and field-specific ability beliefs had a positive effect on IT career pursuit, contrary to what was hypothesized. On the other hand, for two variables—agentic goals and technical learning self-efficacy—significant differences in salience arose, both of those variables being more salient among women for pursuing an IT career.

6.1 Implications for Research

One interesting empirical fact is that we found a significant difference between men and women in IT career pursuit but failed to find differences between men and women in various perceptions that predict IT career pursuit—differences we would expect to see from a mean differences approach. This could mean that men and women tend to be similar in these perceptions—just as Frieze and Quesenberry (2019) suggested that men and women tend to be more similar than different in their attitudes toward computer science—but more research is needed.

Table 6. Explaining IT Career Pursuit Using Field-Specific Ability Beliefs Theory: Testing Gender Differences in Slopes

	Women	Men	Difference Tests	
Predictor	**Estimate (95% C.I.)**	**Estimate (95% C.I.)**	***z***	***p***
Field-specific Ability Beliefs	.29 (.11, .47)	.23 (.06, .41)	0.59	.55

Table 7. Summary of Findings for Hypotheses

Theory	Hypothesis #	Hypothesis statement	Supported?
Mean difference hypotheses			
Expectancy-value	H5c	The relationship between gender and IT career pursuit will be mediated by expectancy and IT career value.	No
Role congruity	H8c	Communal goal endorsement will mediate the relationship between gender and IT career pursuit**.**	No
	H8d	Agentic goal endorsement will mediate the relationship between gender and IT career pursuit.	No
Field-specific ability beliefs	H9c	The relationship between gender and IT career pursuit will be mediated by field-specific ability beliefs.	No
Salience difference hypotheses			
Expectancy-value	H4b	Gender will moderate the relationship between IT career value and IT career pursuit such that the positive relationship will be stronger for men than for women.	No
	H5d	Gender will moderate the relationship between expectancy and IT career pursuit such that the positive relationship will be stronger for women than men.	Yes
Role congruity	H8e	The relationship between communal goals and interest in pursuing an IT career will be moderated by gender such that the negative relationship is stronger for women than men.	No
	H8f	The relationship between agentic goals and interest in pursuing an IT career will be moderated by gender such that the positive relationship is stronger for women than men.	Yes
Field-specific ability beliefs	H9d	The relationship between field-specific ability beliefs and interest in pursuing an IT career will be moderated by gender such that the negative relationship will be stronger for women than men.	No

Two major societal shifts could help explain why we failed to detect gender differences in these self-perceptions. First, college students today are digital natives. Most have owned a smartphone for years. Currently, 95% of teens have a smartphone (Anderson & Jiang, 2018), but only eight years ago that number was 25% (Pew Research Center, 2012). Thus, both men and women use IT each day to accomplish various tasks through smartphone apps. Men and women are likely equally good at making those apps work and perceive themselves to be equally good at it. So, if college students are basing their computer and technical learning self-efficacy on their ability to use their cell phones then it makes sense that men and women today would feel similar levels of self-efficacy. Consistent with this reasoning, one study found that Millennial women evaluated themselves much higher on computer skills than did prior generations of women (Twenge et al., 2012). Because of their consistent IT use, it would also make sense for both men and women to see the value in an IT career even if they do not personally plan to enter the field.

The second societal shift is greater social acceptance of and expectations for women to take on more agentic goals and careers (Croft et al., 2015; Twenge, 2009). Because agentic goals tend to be afforded higher social status (Croft et al., 2015) and women are generally not punished as strongly as men for breaking traditional gender roles (Vandello & Bosson, 2013), it makes sense that many women endorse similar levels of agentic goals as men. In fact, Millennial women especially have shown this increased endorsement of agentic goals (Twenge et al., 2012; Twenge & Campbell, 2008).

The only variable that significantly mediated the relationship between gender and IT career pursuit—and therefore the only support for a mean differences approach in this study—was field-specific ability beliefs. However, this indirect effect did not occur in the expected manner. Our results show that women, on average, have greater field-specific ability beliefs, and these beliefs, in turn, are related to greater desire to pursue an IT career. Notably, we did find a significant direct effect of gender on IT career pursuit in this analysis. And, although the indirect effect through field-specific ability beliefs is significant, it is not a large effect. It could be that many women are not deterred by field-specific ability beliefs, and some could approach it as a challenge or obstacle that they could overcome rather something that should stop them (Quesenberry & Trauth, 2007). Alternatively, perhaps some women feel they have the relevant innate ability and welcome opportunities in a field where they have innate talent. It cannot be determined from our sample but is worth investigating further.

The choice between a mean or salience differences approach also has implications for which constructs are most important. For example, in role congruity theory, communal goals have traditionally been considered more important than agentic goals in explaining women opting out of IT or STEM. In fact, Diekman et al. (2011) suggested that research that examines gender differences in STEM career choice should emphasize communal goals over agentic goals because women and men tend to be different in their endorsement of communal goals. This makes sense from a mean difference approach. However, when using a salience difference approach, we found that agentic goals are the more important construct. Therefore, researchers must be careful not to take for granted which constructs are most important when deciding between mean and salience difference approaches.

By using our salience difference approach, researchers have the benefit of examining gender similarities and differences simultaneously. By taking this approach, we can take a middle ground by not essentializing all gender differences in IT career choice but also not denying gender differences in career motivations that tend to emerge. By combining a salience difference approach with multigroup analysis methods, we can evaluate whether and where gender differences in career choices emerge and how important these differences are. Using this approach allowed us to explain a greater proportion of variance in IT career pursuit for women compared to men for expectancy-value and role congruity theories. Without this approach, we would not have been able to see this difference in explanatory power. But, if the difference in explanatory power had been negligible, we would have seen that too.

The differences in explanatory power have important implications as well. Most research on the gender imbalance in IT has focused on why women tend to opt out of IT and how to make the field more appealing to women. This makes sense given the problem that our field is trying to solve. However, our work suggests a need to theorize about career decisions that men make as well. For two of the theories examined, we were actually able to explain IT career pursuit better for women than men. By gaining a better understanding of men's IT career decisions, we may generate a clearer picture of how the gender imbalance in IT emerges. For example, if men seek out careers that both satisfy their intrapersonal strengths and avoid backlash for breaking gender norms, their feasible career options may feel limited, which could drive more men into careers like IT.

6.2 Implications for Practice

We found no significant differences between women and men in technical learning self-efficacy but, on average, women found it to be a more salient variable for IT career value and pursuit than men. This salience difference resulted in an expectancy-value model that explained 51% of the variance in IT career pursuit for women but only 32% for men. These findings suggest a simple, egalitarian way to increase the number and percentage of women in IT—teach everyone how to code. This will increase everyone's technical learning self-efficacy, and increase the total number of people interested in pursuing a career in IT. However, it will increase women's career interest more than men's because it is more salient to women. This is an elegant solution because it does not single anyone out as needing special attention. Nor does it put special onus on one group because of their gender because it will be expected of everyone.

This implication dovetails with conclusions from efforts made at Carnegie Mellon to increase the presence of women in computer science. That is, women do not need a "female-friendly" curriculum and IT does not have to be made "pink" to fit women's interests (Frieze & Quesenberry, 2019). Rather, both women and men can succeed with the same curriculum, which seems to be a better approach than programs that change the curriculum to "fit" women (Frieze & Quesenberry, 2019). Frieze and Quesenberry (2019) also reported that availability of entry-level classes that required no prior experience helped increase the enrollment of women in computer science courses. Therefore, introductory IT courses may be a good environment for teaching everyone to code. Moreover, this is a solution that can be implemented at the level of society, business schools, or IT/IS/MIS/CIS departments within business schools, because each of these has some control over choosing curriculum.

The second salience differential occurred in agentic goals. These are goals that focus on the self, status, rewards, autonomy, and achievement. Interestingly, men and women showed no mean difference on this variable but they did show a salience difference, with women finding it more salient. This could mean that increases in the power and status of IT careers would tend to have a larger effect on women's IT career pursuit than on men's. This is consistent with findings that relatively poorer countries where IT jobs are more lucrative than other jobs have less of a difference in IT gender composition than richer countries where a wide range of prestigious jobs exist (Stoet & Geary, 2013). Unfortunately, this could work to counterbalance efforts to increase the number of women in IT. If the number of women in IT increased and the number of men did not change, this would tend to increase the supply of labor, which tends to decrease the cost of labor. If the financial and status rewards of IT careers were to decrease, for example, because of decreased labor costs, IT careers could become less fulfilling of agentic goals.

On a societal level, we could teach both boys and girls from a young age about the importance of both agentic and communal goals and avoid affording either type a higher status (Croft et al., 2015). If both men and women could pursue careers based on interest without fear of social backlash, many careers could naturally gain greater gender balance.

6.3 Limitations

Some limitations of this research should be noted. First, this study is rooted in a US-centric perspective. The gender composition in IT varies across countries, and culture plays a big role in this variation. Our subjects were from the US and, while each person is unique, as a group they may have been drawn from a different distribution than would be observed in other countries. Future studies should examine whether results are similar in other countries concerning the gender imbalance in IT and seek to gain a better understanding of countries that do not have this gender imbalance.

Second, intersectionality is an important framework from which the gender imbalance in IT careers can be studied (Trauth, Cain, Joshi, & Kvasny, 2012; Trauth, Cain, Joshi, Kvasny, et al., 2012; Trauth et al., 2016). Although we did not incorporate intersectionality directly into our research, we did ask questions about perceived societal barriers for pursuing IT careers. Although this is certainly not a complete way to address intersectionality, we included these questions to avoid ignoring the issue of societal barriers experienced by people based on identities while still maintaining the focus of this paper. Namely, in this study, we wanted to sample broadly across the United States rather than focusing on a particular intersection of identities. Intersectionality studies tend to focus on specific intersections of identities such as gender and race (Trauth, Cain, Joshi, Kvasny, et al., 2012; Trauth et al., 2016); in this study, we wanted to understand whether higher-level effects exist so that future research could examine these issues in specific intersections. Thus, we suggest that future studies examine whether the results of this study hold up within various populations.

Also, we recognize some concerns with the use of MTurk for data collection. For example, it is possible that MTurk workers are more IT literate and have a greater interest in IT than the general population. It would be useful to attempt to replicate our research through sampling a wide range of college students. This would help assess generalizability and boundary conditions across regions, universities, and cultures. In addition to providing more research with college students on IT career choice, such research could help clarify the perceptions of women and men before they reach college. It would be interesting to understand when the salience of factors such as IT self-efficacy and agentic goals form for women and men and whether this tends to happen before or during college.

6.4 Conclusions

We should take the IT gender gap seriously as academics and professionals. Currently, a dearth of research exists on this topic in top-tier IS journals (Gorbacheva et al., 2019; Loiacono et al., 2016). Only 16 papers—as of this writing—on this topic have been published in the Senior Scholars' Basket of Eight with none of them studying college student career choice (Gorbacheva et al., 2019). It has been suggested that the research in the Basket of Eight journals represents the primary interests of the IS field (Gorbacheva et al., 2019). If this is the case, then the broader IS field does not seem to find this issue very important. We agree with Loiacono et al.'s (2016) assertion that "if we do not acknowledge that a problem exists, we cannot ever hope to solve it" (p. 797). An important step to begin acknowledging the problem is to increase the representation of papers studying this topic in top IS journals. Thus, we call for more IS research on this important issue.

We are not overstating the case when we say that increasing gender representation is the most important question in information systems practice today. The primary limiting factor on what is possible is how many IS professionals are available to design and implement systems. If women went into the field at the same rate as men, we could double the number of people available to make the technology that runs the world. This is how the IS profession contributes to the world and we are undercontributing by a massive amount. Moreover, the problem gets worse as fewer and fewer women choose IS careers. We believe that understanding and addressing the consistent preference of most women to opt-out of IT careers is the single largest opportunity for IS to increase its contribution to the world.

References

ACM (2017): Curriculum Guidelines for Baccalaureate Degree Programs in Information Technology. https://www.acm.org/binaries/content/assets/education/curricula-recommendations/it2017.pdf

Ahuja, M. K. (2002). Women in the information technology profession: A literature review, synthesis and research agenda. *European Journal of Information Systems, 11*(1), 20-34.

Ahuja, M. K., & Thatcher, J. B. (2005). Moving beyond intentions and toward the theory of trying: Effects of work environment and gender on post-adoption information technology use. *MIS Quarterly, 29*(3), 427-459.

Anderson, M., & Jiang, J. (2018). Teens, social media & technology. *Pew Research Center*. http://www.pewinternet.org/2018/05/31/teens-social-media-technology-2018/

Armstrong, D. J., Riemenschneider, C. K., & Giddens, L. G. (2018). The advancement and persistence of women in the information technology profession: An extension of Ahuja's gendered theory of IT career stages. *Information Systems Journal, 28*(6), 1082-1124.

Asparouhov, T., & Muthén, B. O. (2005). Multivariate statistical modeling with survey data. *Proceedings of the Federal Committee on Statistical Methodology (FCSM) Research Conference.*

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191-215.

Bandura, A. (1997). *Self-efficacy: The Exercise of Control*. Freeman.

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (2001). Self-efficacy beliefs as shapers of children's aspirations and career trajectories. *Child Development, 72*(1), 187-206.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588-606.

Bertsimas, D., & Nohadani, O. (2019). Robust maximum likelihood estimation. *INFORMS Journal on Computing, 31*(3), 445-458.

Bessen, J. (2014). Employers aren't just whining—the " skills gap " is real. *Harvard Business Review*. https://hbr.org/2014/08/employers-arent-just-whining-the-skills-gap-is-real1-7.

Beyer, S. (2014). Why are women underrepresented in Computer Science? Gender differences in stereotypes, self-efficacy, values, and interests and predictors of future CS course-taking and grades. *Computer Science Education, 24*(2-3), 153-192.

Bian, L., Leslie, S.-J., & Cimpian, A. (2017). Gender stereotypes about intellectual ability emerge early and influence children's interests. *Science, 355*(6323), 389-391.

Browne, M., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. Bollen & J. Long (Eds.), *Testing Structural Equation Models* (pp. 136–162). SAGE.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(3), 464–504.

Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin, 143*(1), 1-35.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 9*(2), 233–255.

Clark, L., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, *7*(3), 309–319.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189-211

Crenshaw, K. (1989). *Demarginalizing the intersection of race and sex: A Black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics* (pp. 139-168). University of Chicago Legal Forum.

Croft, A., Schmader, T., & Block, K. (2015). An Underexamined inequality: Cultural and psychological barriers to men's engagement with communal roles. *Personality and Social Psychology Review, 19*(4), 343-370.

Diekman, A. B., Brown, E. R., Johnston, A. M., & Clark, E. K. (2010). Seeking congruity between goals and roles: A new look at why women opt out of science, technology, engineering, and mathematics careers. *Psychological Science, 21*(8), 1051-1057.

Diekman, A. B., Clark, E. K., Johnston, A. M., Brown, E. R., & Steinberg, M. (2011). Malleability in communal goals and beliefs influences attraction to STEM careers: Evidence for a goal congruity perspective. *Journal of Personality and Social Psychology, 101*(5), 902-918.

Diekman, A. B., & Eagly, A. H. (2008). Of women, men, and motivation: A role congruity account. In J. Y. Shah & W. L. Gardner (Eds.), *Handbook of motivation science* (pp. 434-447). Guilford Press.

Eagly, A. H., Wood, W., & Diekman, A. B. (2000). Social role theory of sex differences and similarities: A current appraisal. In T. Eckes & H. M. Trautner (Eds.), *The developmental social psychology of gender* (pp. 123-174). Erlbaum.

Eccles, J. S. (2007). Where are all the women? Gender differences in participation in physical science and engineering. In S. J. Ceci & W. M. Williams (Eds.), *Why aren't more women in science? Top researchers debate the evidence*. (pp. 199-210). American Psychological Association.

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*(2), 78-89.

Eccles, J. S., Wigfield, A., & Schiefele, U. (1998). Motivation to succeed. In W. Damon & N. Eisenberg (Eds.), *Social, emotional, and personality development* (pp. 1017-1095). Wiley.

Fabrigar, L. R., & Wegener, D. T. (2012). *Exploratory factor analysis*. Oxford University Press.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272–299.

Floyd, F. J., & Widaman, K. F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. *Psychological Assessment, 7*(3), 286–299.

Frieze, C., & Quesenberry, J. (2015). *Kicking butt in computer science: Women in computing at Carnegie Mellon University*. Dog Ear Publishing.

Frieze, C., & Quesenberry, J. L. (2019). How computer science at CMU is attracting and retaining women. *Communications of the ACM, 62*(2), 23-26.

Fritz, M. S., & MacKinnon, D. P. (2007). Required sample size to detect the mediated effect. *Psychological Science, 18*(3), 233-239.

Fritz, M. S., Taylor, A. B., & MacKinnon, D. P. (2012). Explanation of two anomalous results in statistical mediation analysis. *Multivariate Behavioral Research, 47*(1), 61-87.

Furr, R. M., & Bacharach, V. R. (2014). *Psychometrics: An introduction* (2nd ed.). SAGE.

Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems, 4*, Article 7

Gefen D., E. Rigdon, & Straub D. (2011). Editor's comments: An update and extension to SEM guidelines for administrative and social science research. *MIS Quarterly, 35*(2), iii–xiv.

Gorbacheva, E., Beekhuyzen, J., vom Brocke, J., & Becker, J. (2019). Directions for research on gender imbalance in the IT profession. *European Journal of Information Systems, 28*(1), 43-67.

Gorsuch, R. L. (1980). Factor score reliabilities and domain validities. *Educational and Psychological Measurement, 40*(4), 895-897.

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers' technology acceptance. *Journal of Research on Technology in Education, 43*(4), 343-367.

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika, 30*(2), 179-185.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55.

Huang, H., Kvasny, L., Joshi, K. D., Trauth, E. M., & Mahar, J. (2009). Synthesizing IT job skills identified in academic studies, practitioner publications and job ads. *Proceedings of the Special Interest Group on Management Information System's 47th Annual Conference on Computer Personnel Research.*

Jorgenson, D. W., & Vu, K. M. (2009). Projecting world economic growth: The contribution of information technology. *The Review of Socionetwork Strategies, 3*, 35-49.

Joshi, K. D., & Kuhn, K. (2005). Examining the masculinity and femininity of critical attributes necessary to succeed in IT. *Proceedings of the 2005 ACM SIGMIS CPR Conference on Computer Personnel Research*, 32-35.

Joshi, K. D., Kvasny, L., McPherson, S., Trauth, E., & Kulturel-Konak, S. (2010). Choosing IT as a Career: Exploring the role of Self-efficacy and Perceived Importance of IT skills. *Proceedings of the 31st International Conference on Information Systems*.

Joshi, K. D., & Schmidt, N. L. (2006). Is the information systems profession gendered? Characterization of IS professionals and IS career. *The Data Base for Advances in Information Systems*, *37*(4), 26-41.

Joshi, K. D., Trauth, E., Kvasny, L., & McPherson, S. (2013). Exploring the differences among IT majors and non-majors: Modeling the effects of gender role congruity, individual identity, and IT self-efficacy on IT career choices. *Proceedings of the International Conference on Information Systems*.

Kappelman, L., Johnson, V., McLean, E., & Torres, R. (2016). The 2015 SIM IT issues and trends study: Appendix. *MIS Quarterly Executive*, *16*(1), 55-83.

Kappelman, L., Mclean, E., Torres, R., & David, A. (2018). The 2017 SIM IT issues and trends study. *MIS Quarterly Executive,* 17(1), 53-88.

Kappelman, L., Torres, R., Mclean, E., Snyder, M., Fort, D., & Area, W. (2017). The 2016 SIM IT Issues and Trends Study. *MIS Quarterly Executive*, *16*(1), 47-80.

Kenny, D. A. (2015, November). SEM: Fit. http://davidakenny.net/cm/fit.htm

Korsakienė, R., Stankevičienė, A., Šimelytė, A., & Talačkienė, M. (2015). Factors driving turnover and retention of information technology professionals. *Journal of Business Economics and Management*, *16*(1), 1-17.

Kuhn, K., & Joshi, K. D. (2009). The reported and revealed importance of job attributes to aspiring information technology: A Policy-capturing study of gender differences. *The Data Base for Advances in Information Systems, 40*(3), 40-60.

Kvasny, L. (2006). Let the sisters speak: Understanding information technology from the standpoint of the "other." *The Data Base for Advances in Information Systems, 37*(4), 13-25.

Lenhart, A., Ling, R., Campbell, S., & Purcell, K. (2010). Chapter two: How phones are used with friends—What they can do and how teens use them. *Pew Research Center*. http://www.pewinternet.org/2010/04/20/chapter-two-how-phones-are-used-with-friends-what-they-can-do-and-how-teens-use-them/

Leslie, S.-J., Cimpian, A., Meyer, M., & Freeland, E. (2015). Expectations of brilliance underlie gender distributions across academic disciplines. *Science, 347*(6219).

Li, C. (2013). The contribution of information technology to economic growth. Applied mechanics and materials, *411-414*, 2533-2536.

Loiacono, E., Iyer, L. S., Armstrong, D. J., Beekhuyzen, J., & Craig, A. (2016). AIS women's network: advancing women in is academia. *Communications of the Association for Information Systems*, *38*, 784-802.

MacKinnon, D. P. (2008). *Introduction to statistical mediation analysis.* Taylor & Francis.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of product and resampling methods. *Multivariate Behavioral Research, 39*(1), 99.

Markland, D. (2007). The golden rule is that there are no golden rules: A commentary on Paul Barrett's recommendations for reporting model fit in structural equation modelling. *Personality and Individual Differences*, *42*(5), 851–858.

Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural Equation Modeling: A Multidisciplinary Journal*, *11*(3), 320–341.

Meyer, M., Cimpian, A., & Leslie, S.-J. (2015). Women are underrepresented in fields where success is believed to require brilliance. *Frontiers in Psychology, 6*, https://doi.org/10.3389/fpsyg.2015.00235

Muthén, L. K., & Muthén, B. O. (2017). *Mplus User's Guide* (8th). https://www.statmodel.com/orderonline/products.php?product=Mplus-Version-8-User%27s-Guide

Natale, M. J. (2002). The effect of a male-oriented computer gaming culture on careers in the computer industry. *SIGCAS Computer and Society*, *32*(2), 24-31.

National Association for Women & Information Technology. (2018). NCWIT fact sheet. https://www.ncwit.org/ncwit-fact-sheet

National Center for Education Statistics (2016). Annual reports. https://nces.ed.gov/programs/digest/2016menu_tables.asp

National Center for Women & Information Technology. (2018). Women and information technology by the numbers. https://www.ncwit.org/resources/numbers

Organisation for Economic Co-operation and Development. (2015). Share of women graduates by field of education. http://www.oecd.org/gender/data/shareofwomengraduatesbyfieldofeducation.htm

Pew Research Center (2012). Teens, smartphones & texting. http://www.pewinternet.org/2012/03/19/teens-smartphones-texting/

Pew Research Center (2019). Demographics of mobile device ownership and adoption in the United States. https://www.pewresearch.org/internet/fact-sheet/mobile/

Quesenberry, J. L., & Trauth, E. M. (2012). The (dis)placement of women in the IT workforce: An investigation of individual career values and organisational interventions: *Information Systems Journal*, *22*(6), 457-473.

Quesenberry, J. L., & Trauth, E. M. (2007). What do women want? An investigation of career anchors among women in the IT workforce. *Proceedings of the 2007 ACM SIGMIS CPR Conference on Computer personnel research: The Global Information Technology Workforce*, 122-127.

Reid, M. F., Allen, M. W., Armstrong, D. J., & Riemenschneider, C. K. (2010). Perspectives on challenges facing women in IS: The cognitive gender gap. *European Journal of Information Systems, 19*(5), 526-539.

Rosenbloom, J. L., Ash, R. A., Dupont, B., & Coder, L. A. (2008). Why are there so few women in information technology? Assessing the role of personality in career choices. *Journal of Economic Psychology, 29*(4), 543-554.

Rosson, M. B., Carroll, J. M., & Sinha, H. (2011). Orientation of undergraduates toward careers in the computer and information sciences. *ACM Transactions on Computing Education*, *11*(3), Article 14.

Shook, C. L., Ketchen, D. J., Hult, G. T. M., & Kacmar, K. M. (2004). An assessment of the use of structural equation modeling in strategic management research. *Strategic Management Journal*, *25*(4), 397–404.

Stephens-Davidowitz, S. (2014, January 18). Google, tell me. Is my son a genius? *The New York Times.* https://www.nytimes.com/2014/01/19/opinion/sunday/google-tell-me-is-my-son-a-genius.html

Stoet, G., & Geary, D. C. (2013). Sex differences in mathematics and reading achievement are inversely related: Within- and across-nation assessment of 10 Years of PISA Data. *PLOS ONE*, *8*(3), e57988.

Stoet, G., & Geary, D. C. (2018). The gender-equality paradox in science, technology, engineering, and mathematics education. *Psychological Science*, *29(4)*, 581-593.

Storage, D., Horne, Z., Cimpian, A., & Leslie, S.-J. (2016). The frequency of “brilliant” and “genius” in teaching evaluations predicts the representation of women and African Americans across fields. *PLoS ONE, 11*(3), e0150194. https://doi.org/10.1371/journal.pone.0150194

Trauth, E. M. (2002). Odd girl out: An individual differences perspective on women in the IT profession. *Information Technology & People, 15*(2), 98-118.

Trauth, E. M., Cain, C. C., Joshi, K. D., Kvasny, L., & Booth, K. M. (2016). The influence of gender-ethnic intersectionality on gender stereotypes about IT skills and knowledge. *The Data Base for Advances in Information Systems*, *47*(3), 9-39.

Trauth, E. M., Cain, C., Joshi, K. D., & Kvasny, L. (2012). The future of gender and IT research: Embracing intersectionality. *Proceedings of the ACM SIGMIS Computers and People Research Conference*.

Trauth, E. M., Cain, C., Joshi, K. D., Kvasny, L., & Booth, K. (2012). The future of gender and IT research: Embracing intersectionality. Available at https://www.researchgate.net/publication/265002388_The_Future_of_Gender_and_IT_Research_Embracing_Intersectionality

Trauth, E. M., Nielsen, S. H., & Von Hellens, L. A. (2003). Explaining the IT gender gap: Australian stories for the new millennium. *Journal of Research and Practice in Information Technology, 35*(1), 7-20.

Trauth, E. M., & Quesenberry, J. L. (2006). Are women an underserved community in the information technology profession? *Proceedings of the International Conference on Information Systems*.

Twenge, J. M. (2001). Changes in women’s assertiveness in response to status and roles: A cross-temporal meta-analysis, 1931-1993. *Journal of Personality and Social Psychology, 81*(1), 133-145.

Twenge, J. M. (2009). Status and gender: The paradox of progress in an age of narcissism. *Sex Roles, 61*, 338-340.

Twenge, J. M., & Campbell, S. M. (2008). Generational differences in psychological traits and their impact on the workplace. *Journal of Managerial Psychology, 23*(8), 862-877.

Twenge, J. M., Campbell, W. K., & Gentile, B. (2012). Generational increases in agentic self-evaluations among American college students, 1966-2009. *Self and Identity, 11*(4), 409-427.

Tyler-Wood, T., Knezek, G., & Christensen, R. (2010). Instruments for assessing interest in STEM content and careers. *Journal of Technology and Teacher Education, 18*(2), 341-363.

Vandello, J. A., & Bosson, J. K. (2013). Hard won and easily lost: A review and synthesis of theory and research on precarious manhood. *Psychology of Men & Masculinity, 14*(2), 101-113.

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: suggestions, practices, and recommendations for organizational research. *Organizational Research Methods, 3*(1), 4-70.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24*(1), 115-139.

Wang, M.-T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy-value perspective to understand individual and gender differences in STEM fields. *Developmental Review, 33*(4), 304-340.

Wang, M.-T., & Degol, J. L. (2017). Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions. *Educational Psychology Review, 29*(1), 119-140.

Wang, M.-T., Eccles, J. S., & Kenny, S. (2013). Not lack of ability but more choice: Individual and gender differences in choice of careers in science, technology, engineering, and mathematics. *Psychological Science, 24*(5), 770-775.

Weitzel, T., Eckhardt, A., & Laumer, S. (2009). A Framework for recruiting IT talent: Lessons from Siemens. *MIS Quarterly Executive, 8*(4), 175-189.

Widaman, K. F., & Reise, S. P. (1997). Exploring the measurement invariance of psychological instruments: Applications in the substance use domain. In K. J. Bryant, M. Windle, & S. G. West (Eds.), *The science of prevention: Methodological advances from alcohol and substance abuse research.* (pp. 281–324). American Psychological Association.

Wikipedia (2019). Information technology. https://en.wikipedia.org/w/index.php?title=Information_technology&oldid=931573687

Yates, A. (1987). *Multivariate exploratory data analysis: A perspective on exploratory factor analysis.* Albany: State University of New York Press.

Appendix A: IT Learning Self-Efficacy Scale Development

Several studies have operationalized self-efficacy as computer self-efficacy, which is belief in one's ability to use a computer (Compeau & Higgins, 1995). Computer self-efficacy has been used to examine gender composition in computing professions (Beyer, 2014; Rosson et al., 2011). People with greater computer self-efficacy express greater interest in computing professions and are more likely to enroll in a computer science course in the future than those with less computer self-efficacy.

However, computer self-efficacy invokes two issues for studying IT career choice. It is focused on current skills, and it is focused on system use. The real issue for people choosing a career when in college is whether they can learn the skills necessary to build, implement and maintain systems. Thus, we developed a new type of self-efficacy—and its measure—called IT learning self-efficacy, which measures people's self-efficacy for learning the skills needed to become IT professionals. This is based on prior research looking at students' IT skills self-efficacy (Joshi et al., 2010) and assesses self-efficacy related to the ability to learn a skill rather than current proficiency with a skill.

Although self-efficacy for IT skills has been previously studied (Joshi et al., 2010), it has only been examined with students who were in IT classes, nearly half of which were IT majors. However, we are interested in IT learning self-efficacy for people who may have little to no exposure to IT as well as those who have had some exposure. Thus, we created this scale with the intention of including items that would be understandable for those of all experience levels. For example, we were concerned that terms such as "system implementation skills" or "process analysis" would not be understood by those with little exposure to IT.

Early in scale development, it is important to identify the scope and generality of the construct that one intends to measure (Clark & Watson, 1995); thus, this is where we began. Although computer self-efficacy is an important construct in IS research, it is best used to understand user acceptance of IT, rather than self-efficacy for learning how to develop IT, because computer self-efficacy questions ask about the use of software rather than the development of software. Since we were interested in what influences decisions to pursue an IT career, it was important to use a measure of self-efficacy for learning the skills needed for an IT career. In addition, we wanted a measure of people's beliefs that they could learn the skills necessary, not whether they currently had these skills. Finally, we wanted a measure that is general enough to use with people who have had little or no exposure to the IT field as well as with people who have had some exposure.

With these goals in mind, we created our construct definition so that content for the items we developed would reflect the important aspects of the construct (Clark & Watson, 1995; Furr & Bacharach, 2014). We defined IT learning self-efficacy as "the belief that one can learn the skills needed to be an information technology professional."

After defining the construct, it was important to generate items that measure all of the aspects of the construct of interest (Clark & Watson, 1995; Furr & Bacharach, 2014). In this regard, it is better to err on the side of being overinclusive than risk being underinclusive, which makes it necessary to generate more items than one hopes to end up with (Clark & Watson, 1995).

To develop a list of items that reflected our construct definition and scope, we began with skills that were identified to be important for IT professionals in academic studies, practitioner publications, and job advertisements (Huang et al., 2009). In addition to these skills, we added to our list competencies that are included in curriculum guidelines for baccalaureate programs in IT put forth by the Association for Computing Machinery (ACM, 2017). From this set of skills, we created items that reflect these skills while adjusting the language used to describe some skills so that they would be interpretable by someone with little or no exposure to the IT field. After generating this list, we asked two content experts for input. The two content experts are IS professors who have expertise in pedagogy for IT students and developed the current undergraduate educational program for IT majors at a large university in the United States. Based on the experts' feedback, we reworded some items and added additional items. We pilot tested these items with Introduction to IT students to gain a preliminary understanding of how these items were functioning. Based on these piloted responses and expert feedback, we refined the instrument once more. This resulted in our initial list of 48 items, which are presented in Table A1. Within these 48 items, we identified six content areas that we believed would emerge as six factors. The expected factor for each item is given in parentheses in Table A1.[3]

[3] Although the items are listed in this order for ease of interpretation, participants completed the items in random order.

Table A1. IT Learning Self-Efficacy Initial Item Set

Directions: For the following questions, please rate your confidence that you could **successfully learn** to do the following on a scale from 1 (*Not at All Confident*) to 7 (*Completely Confident*).
Item
1. Program computers (**Technical)**
2. Design computer applications (**Technical)**
3. Program computer applications (**Technical)**
4. Design computer systems (**Technical)**
5. Program software (**Technical)**
6. Design software (**Technical)**
7. Program computer systems (**Technical)**
8. Program in a software language (**Technical)**
9. Find technology-based solutions for business needs **(Business)**
10. Make an economic case for new technologies **(Business)**
11. Define the business case for the deployment of new technologies **(Business)**
12. Evaluate if a computing-based solution meets business requirements **(Business)**
13. Integrate computing technologies to meet organizational goals **(Business)**
14. Understand business processes supported by information technology systems **(Business)**
15. Identify economic advantages and disadvantages of different technologies **(Business)**
16. Identify strategic advantages and disadvantages of different technologies **(Business)**
17. Consider computer user needs when selecting computer-based systems **(User Experience)**
18. Understand computer users' system requirements **(User Experience)**
19. Understand the information needs of different jobs **(User Experience)**
20. Present data in a way that is usable by individuals **(User Experience)**
21. Understand what sort of interfaces different people need **(User Experience)**
22. Understand what information people need to do their jobs effectively **(User Experience)**
23. Relate to end user perspectives **(User Experience)**
24. Empathize with users' needs **(User Experience)**
25. Show people how to use an information system **(Training)**
26. Teach people how to use new software **(Training)**
27. Demonstrate the use of a computer system **(Training)**
28. Provide effective training for users **(Training)**
29. Provide instructions for the use of a computer system **(Training)**
30. Show people how to effectively use new features of a software **(Training)**
31. Provide ongoing training to users **(Training)**
32. Train novice users how to use a system **(Training)**
33. Create data visualizations **(Data Management/Presentation)**
34. Apply analytical approaches to solve problems **(Data Management/Presentation)**
35. Format information **(Data Management/Presentation)**
36. Find information to solve problems **(Data Management/Presentation)**
37. Search for information in company databases **(Data Management/Presentation)**
38. Link different data sources together **(Data Management/Presentation)**
39. Query databases for specific answers **(Data Management/Presentation)**
40. Find information to answer questions **(Data Management/Presentation)**
41. Adapt to changes in technology **(New Technology)**
42. Research new technologies **(New Technology)**
43. Learn how to use new technologies **(New Technology)**
44. Understand innovations in information technology **(New Technology)**
45. Keep informed about upcoming technologies **(New Technology)**
46. Stay at the forefront of technological innovations **(New Technology)**
47. Discover new technologies **(New Technology)**
48. Keep up with technology trends **(New Technology)**
Note: Parentheses include the expected factor for each item.

Testing Initial Item Set

Participants and Procedure

We collected responses for our initial item set using Amazon's Mechanical Turk (MTurk). We limited the sample to people with the MTurk qualification of being between the ages of 18 and 25. Participation was also limited to workers who had completed at least 100 tasks and had an approval rate above 95%. We collected 615 responses and paid each person $0.75. Each participant completed our IT self-efficacy measure as well as demographic questions including age, sex, race/ethnicity, and college status. [4] The survey also included two attention check questions. We thought it possible that someone could miss one attention check on accident or because of "fat fingers" so we only excluded participants from analyses if they missed both check questions. We then screened responses for any careless responding. We noticed that some people with the MTurk qualification of being between 18 and 25 were either no longer in this age range or had incorrectly been given this qualification. We excluded from analyses any participants who were well outside of this age range. Specifically, anyone above 29 was excluded from analyses. After removing those over 29 and those who missed both check questions, 603 observations remained. Participant demographic characteristics are presented in Table A2.

Table A2. Scale Development Sample 1 Demographics (N = 603)

	Mean	Standard Deviation	Median	Min	Max
Age	24.15	1.95	24	18	29
	Frequency	**Proportion**			
Gender					
Women	350	58.0%			
Men	253	42.0%			
Race/ethnicity					
White/European American	381	63.20%			
Biracial/Multiracial	67	11.11%			
African/African American/Black	59	9.78%			
Asian/Asian American	41	6.80%			
Hispanic/Latino(a)	36	5.97%			
Asian Indian	4	0.66%			
American Indian/Native American	4	0.66%			
Arab American/Middle Eastern	2	0.33%			
Other	4	0.66%			
Preferred not to answer	5	0.83%			
College status					
First-year	13	2.16%			
Sophomore	48	7.96%			
Junior	50	8.29%			
Not in college but plan to go	59	9.78%			
Senior	73	12.11%			
Graduate student	79	13.10%			
Already graduated from college	225	37.31%			
Not in college and do not plan to go	56	9.29%			

[4] For college status, participants chose from the following responses to describe their college status: "Freshman," "Sophomore," "Junior," "Senior," "Graduate Student," "Not in college but plan to go," "Already graduated from college," or "Not in college and do not plan to go."

Analysis

During scale development, one can begin analyzing responses with exploratory factor analysis (EFA) or confirmatory factor analysis (CFA) depending on knowledge of the topic area and if there are expectations of what factors may emerge (Floyd & Widaman, 1995). If there are no expectations for what factors may emerge, EFA is more appropriate. If one has expectations, then CFA is more appropriate. Because we expected six factors to emerge from the data, we first used CFA to test this expected solution.

Confirmatory Factor Analysis (CFA)

For all CFAs, variances of latent variables were fixed to one and latent variables were allowed to correlate with one another. We used maximum likelihood estimation with robust standard errors (MLR) for all CFAs. MLR is available in Mplus software and corrects for any violations of normality in manifest variables when computing standard errors (Asparouhov & Muthén, 2005; Bertsimas & Nohadani, 2019; Muthén & Muthén, 2017).

To evaluate model fit, we followed recommendations to examine multiple fit indices (Hu & Bentler, 1999). Specifically, we examined the root mean squared error of approximation (RMSEA), comparative fit index (CFI), and standardized root mean squared residual (SRMR). For RMSEA and SRMR, a lower value indicates better model fit with a value of zero as theoretical perfect fit. CFI ranges from zero to one with a larger value indicating better model fit. We also followed the convention of reporting the $\chi 2$ test of model fit but did consult it in determining the adequacy of each model because of its sensitivity to sample size (Bentler & Bonett, 1980). Although several authors have suggested guidelines for evaluating model fit based on fit indices, there are no "golden rules" (Markland, 2007; Marsh et al., 2004). Thus, we used these criteria as guidelines but did not treat them as strict cutoffs like hypothesis tests but instead evaluated several criteria to take a holistic approach to finding a model that seemed most appropriate for the data. These criteria included evaluation of model fit indices, theoretical implications, and construct validity (Markland, 2007).

With these considerations in mind, guidelines for evaluating RMSEA vary from "a cutoff value close to .06" (Hu & Bentler, 1999, p. 27) to < 0.05 representing close approximate fit, between 0.05 and 0.08 representing fair fit, between 0.08 and 0.10 representing mediocre fit, and > 0.10 representing unacceptable fit (Browne & Cudeck, 1993). Guidelines for CFI range from > 0.90 (Bentler & Bonett, 1980) to close to 0.95 (Hu & Bentler, 1999) indicating good fit. However, to allow enough items for adequate construct validity, some have suggested the CFI > 0.90 guideline may even be too strict (Marsh et al., 2004) A SRMR cutoff value close to 0.08 has also been suggested (Hu & Bentler, 1999) to indicate good fit. Again, although these can serve as good guideposts, there are no golden rules—models should be evaluated with multiple fit indices along with substantive meaning and construct validity in mind (Hu & Bentler, 1999; Kenny, 2015; Markland, 2007; Marsh et al., 2004).

The model fit for the proposed six-factor solution was acceptable, $\chi 2(1065) = 2693.07$, $p < 0.001$, RMSEA = 0.050, CFI = 0.904, SRMR = 0.060. The factor loadings for this model can be seen in Table A3.

Table A3. Confirmatory Factor Analysis Standardized Factor Loadings

Factor	Technical		Business		User experience		Training		Data analysis		New technology	
	Item 1	.92	Item 9	.84	Item 17	.73	Item 25	.81	Item 33	.72	Item 41	.68
	Item 2	.88	Item 10	.76	Item 18	.74	Item 26	.86	Item 34	.72	Item 42	.72
	Item 3	.88	Item 11	.77	Item 19	.73	Item 27	.80	Item 35	.68	Item 43	.78
	Item 4	.85	Item 12	.75	Item 20	.73	Item 28	.83	Item 36	.75	Item 44	.76
	Item 5	.91	Item 13	.77	Item 21	.77	Item 29	.79	Item 37	.70	Item 45	.79
	Item 6	.89	Item 14	.81	Item 22	.69	Item 30	.80	Item 38	.70	Item 46	.62
	Item 7	.90	Item 15	.74	Item 23	.66	Item 31	.82	Item 39	.65	Item 47	.71
	Item 8	.88	Item 16	.77	Item 24	.55	Item 32	.58	Item 40	.69	Item 48	.77

Note: All factor loadings are standardized and statistically significant ($p < .01$).

Although model fit indices and factor loadings seemed acceptable, it is also important to consider discriminant validity in multiple factor solutions (Gefen et al., 2000; Shook et al., 2004). Discriminant validity refers to whether each factor is distinguishable and sufficiently different from other factors. Discriminant validity can be assessed both by examining interfactor correlations and by assessing if the average variance extracted (AVE) for each factor is larger than its correlations with other variables (Gefen et al., 2011, 2000; Shook et al., 2004). If interfactor correlations are large, this may suggest that two factors belong to one construct rather than being two separate constructs. Similarly, if the AVE for a factor is below that factor's correlations with other factors, it may mean that those factors are not sufficiently different from one another and may be one underlying factor. Interfactor correlations and AVE for each factor can be seen in Table A4.

Table A4. Confirmatory Factor Analysis Interfactor Correlations

Factor	Technical	Business	User experience	Training	Data analysis	New technology
Technical	**.79**					
Business	.65**	**.60**				
User experience	.53**	.91**	**.49**			
Training	.55**	.85**	.93**	**.62**		
Data analysis	.50**	.86**	.96**	.83**	**.49**	
New technology	.54**	.86**	.92**	.85**	.89**	**.53**

Note: Bolded in the diagonal is the average variance extracted (AVE) for each factor. ***p* < .01.

The only factor with clear discriminant validity was the technical factor. All interfactor correlations for other factors were above 0.8—many above 0.9—and each of the other factors had AVEs well below their interfactor correlations. Based on these considerations, we did not think our proposed six-factor solution was appropriate for the scale. Therefore, we then conducted an EFA to better understand the factor structure for the scale.

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) is a tool used in scale development to understand the dimensionality of a scale. Several decisions must be made through the course of conducting EFA. We followed the recommendations of the seminal Fabrigar et al. (1999) paper, which have received considerable empirical support and were further expanded on in a book (Fabrigar et al., 1999; Fabrigar & Wegener, 2012).

One of the first considerations in EFA is the choice of extraction method. Although principal component analysis (PCA) is often misunderstood as being an extraction method, this is not appropriate (Fabrigar et al., 1999; Fabrigar & Wegener, 2012). EFA and PCA should not be confused—although they have some similar properties, they are different techniques based on different mathematical models with different purposes and theoretical implications (Fabrigar et al., 1999; Fabrigar & Wegener, 2012). PCA is a data reduction method, whereas EFA allows us to understand latent factors that explain the correlations between variables. In addition, EFA partitions item variance into common variance and unique (error) variance, whereas PCA does not (Fabrigar et al., 1999). Therefore, EFA can account for measurement error whereas PCA does not. Thus, we chose from EFA extraction methods. Of these, we chose maximum likelihood—specifically, we chose MLR estimation again.

Another important decision for multiple factor solutions is the factor rotation method. Factor rotation aids in interpretability and allows the attainment of a solution with a simple structure (Fabrigar & Wegener, 2012). In simple structure solutions, each factor is represented by a subset of items that have large loadings for that factor but near-zero loadings for other factors. In addition, there should be little overlap in the item subsets that load on different factors (Fabrigar & Wegener, 2012). Two general categories of factor rotation are available: orthogonal and oblique rotations. Orthogonal rotations constrain factors to be uncorrelated, and oblique rotations allow factors to be correlated (Fabrigar et al., 1999). Oblique rotations do not force factors to be correlated—if factors are unrelated, the simple structure for the oblique rotation will result in uncorrelated factors. However, most constructs tend to be correlated meaning that oblique rotations tend to provide a more accurate representation of the relationships between factors (Fabrigar et al., 1999). For these reasons, we chose to use the Geomin oblique rotation (Yates, 1987).

Another decision that must be made is the number of factors to extract from the EFA. One of the most commonly employed methods is often called the "Kaiser criterion" in which factors with an eigenvalue greater than 1 are retained (Fabrigar & Wegener, 2012). Although this method provides a simple criterion against which to compare eigenvalues, it has serious shortcomings (Fabrigar et al., 1999; Fabrigar & Wegener, 2012; Floyd & Widaman, 1995). First, this criterion is a holdover from PCA—which we have already stated is not the same as EFA—that is not appropriate for use with the common factor model (Fabrigar & Wegener, 2012; Gorsuch, 1980). Second, a cutoff of one provides an arbitrary point at which to divide factors that are meaningful or not meaningful (Fabrigar et al., 1999). Third, numerous studies have found that this criterion routinely leads to overfactoring and occasionally underfactoring (Fabrigar et al., 1999). Fabrigar et al. (1999) added that they knew of no studies that provided evidence of this rule working well.

Another commonly used strategy for determining the number of factors to retain is the scree plot, which plots the eigenvalues in descending order for each factor. The recommendation is to retain the number of factors that precede the last major drop (Fabrigar & Wegener, 2012). The idea is that once an additional factor stops providing much additional explanatory power, the incremental validity in adding a new factor decreases. Although scree plots can be useful, there is some subjectivity involved in determining what constitutes a major drop (Fabrigar & Wegener, 2012). A technique that can be combined with scree plots is parallel analysis (Horn, 1965). Parallel analysis involves simulating many random datasets with the same number of observations and variables as the actual data. An EFA is conducted on each random dataset and the eigenvalues found for each factor. Eigenvalues from the actual data can then be compared to the distribution of eigenvalues from these random data for each factor (Fabrigar & Wegener, 2012). If actual eigenvalues do not exceed the 95th percentile of eigenvalues for the random data, then it is thought that those factors likely do not contain useful information.

Because we originally expected six factors, we examined sample eigenvalues and parallel analysis eigenvalues for six factors, which can be seen in Table A5. We conducted parallel analysis with 1000 random data sets. Sample eigenvalues as well as the 95th percentile parallel analysis eigenvalues are included in a scree plot in Figure A1.

Table A5. Sample Eigenvalues Compared to Parallel Analysis Eigenvalues

Factor	Sample Eigenvalues	Average Eigenvalues from PA	95% Percentile Eigenvalues from PA
1	22.99	1.59	1.64
2	4.59	1.53	1.57
3	1.61	1.49	1.52
4	1.36	1.45	1.48
5	1.23	1.41	1.44
6	0.92	1.38	1.41

Notes: PA = Parallel Analysis. Factors are the first six factors extracted from the exploratory factor analysis using maximum likelihood with robust standard errors. Geomin oblique rotation was used. One thousand random samples were used for parallel analysis.

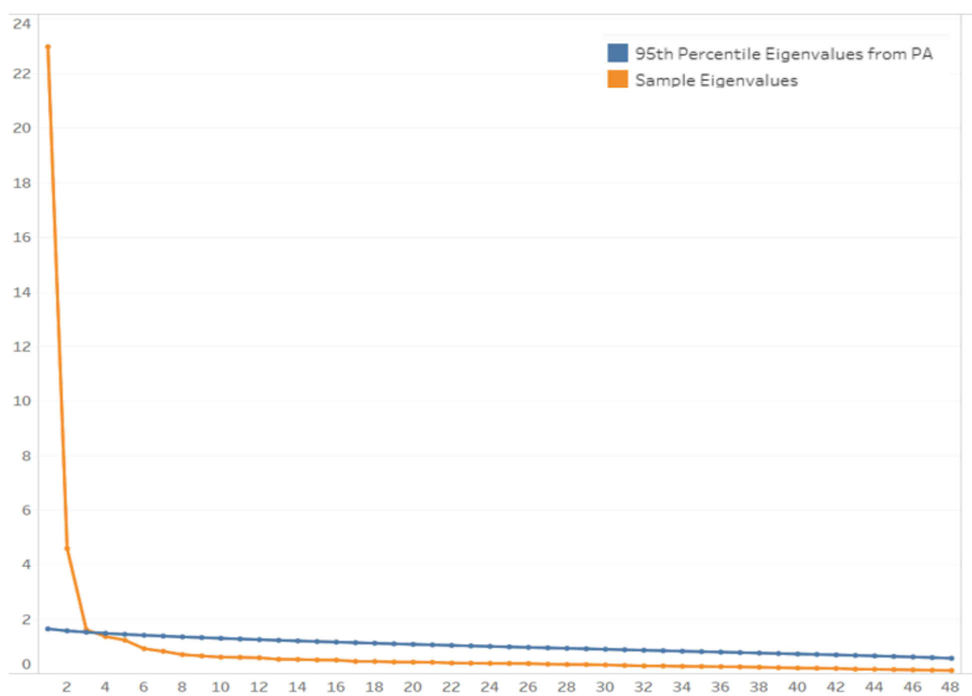

Figure A1. Screen Plot of Sample Eigenvalues and 95th Percentile of Eigenvalues from Parallel Analysis

The plot of sample eigenvalues suggests the presence of two factors. Comparing the sample eigenvalues to parallel analysis eigenvalues suggests the presence of two or perhaps three factors—the third factor has sample eigenvalues barely above the 95th percentile of parallel analysis eigenvalues. To resolve this, we looked at the interpretability of factor loadings from both two- and three-factor solutions. Loadings for the two-factor solution are given in Table A6. Loadings from the two-factor solution suggest the technical factor that we originally proposed for items 1 through 8. The rest of the items load onto the second factor, which can be interpreted as a business factor. Factor loadings for the three-factor solution are presented in Table A7.

Table A6. Exploratory Factor Analysis Two-Factor Solution

Item	Factor 1	Factor 2
1. Program computers	0.895*	0.032
2. Design computer applications	0.855*	0.050*
3. Program computer applications	0.905*	-0.042
4. Design computer systems	0.811*	0.073*
5. Program software	0.879*	0.055
6. Design software	0.896*	-0.003
7. Program computer systems	0.903*	-0.017
8. Program in a software language	0.872*	0.014
9. Find technology-based solutions for business needs	0.150*	0.698*
10. Make an economic case for new technologies	0.147*	0.605*
11. Define the business case for the deployment of new technologies	0.255*	0.530*
12. Evaluate if a computing-based solution meets business requirements	0.284*	0.526*
13. Integrate computing technologies to meet organizational goals	0.215*	0.619*
14. Understand business processes supported by information technology systems	0.126*	0.682*
15. Identify economic advantages and disadvantages of different technologies	0.029	0.686*
16. Identify strategic advantages and disadvantages of different technologies	0.02	0.754*
17. Consider computer user needs when selecting computer-based systems	0.122*	0.658*
18. Understand computer users’ system requirements	0.153*	0.663*
19. Understand the information needs of different jobs	-0.184*	0.827*
20. Present data in a way that is usable by individuals	-0.087*	0.764*
21. Understand what sort of interfaces different people need	0.023	0.754*
22. Understand what information people need to do their jobs effectively	-0.208*	0.800*
23. Relate to end user perspectives	0.006	0.645*
24. Empathize with users’ needs	-0.304*	0.706*
25. Show people how to use an information system	0.003	0.772*
26. Teach people how to use new software	0.026	0.782*
27. Demonstrate the use of a computer system	-0.008	0.765*
28. Provide effective training for users	-0.008	0.767*
29. Provide instructions for the use of a computer system	0.047	0.710*
30. Show people how to effectively use new features of a software	-0.008	0.763*
31. Provide ongoing training to users	0.01	0.765*
32. Create data visualizations	0.123*	0.543*
33. Apply analytical approaches to solve problems	0.03	0.655*
34. Format information	0.046	0.657*
35. Find information to solve problems	-0.197*	0.736*
36. Search for information in company databases	-0.152*	0.782*
37. Link different data sources together	0.254*	0.556*
38. Query databases for specific answers	0.095*	0.594*
39. Find information to answer questions	-0.291*	0.749*
40. Adapt to changes in technology	-0.166*	0.766*
41. Research new technologies	-0.031	0.652*
42. Learn how to use new technologies	-0.195*	0.790*
43. Understand innovations in information technology	0.075	0.700*
44. Keep informed about upcoming technologies	-0.100*	0.750*
45. Stay at the forefront of technological innovations	0.160*	0.653*
46. Discover new technologies	0.241*	0.417*
47. Train novice users how to use a system	0.011	0.760*
48. Keep up with technology trends	-0.066	0.715*

Note: Factors were extracted using maximum likelihood with robust standard errors. Geomin oblique rotation was used.
**p* < .05.

Table A7. Exploratory Factor Analysis Three Factor Solution

Item	Factor 1	Factor 2	Factor 3
1. Program computers	0.900*	0.029	0.027
2. Design computer applications	0.853*	0.053	-0.023
3. Program computer applications	0.904*	-0.04	0.02
4. Design computer systems	0.813*	0.072*	-0.017
5. Program software	0.887*	0.051*	0.04
6. Design software	0.897*	-0.004	0.01
7. Program computer systems	0.902*	-0.015	0.015
8. Program in a software language	0.879*	0.010	0.041
9. Find technology-based solutions for business needs	0.191*	0.673*	-0.01
10. Make an economic case for new technologies	0.171*	0.590*	-0.089
11. Define the business case for the deployment of new technologies	0.271*	0.519*	-0.116
12. Evaluate if a computing-based solution meets business requirements	0.301*	0.516*	-0.096
13. Integrate computing technologies to meet organizational goals	0.248*	0.600*	-0.024
14. Understand business processes supported by information technology systems	0.160*	0.661*	-0.047
15. Identify economic advantages and disadvantages of different technologies	0.074	0.658*	0.024
16. Identify strategic advantages and disadvantages of different technologies	0.074	0.721*	0.061
17. Consider computer user needs when selecting computer-based systems	0.155*	0.641*	-0.030
18. Understand computer users' system requirements	0.197*	0.638*	0.048
19. Understand the information needs of different jobs	-0.135*	0.798*	0.008
20. Present data in a way that is usable by individuals	-0.055	0.748*	-0.064
21. Understand what sort of interfaces different people need	0.064	0.732*	-0.011
22. Understand what information people need to do their jobs effectively	-0.167*	0.779*	-0.022
23. Relate to end user perspectives	0.035	0.628*	-0.065
24. Empathize with users' needs	-0.255*	0.678*	0.061
25. Show people how to use an information system	0.007	0.777*	-0.23
26. Teach people how to use new software	0.026	0.794*	-0.249
27. Demonstrate the use of a computer system	0.003	0.767*	-0.172
28. Provide effective training for users	-0.033	0.798*	-0.379*
29. Provide instructions for the use of a computer system	0.041	0.722*	-0.268
30. Show people how to effectively use new features of a software	0.005	0.764*	-0.158
31. Provide ongoing training to users	-0.011	0.792*	-0.365*
32. Create data visualizations	0.146*	0.528*	-0.073
33. Apply analytical approaches to solve problems	0.087	0.620*	0.116
34. Format information	0.091	0.629*	0.036
35. Find information to solve problems	-0.127*	0.696*	0.202
36. Search for information in company databases	-0.093*	0.747*	0.085
37. Link different data sources together	0.281*	0.539*	-0.042
38. Query databases for specific answers	0.141*	0.563*	0.054
39. Find information to answer questions	-0.217*	0.707*	0.220
40. Adapt to changes in technology	-0.091	0.725*	0.233
41. Research new technologies	0.048	0.607*	0.278*
42. Learn how to use new technologies	-0.121*	0.751*	0.229
43. Understand innovations in information technology	0.137*	0.664*	0.143
44. Keep informed about upcoming technologies	-0.022	0.709*	0.269
45. Stay at the forefront of technological innovations	0.215*	0.623*	0.132
46. Discover new technologies	0.292*	0.388*	0.183
47. Train novice users how to use a system	0.001	0.777*	-0.299
48. Keep up with technology trends	0.016	0.672*	0.315

Note: Notes: Factors were extracted using maximum likelihood with robust standard errors. Geomin oblique rotation was used.
**p* < .05.

The third factor seems to be mainly noise. In addition to the first two factors identified above, the third factor does not have any strong loadings and does not provide a coherent interpretable factor. Thus, we moved forward with the two-factor solution naming the first factor "technical learning self-efficacy" and the second factor "business learning self-efficacy."

After finding evidence for this two-factor structure, we sought to reduce our number of items to have a scale that is brief and easy to complete. We retained the eight items that loaded on the technical learning self-efficacy factor. Then, although the remaining items loaded on a business learning self-efficacy factor, we wanted to maintain the full content range of the construct in support of content and construct validity (Clark & Watson, 1995; Furr & Bacharach, 2014;

Marsh et al., 2004). Thus, we kept the two highest loading items from each content area of business learning self-efficacy we had included (strategy, user experience, training, data management, and new technology). This allowed us to balance retaining items with the strongest factor loadings with maintaining content and construct validity. This resulted in 10 items for business learning self-efficacy and 18 total items for the scale. This reduced set of items can be seen in Table A8.

To make sure the factor structure was maintained with this reduced set of items, we conducted another CFA with items 1-8 in Table 8 loading on technical learning self-efficacy and items 9-18 loading on business learning self-efficacy. This model showed acceptable fit to the data, $\chi 2(134) = 477.19$, $p < 0.001$, RMSEA = 0.065, CFI = 0.944, SRMR = 0.056. The factor loadings—as seen in Table A8 all appeared strong and were statistically significant. Item correlations are given in Table A9.

We then looked at the interfactor correlations and AVEs for the two factors, which are presented in Table A10. Technical learning self-efficacy and business learning self-efficacy were correlated at 0.52—not so strong to think they should be one factor. Comparing this correlation with the AVEs of the two factors corroborated this conclusion. Therefore, we moved forward with this reduced, 18 item version of the scale.

Table A8. IT Learning Self-Efficacy Standardized Factor Loadings: Sample (N = 603)

Factor	Item	Loading
Technical		
	1. Program computers	.92
	2. Design computer applications	.88
	3. Program computer applications	.88
	4. Design computer systems	.85
	5. Program software	.91
	6. Design software	.89
	7. Program computer systems	.90
	8. Program in a software language	.88
Business		
	9. Find technology-based solutions for business needs	.75
	16. Identify strategic advantages and disadvantages of different technologies	.75
	19. Understand the information needs of different jobs	.72
	22. Understand what information people need to do their jobs effectively	.69
	25. Show people how to use an information system	.79
	26. Teach people how to use new software	.81
	36. Search for information in company databases	.69
	39. Find information to answer questions	.78
	40. Adapt to changes in technology	.66
	42. Learn how to use new technologies	.69
Note: All loadings are statistically significant, $p < .001$.		

Table A9. Item Correlations

Item	1	2	3	4	5	6	7	8	9	16	19	22	25	26	36	39	40	42
1. Program computers	-																	
2. Design computer applications	.78	-																
3. Program computer applications	.82	.76	-															
4. Design computer systems	.77	.80	.72	-														
5. Program software	.84	.79	.83	.76	-													
6. Design software	.80	.84	.75	.81	.81	-												
7. Program computer systems	.84	.78	.81	.74	.83	.78	-											
8. Program in a software language	.82	.77	.80	.72	.81	.78	.78	-										
9. Find technology-based solutions for business needs	.50	.49	.45	.52	.48	.48	.43	.49	-									

16. Identify strategic advantages and disadvantages of different technologies	.41	.41	.36	.40	.43	.37	.38	.40	.64	-								
19. Understand the information needs of different jobs	.28	.26	.23	.28	.30	.23	.25	.22	.52	.57	-							
22. Understand what information people need to do their jobs effectively	.26	.23	.18	.25	.24	.19	.22	.22	.50	.53	.60	-						
25. Show people how to use an information system	.40	.42	.38	.38	.41	.37	.39	.38	.57	.59	.53	.52	-					
26. Teach people how to use new software	.43	.44	.39	.43	.45	.41	.41	.39	.57	.58	.56	.52	.70	-				
36. Search for information in company databases	.28	.26	.23	.25	.31	.25	.24	.27	.53	.51	.58	.52	.54	.52	-			
39. Find information to answer questions	.41	.41	.35	.40	.40	.39	.39	.37	.57	.53	.52	.52	.69	.72	.47	-		
40. Adapt to changes in technology	.27	.26	.20	.24	.27	.23	.24	.25	.51	.50	.50	.47	.45	.47	.50	.50	-	
42. Learn how to use new technologies	.25	.26	.20	.21	.27	.22	.22	.22	.49	.50	.50	.50	.50	.55	.54	.49	.63	-
Note: All correlations are statistically significant, $p < .001$.																		

Table A10. Interfactor Correlations Between IT Learning Self-efficacy Factors and Computer Self-Efficacy

Factor	Technical	Business
Technical learning self-efficacy	**.79**	
Business learning self-efficacy	.52**	**.54**
Note: Bolded in the diagonal is the average variance extracted for each factor. $^{**}p < .01$.		

Measurement Invariance

An important step in scale development and validation is investigating measurement invariance; this is particularly true when one wants to compare groups on a scale (Vandenberg & Lance, 2000). Measurement invariance is a matter of whether a scale functions in the same way in different groups (Vandenberg & Lance, 2000; Widaman & Reise, 1997). If invariance between groups does not hold, comparisons of scores on that scale between groups are not interpretable.

Three levels of measurement invariance should be tested before making group comparisons: configural, metric, and scalar (Widaman & Reise, 1997). Configural invariance is a test of whether the factor structure is the same in two groups. That is, all items load onto the same factors in each group. If configural invariance is found, we know that at least a similar construct is being measured in both groups but are not yet certain if it is the same (Widaman & Reise, 1997). Configural invariance can be assessed by freely estimating the model for each group simultaneously and assessing if the model fit is adequate. Metric invariance tests whether factor loadings are equivalent between groups. If factor loadings are equivalent, then the scale has the same metric, and a one-unit increase on the latent factor would result in the same increase on an observed item for someone from each group. If metric invariance is found, one can compare correlational relationships such as regression slopes between groups but not necessarily means (Chen, 2007). Scalar invariance assesses whether item intercepts are equivalent between groups. If items intercepts are not equal, this would mean that groups had a different "starting point" or origin when responding to scale items (Chen, 2007). People from different groups with the same latent factor score would systematically respond differently on the observed item. Scalar invariance must hold to be able to compare means between groups (Widaman & Reise, 1997).

Testing measurement invariance begins with the least constrained model (i.e., configural invariance) and progresses to the most constrained model (i.e., scalar invariance). Configural invariance can first be assessed with traditional model fit indices. After establishing configural invariance, the constraint of equal factor loadings between groups for metric invariance is added. Model fit indices from the metric model are compared with those of the configural model. If model fit is not meaningfully worse with the metric model compared to the configural model, then metric invariance holds. If metric invariance holds, then scalar invariance can be assessed. The scalar model maintains the constraint of equality of factor loadings and adds the constraint of equal item intercepts between groups. If model fit of the scalar model is not meaningfully worse than that of the metric model, then scalar invariance holds. As with evaluating fit of single group models, the $\chi 2$ is limited in its sensitivity to sample size and other indices are typically referenced when testing measurement invariance (Chen, 2007; Cheung & Rensvold, 2002). We followed Chen's (2007) recommendation to evaluate the following metrics when assessing the change in model fit: change in CFI (ΔCFI), change in RMSEA (ΔRMSEA), and change in SRMR (ΔSRMR). For testing metric invariance, ΔCFI < -0.01, ΔRMSEA < 0.015, and ΔSRMR < 0.03 would suggest metric invariance holds (Chen, 2007). For testing scalar invariance, ΔCFI < -0.01, ΔRMSEA < 0.015, and ΔSRMR < 0.01 suggest invariance (Chen, 2007). As with global model fit, it is important to examine multiple indices as we are here, because no index is perfect (Chen, 2007).

Because the focus of this study was comparing genders on IT learning self-efficacy and its relationship with other variables, we thought it prudent to assess measurement invariance between genders. The configural model showed adequate model fit, $\chi 2(268) = 673.36$, $p < 0.001$, RMSEA = 0.071, CFI = 0.937, SRMR = 0.057. Thus, configural invariance was achieved. The metric model maintained adequate fit, $\chi 2(284) = 690.94$, $p < 0.001$, RMSEA = 0.069, CFI = 0.936, SRMR = 0.062. Comparing the metric model to the configural model, ΔRMSEA = -0.002 ΔCFI = -0.001, and ΔSRMR = 0.005. Thus, metric invariance was achieved. The scalar model also maintained adequate fit, $\chi 2(300) = 737.88$, $p < 0.001$, RMSEA = 0.070, CFI = 0.932, SRMR = 0.065. Comparing the scalar model to the metric model, ΔRMSEA = 0.001 ΔCFI = -0.004, and ΔSRMR = 0.003. Thus, scalar invariance was achieved.

Through testing gender measurement invariance, we can conclude that our scale is measuring the same construct in both women and men and functions similarly. We can also conclude that we can compare both means and regression slopes using this scale between women and men.

We also assessed measurement invariance between those in the sample who met our desired sample characteristics for the main study (i.e., those who were freshmen, sophomores, or juniors in college and those who were not in college but planned on attending) and other respondents. We believed the IT learning self-efficacy construct should exist for all people, but we wanted to see if there were any differences in measurement properties. If measurement invariance held between these groups, we could conduct further validation tests using all participants rather than restricting it to the main study's population of interest.

The configural model for these invariance tests showed adequate model fit, $\chi 2(268) = 660.11$, $p < 0.001$, RMSEA = 0.070, CFI = 0.940, SRMR = 0.058. Thus, configural invariance was achieved. The metric model maintained adequate fit, $\chi 2(284) = 673.39$, $p < 0.001$, RMSEA = 0.067, CFI = 0.941, SRMR = 0.059. Comparing the metric model to the configural model, ΔRMSEA = -0.003 ΔCFI = 0.001, and ΔSRMR = 0.001. Thus, metric invariance was achieved. The scalar model also maintained adequate fit, $\chi 2(300) = 704.62$, $p < 0.001$, RMSEA = 0.067, CFI = 0.938, SRMR = 0.060. Comparing the scalar model to the metric model, ΔRMSEA = < 0.001, ΔCFI = -0.003, and ΔSRMR = 0.001. Thus, scalar invariance was achieved.

Confirmatory Factor Analysis in a New Sample

Because our analyses in the first sample were somewhat exploratory in nature so that we could identify the IT learning self-efficacy factor structure, we wanted to validate our findings in a new sample. Because we found measurement invariance between our desired population for the main study and all other participants, we opened this survey to all participants on MTurk. In addition, because IT is a worldwide profession, we wanted to see if this scale showed evidence of validity for people in different countries as well. Thus, we opened the survey on MTurk to people located anywhere in the world.

We again included attention check questions to exclude participants who were not paying attention from analyses. We collected 1,000 responses and paid each person $1.00 for their participation. Thirty-two responses were excluded from analyses they failed both attention checks. We also screened responses for any in which the participant did not seem to be taking the task seriously. We eliminated one response in which the participant reported being 99 years old and gave the same numeric response to every question throughout the survey. This left 967 responses for analyses. Demographic characteristics of this sample can be seen in Table A11.

In this survey, we also included a measure of computer self-efficacy (Compeau & Higgins, 1995). We included this because a major reason for creating the IT self-efficacy measure was the belief that computer self-efficacy was not the appropriate measure for learning the skills needed for an IT career. Although we would expect the variables to be correlated, we would expect them to be sufficiently different to be two separate constructs. Including computer self-efficacy allowed us to examine the discriminant validity between the constructs.

The two factor CFA of IT self-efficacy revealed adequate model fit, $\chi2(134) = 682.15$, $p < 0.001$, RMSEA = 0.065, CFI = 0.939, SRMR = 0.086. Although the SRMR was a bit higher than in the first sample, overall the results corroborated the findings in the first sample that this two-factor solution is a reasonable representation of the data. Factor loadings can be seen in Table A12.

Table A11. Scale Development Sample 2 Demographics (N=967)

	Mean	Standard deviation	Median	Min	Max
Age	34.68	10.53	31	18	74
	Frequency	**Proportion**			
Gender					
Women	370	38.26%			
Men	594	61.43%			
Other	1	0.10%			
Prefer not to answer	2	0.21%			
Race/ethnicity					
White/European American	497	51.40%			
Asian Indian	208	21.51%			
African/African American/Black	94	9.72%			
Asian/Asian American	66	6.83%			
Hispanic/Latino(a)	50	5.17%			
Biracial/Multiracial	35	3.62%			
American Indian/Native American	7	0.72%			
Arab American/Middle Eastern	2	0.21%			
Pacific Islander	1	0.10%			
Other	6	0.62%			
Preferred not to answer	1	0.10%			
Country of residence					
United States	699	72.29%			
India	209	21.61%			
Brazil	23	2.38%			
Armenia	5	0.52%			
Canada	5	0.52%			
Andorra	4	0.41%			
United Kingdom	4	0.41%			
Angola	2	0.21%			
Germany	2	0.21%			
Indonesia	2	0.21%			
Philippines	2	0.21%			
Albania	1	0.10%			
Algeria	1	0.10%			
Botswana	1	0.10%			
Greece	1	0.10%			
Ireland	1	0.10%			
Italy	1	0.10%			
Mexico	1	0.10%			
Portugal	1	0.10%			
Russia	1	0.10%			
Spain	1	0.10%			
College status					
First-year	19	1.96%			
Sophomore	40	4.14%			
Junior	28	2.90%			
Not in college but plan to go	37	3.83%			
Senior	48	4.96%			
Graduate student	206	21.30%			
Already graduated from college	474	49.02%			
Not in college and do not plan to go	115	11.89%			

Table A12. IT Learning Self-efficacy Standardized Factor Loadings: Sample 2 (N=968)

Factor	Item	Loading
Technical		
	1. Program computers	.89
	2. Design computer applications	.91
	3. Program computer applications	.91
	4. Design computer systems	.88
	5. Program software	.92
	6. Design software	.90
	7. Program computer systems	.91
	8. Program in a software language	.91
Business		
	9. Find technology-based solutions for business needs	.72
	16. Identify strategic advantages and disadvantages of different technologies	.71
	19. Understand the information needs of different jobs	.70
	22. Understand what information people need to do their jobs effectively	.67
	25. Show people how to use an information system	.73
	26. Teach people how to use new software	.70
	36. Search for information in company databases	.64
	39. Find information to answer questions	.48
	40. Adapt to changes in technology	.68
	42. Learn how to use new technologies	.66

Note: All loadings are statistically significant, $p < .001$

After confirming this factor structure, we ran the model again while including computer self-efficacy. We examined the correlations between factors to assess discriminant validity. These correlations can be seen in Table A13.

To further assess the generalizability of the IT learning self-efficacy scale, we assessed cross-country measurement invariance. The only countries with enough participants in the sample to conduct analyses with were the United States and India, so we only included participants from these two countries for these invariance analyses.

The configural model for these invariance tests showed adequate model fit, $\chi2(268) = 792.91$, $p < 0.001$, RMSEA = 0.066, CFI = 0.939, SRMR = 0.074. Thus, configural invariance was achieved. The metric model maintained adequate fit, $\chi2(284) = 813.27$, $p < 0.001$, RMSEA = 0.064, CFI = 0.939, SRMR = 0.081. Comparing the metric model to the configural model, ΔRMSEA = -0.002, ΔCFI = < 0.001, and ΔSRMR = 0.007. Thus, metric invariance was achieved. The scalar model also maintained adequate fit, $\chi2(300) = 1024.48$, $p < 0.001$, RMSEA = 0.073, CFI = 0.916, SRMR = 0.091, although the SRMR was a bit high. Comparing the scalar model to the metric model, ΔRMSEA = 0.009, ΔCFI = -0.023, and ΔSRMR = 0.010. Thus, scalar invariance did not hold, because the decrement in fit when constraining intercepts to be equal between those in the United States and India was more severe than recommended with the ΔCFI well above the 0.01 recommended threshold. limits.

Although configural and metric invariance were found between participants in the United States and India, scalar invariance did not hold. This suggests researchers may be able to look for correlational differences between people in the United States and India using this scale, such as difference in regression slopes, but mean comparisons cannot be made. Measurement invariance between these groups was not needed for the primary study in this paper, but researchers in the future may want to explore where differences in measurement arise from between these two groups.

United States Analyses

Because we did not find scalar invariance and because the current paper's focus is on people in the United States, we ran the CFA again with only United States participants (n = 699). The model fit indices indicated the model was a reasonable fit to the data, $\chi2(134) = 580.71$, $p < 0.001$, RMSEA = 0.069, CFI = 0.934, SRMR = 0.079. Factor loadings can be seen in Table A14. Item correlations are given in Table A15.

We looked at the interfactor correlations and AVEs, which are presented in Table A16. We again see that technical learning self-efficacy appears to be a separate factor from business learning self-efficacy and is distinct from computer self-efficacy with the correlation between the two being 0.39. This provides evidence for meeting our goal of measuring self-efficacy for learning to build software rather than for using software and that these are distinct self-efficacies. Interestingly, business learning self-efficacy and computer self-efficacy seem to be strongly related. Our main interest in this study was technical learning self-efficacy, because it is unique to the IT field, but future research should examine the similarities and differences between business learning self-efficacy and computer self-efficacy.

Table A13. Interfactor Correlations Between IT Learning Self-Efficacy Factors and Computer Self-Efficacy

Factor	Technical	Business	Computer self-efficacy
Technical Learning Self-efficacy	**.82**		
Business Learning Self-efficacy	.55**	**.45**	
Computer Self-efficacy	.39**	.73**	**.53**
Note: Bolded in the diagonal is the average variance extracted for each factor. ***p* < .01.			

Table A14. IT Learning Self-Efficacy Standardized Factor Loadings: Sample 2 (N = 699)

Factor	Item	Loading
Technical		
	1. Program computers	.90
	2. Design computer applications	.92
	3. Program computer applications	.91
	4. Design computer systems	.89
	5. Program software	.94
	6. Design software	.91
	7. Program computer systems	.91
	8. Program in a software language	.92
Business		
	9. Find technology-based solutions for business needs	.74
	16. Identify strategic advantages and disadvantages of different technologies	.74
	19. Understand the information needs of different jobs	.74
	22. Understand what information people need to do their jobs effectively	.70
	25. Show people how to use an information system	.73
	26. Teach people how to use new software	.72
	36. Search for information in company databases	.67
	39. Find information to answer questions	.57
	40. Adapt to changes in technology	.71
	42. Learn how to use new technologies	.70

Table A15. Sample 2 Item Correlations for United States Participants (N = 699)

Item	1	2	3	4	5	6	7	8	9	16	19	22	25	26	36
1. Program computers	-														
2. Design computer applications	.82	-													
3. Program computer applications	.82	.83	-												
4. Design computer systems	.80	.83	.79	-											
5. Program software	.83	.85	.86	.82	-										
6. Design software	.79	.88	.81	.82	.85	-									
7. Program computer systems	.85	.82	.83	.82	.86	.81	-								
8. Program in a software language	.83	.86	.84	.79	.87	.82	.82	-							
9. Find technology-based solutions for business needs	.49	.54	.53	.53	.52	.52	.50	.50	-						
16. Identify strategic advantages and disadvantages of different technologies	.49	.51	.49	.47	.50	.51	.48	.50	.67	-					
19. Understand the information needs of different jobs	.26	.31	.28	.27	.29	.30	.26	.29	.52	.51	-				
22. Understand what information people need to do their jobs effectively	.25	.26	.25	.25	.27	.25	.27	.26	.51	.50	.68	-			

25. Show people how to use an information system	.48	.52	.49	.47	.49	.49	.49	.51	.57	.57	.51	.45	-		
26. Teach people how to use new software	.43	.42	.42	.40	.42	.41	.40	.43	.52	.51	.48	.43	.68	-	
36. Search for information in company databases	.18	.23	.21	.16	.20	.20	.17	.23	.44	.39	.53	.49	.44	.49	-
39. Find information to answer questions	.15	.18	.14	.13	.15	.16	.11	.17	.33	.36	.48	.44	.32	.36	.53
40. Adapt to changes in technology	.30	.33	.29	.25	.31	.29	.28	.32	.48	.50	.52	.47	.43	.49	.56
42. Learn how to use new technologies	.28	.30	.28	.26	.29	.29	.24	.31	.46	.47	.54	.47	.47	.50	.52
Note: All correlations are statistically significant, $p < .001$.															

Table A16. Interfactor Correlations Between IT Learning Self-Efficacy Factors and Computer Self-Efficacy for United States Participants

Factor	Technical	Business	Computer self-efficacy
Technical learning self-efficacy	**.83**		
Business Learning Self-efficacy	.55**	**.49**	
Computer Self-efficacy	.39**	.73**	**.56**
Note: Bolded in the diagonal is the average variance extracted for each factor. $^{**}p < .01$.			

Measurement Invariance

To corroborate our findings from our first sample, we conducted measurement invariance analyses again for both gender and based on participants college status.

We first present the results of the college status measurement invariance analyses. The configural model for these invariance tests showed adequate model fit, $\chi2(268) = 800.20$, $p < 0.001$, RMSEA = 0.075, CFI = 0.930, SRMR = 0.080. Thus, configural invariance was achieved. The metric model maintained adequate fit, $\chi2(284) = 820.11$, $p < 0.001$, RMSEA = 0.073, CFI = 0.930, SRMR = 0.083. Comparing the metric model to the configural model, ΔRMSEA = -0.002, ΔCFI = <.001, and ΔSRMR = 0.003. Thus, metric invariance was achieved. The scalar model also maintained adequate fit, $\chi2(300) = 842.37$, $p < 0.001$, RMSEA = 0.072, CFI = 0.929, SRMR = 0.083. Comparing the scalar model to the metric model, ΔRMSEA = -0.001, ΔCFI = -0.001, and ΔSRMR = < 0.001. Thus, scalar invariance was achieved. We confirmed our findings from the first sample that the scale functions similarly for people in the United States regardless of college status.

We then moved forward to assess gender invariance using the full United States sample. Two participants reported genders other than woman or man and were not included in the gender invariance analyses. The configural model showed adequate model fit, $\chi2(268) = 745.38$, $p < 0.001$, RMSEA = 0.071, CFI = 0.932, SRMR = 0.080. Thus, configural invariance was achieved. The metric model maintained adequate fit, $\chi2(284) = 764.17$, $p < 0.001$, RMSEA = 0.070, CFI = 0.931, SRMR = 0.083. Comparing the metric model to the configural model, ΔRMSEA = -0.001, ΔCFI = -0.001, and ΔSRMR = 0.003. Thus, metric invariance was achieved. The scalar model also maintained adequate fit, $\chi2(300) = 838.63$, $p < 0.001$, RMSEA = 0.072, CFI = 0.923, SRMR = 0.086. Comparing the scalar model to the metric model, ΔRMSEA = 0.002 ΔCFI = -0.008, and ΔSRMR = 0.003. Thus, scalar invariance was achieved.

The results of gender measurement invariance analyses were robust after finding evidence for invariance in two samples. Therefore, we conclude that this scale can be used to make interpretable comparisons between women and men.

For the scale used in the main study of this paper, we made a couple of small adjustments. For questions that ask about technology, we added the word "information" before it for clarity's sake. The final list of questions used in this paper's main study can be seen in Table A17.

Table A17. IT Learning Self-Efficacy Scale Items

Directions: For the following questions, please rate your confidence that you could **successfully learn** to do the following on a scale from 1 (*Not at All Confident*) to 7 (*Completely Confident*).	
Factor	**Item**
Technical learning Self-efficacy	
	Program computers
	Design computer applications
	Program computer applications
	Design computer systems
	Program software
	Design software
	Program computer systems
	Program in a software language
Business learning Self-efficacy	
	Find information technology-based solutions for business needs
	Identify strategic advantages and disadvantages of different technologies
	Understand the information needs of different jobs
	Understand what information people need to do their jobs effectively
	Show people how to use an information system
	Teach people how to use new software
	Search for information in company databases
	Find information to answer questions
	Adapt to changes in information technology
	Learn how to use new information technologies

Appendix B: Barriers and Supplemental Analyses

Although our focus is on individual perceptions rather than cultural factors in this study, we acknowledge the importance of culture. Thus, we included some questions about individual perceptions of barriers to a career in IT that may have been influenced by culture. Intersectionality is an important feature of individual barriers. Intersectionality was originally proposed by Kimberlé Crenshaw (Crenshaw, 1989) in the University of Chicago Legal Forum. The paper used the example of DeGraffenreid v. General Motors (1974) to illustrate intersectionality. In this case, five Black women brought suit against General Motors claiming that the seniority system in place was discriminatory because prior to 1964, General Motors did not hire any Black women. General Motors hired Black men to work in manufacturing and white women to work in the secretarial pool, but it hired neither Black secretaries nor female manufacturing workers. The point of Intersectionality is that there may be interactions in bias such that, for example, Black women may face biases different from the linear combination of Blackness and womeness. Of course, this is not limited to Black and white and male and female. Intersectionality can occur across any bias, such as sexuality, socioeconomic class, disability, nationality, or a variety of other factors. This is an extremely important issue as there seems to be Intersectionality in IT career choice (Trauth et al., 2012, 2016). For example, according to the US Department of Labor, Bureau of Labor Statistics about 8% of male IT workers are Black, but only 3% of female IT workers are Black.

Unfortunately, Intersectionality is problematic to study because, by definition, minority populations contain few people, but Intersectionality leads to a combinatorial need for more data. For example, if 12% of the United States population is Black, approximately half of whom are women, then in a sample of 200 people, only 12, on average, will be Black females. And it is difficult to draw inferences from just 12 people. The problem gets worse if more factors are included. For this reason, Intersectionality studies typically need to have specialized data collection and/or use qualitative methods to obtain sufficient numbers of people from each intersection to draw conclusions. However, the current study used survey methodology with participants across the United States.

We adopted a workaround for this paper so that we did not ignore this issue while still working within the parameters of a large survey design. We asked people if they believed society placed barriers against people like them pursuing IT careers. This removed interesting details about the types of barriers and root causes of those barriers, but it has the advantage of being general across a variety of types of Intersectionality. This also has the advantage of measuring people's individual perceptions of barriers, because people respond to and perceive barriers in various ways depending on their identities (Kvasny, 2006; Trauth et al., 2016). We also asked specifically about people of your sex, people of your race, and people of your socioeconomic class. This will shed little light on causes and types of barriers but will allow for us to control for and examine barriers in general.

Analyses Including Barriers Questions

First, it is interesting to note that when men and women were asked if society posed barriers against "people like you" from pursuing an IT career, that there was a significant difference with men averaging 3.28 and women 3.81 on a seven-point scale. Both numbers are below 4.0, which would be a neutral response, so respondents leaned more toward disagree than agree. However, when subjects were asked if there were barriers against people of their gender, men averaged 2.77 and women averaged 4.16, which was the only place where respondents leaned above the midpoint in agreeing with the idea of barriers. Also, men's 2.77 average was the most extreme example of disagreeing with the barriers question. So, it seems that women think that women other than themselves face greater barriers, and men feel the exact opposite (i.e., that other men face fewer barriers). We do not have an explanation for this, and some of it may be because our sample was from MTurk, but it would be worthwhile for future research to look into this issue in more detail, to determine what those barriers are and why men and women seem to have opposite perceptions about how those barriers affect themselves relative to others of the same gender. In addition to these mean comparisons, we ran each model again with each of the four barrier types as control variables. The results of these analyses can be seen below.

Expectancy-Value Theory Models

For the sake of space, we only report the models with technical learning self-efficacy, because that was the main variable of interest for expectancy in these models.

Mean Difference

The mean difference expectancy-value models for each barrier can be seen in Table B1. Each indirect effect as well as the total effect from gender to IT career pursuit is included as well as percentile bootstrap confidence intervals. Interpretation of results remained identical to that of the original model with none of the indirect effects being significant, contrary to hypothesis H5c, and the total effect of gender on IT career pursuit being significant.

Table B1. Expectancy-Value Mediation Analysis of the Relationship Between Gender and IT Career Pursuit Controlling for Perceived Barriers

Effect	Estimate (95% C.I.)	Estimate (95% C.I.)	Estimate (95% C.I.)	Estimate (95% C.I.)
Total effect	-.19 (-.32, -.06)	-.24 (-.37, -.10)	-.18 (-.31, -.05)	-.17 (-.30, -.04)
Indirect effects				
IT career value	-.02 (-.07, .04)	-.02 (-.08, .04)	-.02 (-.08, .04)	-.02 (-.08, .04)
TLSE	-.04 (-.09, .01)	-.04 (-.09, .01)	-.03 (-.08, .01)	-.03 (-.08, .01)
TLSE→IT Career Value	-.02 (-.04, .01)	-.02 (-.04, .01)	-.02 (-.05, .01)	-.02 (-.04, .01)
Controls				
Barrier – Like You	.16 (.05, .26)			
Barrier – Gender		.211 (.11, .31)		
Barrier – Race			.23 (.13, .33)	
Barrier – SES				.18 (.07, .28)

Note: IT career value = interest in the field of information technology; TLSE = Technical learning self-efficacy; Barrier – Like You = degree of the belief that society places barriers on "people like you" from pursuing IT careers; Barrier – Gender = degree of the belief that society places barriers on "people of your gender" from pursuing IT careers; Barrier – Race = degree of the belief that society places barriers on "people of your race" from pursuing IT careers; Barrier – SE = degree of the belief that society places barriers on "people of your social class" from pursuing IT careers. Gender was dummy coded with men coded as 0 and women coded as 1. All estimates are standardized. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.

Salience Difference

The salience difference expectancy-value models for each barrier can be seen in Table B2 with the indirect effects, total effects, direct effects, and the a and b paths for each gender. It also includes bootstrap percentile confidence intervals for each parameter estimate and tests for difference in estimates between women and men. The original analysis showed that although men and women had similar mean levels of IT learning self-efficacy, this construct's relationship with IT career pursuit was stronger for women than for men. The same general results hold after controlling for different perceived barriers.

Table B2. Multigroup Mediation Analysis: The Relationship Between Technical Learning Self-Efficacy and IT Career Pursuit Mediated by IT Career Value Controlling for Perceived Barriers

	Women	Men	Difference tests	
Parameter	**Estimate (95% C.I.)**	**Estimate (95% C.I.)**	***z***	***p***
Barrier 1				
a	.42 (.19, .51)	.28 (.07, .47)	0.75	.46
b	.40 (.23, .58)	.48 (.29, .64)	-0.43	.67
c	.61 (.40, .68)	.35 (.17, .53)	1.90	.06
ab	.17 (.06, .25)	.13 (.03, .24)	0.34	.73
c'	.45 (.24, .56)	.22 (.06, .40)	1.69	.09
Barrier – Like You	.12 (-.01, .30)	.17 (.01, .32)	-0.13	.90
Barrier 2				
a	.42 (.19, .51)	.28 (.07, .47)	0.75	.46
b	.39 (.24, .57)	.51 (.33, .65)	-0.86	.39
c	.62 (.41, .68)	.35 (.17, .52)	1.91	.06
ab	.16 (.06, .24)	.14 (.03, .25)	0.16	.88
c'	.46 (.26, .56)	.21 (.07, .38)	1.86	.06
Barrier – Gender	.18 (.07, .35)	.22 (.05, .36)	-0.03	.98
Barrier 3				
a	.42 (.19, .51)	.28 (.07, .47)	0.75	.46
b	.41 (.28, .59)	.54 (.36, .69)	-1.00	.32
c	.58 (.37, .66)	.34 (.16, .52)	1.61	.11
ab	.17 (.07, .25)	.15 (.03, .27)	0.13	.90
c'	.41 (.22, .53)	.19 (.04, .36)	1.62	.11
Barrier – Race	.22 (.10, .37)	.24 (.08, .39)	-0.04	.97
Barrier 4				
a	.42 (.19, .51)	.28 (.07, .47)	0.75	.46
b	.41 (.26, .58)	.48 (.29, .65)	-0.36	.72
c	.60 (.38, .66)	.34 (.16, .52)	1.87	.06
ab	.17 (.07, .24)	.13 (.03, .25)	0.41	.68
c'	.43 (.23, .53)	.21 (.05, .39)	1.66	.10
Barrier – SES	.19 (.07, .36)	.15 (-.03, .32)	0.67	.50

Note: a = path from technical learning self-efficacy to IT career value; b = path from IT career value to IT career pursuit; c = the total effect from technical learning self-efficacy to IT career pursuit; ab = the indirect effect from technical learning self-efficacy to IT career pursuit via IT career value; c' = the direct effect from technical learning self-efficacy to IT career pursuit (after the indirect effect is accounted for); Barrier – Like You = degree of the belief that society places barriers on "people like you" from pursuing IT careers; Barrier – Gender = degree of the belief that society places barriers on "people of your gender" from pursuing IT careers; Barrier – Race = degree of the belief that society places barriers on "people of your race" from pursuing IT careers; Barrier – SE = degree of the belief that society places barriers on "people of your social class" from pursuing IT careers. All estimates are standardized. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.

Role Congruity Theory Models

Mean Difference

Indirect effects and total effects for the mean difference role congruity models controlling for barriers can be seen in Table B3. The associated percentile bootstrap confidence intervals can be seen as well. As in the original model, neither the indirect effect through communal goals nor through agentic goals was statistically significant in any of the models contrary to H8c and H8d.

Table B3. Role Congruity Theory: Total and Indirect Effects of the Relationship Between Gender and IT Career Pursuit Controlling for Barriers

Effect	Estimate (95% C.I.)	Estimate (95% C.I.)	Estimate (95% C.I.)	Estimate (95% C.I.)
Total Effect	-.18 (-.31, -.04)	-.20 (-.34, -.06)	-.18 (-.31, -.04)	-.17 (-.30, -.04)
Indirect Effects				
Communal goals	.01 (-.02, .04)	.01 (-.02, .04)	.01 (-.02, .04)	.01 (-.02, .04)
Agentic goals	.03 (-.02, .08)	.03 (-.02, .08)	.03 (-.02, .08)	.03 (-.02, .08)
Controls				
Barrier – Like You	.05 (-.08, .20)			
Barrier – Gender		.09 (-.06, .23)		
Barrier – Race			.07 (-.06, .20)	
Barrier – SES				.10 (-.03, .23)

Notes: Barrier – Like You = degree of the belief that society places barriers on "people like you" from pursuing IT careers; Barrier – Gender = degree of the belief that society places barriers on "people of your gender" from pursuing IT careers; Barrier – Race = degree of the belief that society places barriers on "people of your race" from pursuing IT careers; Barrier – SE = degree of the belief that society places barriers on "people of your social class" from pursuing IT careers. Gender was dummy coded with men coded as 0 and women coded as 1. All estimates are standardized. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.

Salience Difference

Path coefficients and confidence intervals for the salience difference role congruity theory models controlling for barriers can be seen in Table B4. The table also includes tests for differences in path coefficients between genders for both communal goals and agentic goals. Interpretation of results remained similar to that of the original models. The difference in coefficients for communal goals in each model was not statistically significant, contrary to H8e. However, the positive relationship between agentic goals and IT career pursuit was stronger for women than for men at the 5% level for three of the barriers and at the 10% level for the race barrier, providing support for H8f.

Table B4. Explaining IT Career Pursuit Using Role Congruity Theory: Tests for Gender Differences in Slopes

	Women	Men	Difference Tests	
Predictor	**Estimate (95% C.I.)**	**Estimate (95% C.I.)**	***z***	***p***
Barrier 1				
Communal goals	-.08 (-.29, .13)	.15 (-.04, .35)	-1.54	.13
Agentic goals	.49 (.29, .69)	.21 (.02, .41)	2.12	.03
Barrier – Like You	.04 (-.15, .22)	.04 (-.14, .22)	0.026	.98
Barrier 2				
Communal goals	-.08 (-.28, .13)	.16 (-.03, .36)	-1.56	.12
Agentic goals	.47 (.27, .67)	.21 (.02, .40)	1.99	.046
Barrier – Gender	.10 (-.08, .28)	.05 (-.13, .23)	0.55	.59
Barrier 3				
Communal goals	-.07 (-.27, .14)	.17 (-.03, .36)	-1.53	.13
Agentic goals	.45 (.24, .65)	.22 (.03, .41)	1.74	.08
Barrier – Race	.14 (-.04, .32)	-.03 (-.21, .15)	1.34	.18
Barrier 4				
Communal goals	-.08 (-.28, .13)	.15 (-.05, .35)	-1.50	.13
Agentic goals	.47 (.27, .67)	.22 (.03, .41)	1.95	.05
Barrier – SES	.11 (-.07, .29)	.06 (-.12, .24)	0.49	.62

Note: Barrier – Like You = degree of the belief that society places barriers on "people like you" from pursuing IT careers; Barrier – Gender = degree of the belief that society places barriers on "people of your gender" from pursuing IT careers; Barrier – Race = degree of the belief that society places barriers on "people of your race" from pursuing IT careers; Barrier – SE = degree of the belief that society places barriers on "people of your social class" from pursuing IT careers. All estimates are standardized.

Field-Specific Ability Beliefs Theory Models

Mean Difference

The analyses of field-specific ability beliefs mediating the relationship between gender and IT career pursuit controlling for each barrier can be seen in Table B5. Similar to the original model, the indirect effect was statistically significant in each of these models but in the opposite direction as what was hypothesized in H9c. Similar to the original model,

Table B5. Field-Specific Ability Beliefs Theory: Total and Indirect Effects of the Relationship Between Gender and IT Career Pursuit Controlling for Barriers

Effect	Estimate (95% C.I.)	Estimate (95% C.I.)	Estimate (95% C.I.)	Estimate (95% C.I.)
Total effect	-.18 (-.31, -.04)	-.20 (-.34, -.04)	-.18 (-.31, -.04)	-.17 (-.30, -.04)
Indirect effect				
Field-specific ability beliefs	.04 (.01, .08)	.04 (.01, .09)	.04 (.01, .08)	.04 (.01, .08)
Controls				
Barrier – Like You	.06 (-.09, .23)			
Barrier – Gender		.08 (-.10, .25)		
Barrier – Race			.07 (-.08, .23)	
Barrier – SES				.09 (-.05, .25)

Notes: Barrier – Like You = degree of the belief that society places barriers on “people like you” from pursuing IT careers; Barrier – Gender = degree of the belief that society places barriers on “people of your gender” from pursuing IT careers; Barrier – Race = degree of the belief that society places barriers on “people of your race” from pursuing IT careers; Barrier – SE = degree of the belief that society places barriers on “people of your social class” from pursuing IT careers. Gender was dummy coded with men coded as 0 and women coded as 1. All estimates are standardized. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.

Salience Difference

We tested whether there were differences between women and men in the relationship between field-specific ability beliefs and IT career pursuit while controlling for each barrier. The results of these difference tests and parameter estimates for both genders and their confidence intervals can be seen in Table B6. Similar to the original model, there were not significant differences in parameter estimates for field-specific ability beliefs, contrary to H9d.

Table B6. Explaining IT Career Pursuit Using Field-Specific Ability Beliefs Theory: Tests for Gender Differences in Slopes Controlling for Barriers

	Women	Men	Difference Tests	
Predictor	**Estimate (95% C.I.)**	**Estimate (95% C.I.)**	***z***	***p***
Barrier 1				
Field-specific ability beliefs	.26 (.07, .45)	.23 (.03, .43)	0.34	.73
Barrier – Like You	.11 (-.08, .31)	.01 (-.19, .21)	0.79	.43
Barrier 2				
Field-specific ability beliefs	.25 (.06, .43)	.26 (.05, .46)	0.11	.91
Barrier – Gender	.18 (-.01, .36)	-.04 (-.25, .17)	1.62	.11
Barrier 3				
Field-specific ability beliefs	.23 (.04, .41)	.30 (.10, .50)	-0.32	.75
Barrier – Race	.23 (.05, .42)	-.13 (-.33, .08)	2.57	.01
Barrier 4				
Field-specific ability beliefs	.24 (.05, .43)	.23 (.04, .42)	0.26	.79
Barrier – SES	.17 (-.03, .36)	.02 (-.17, .21)	1.17	.24

Note: Barrier – Like You = degree of the belief that society places barriers on “people like you” from pursuing IT careers; Barrier – Gender = degree of the belief that society places barriers on “people of your gender” from pursuing IT careers; Barrier – Race = degree of the belief that society places barriers on “people of your race” from pursuing IT careers; Barrier – SE = degree of the belief that society places barriers on “people of your social class” from pursuing IT careers. All estimates are standardized.

Appendix C: Measures

Computer Self-Efficacy Measure (Compeau & Higgins, 1995)

In general, I could complete any desired task using any computer/internet application if ...

1. ... there was no one around to tell me what to do
2. ... I had never used a package like it before.
3. ... I had only the software manuals for reference.
4. ... I had seen someone else using it before trying it myself.
5. ... I could call someone for help if I got stuck.
6. ... someone else helped me get started.
7. ... I had a lot of time to complete the job for which the software was provided.
8. ... I had just the built-in help facility for assistance
9. ... someone showed me how to do it first.

10 ... I had used similar packages like this one before to do the job.

STEM Career Interest Questionnaire Subscale (Adapted) (Tyler-Wood et al., 2010)

To me, a CAREER in information technology (is)

		1	2	3	4	5	6	7	
1	means nothing								means a lot
2	boring								interesting
3	exciting								unexciting
4	fascinating								mundane
5	appealing								unappealing

Note. Items 3 through 5 were reverse coded so that higher scores would represent greater IT career value. Item 1 was dropped because it decreased the internal consistency reliability estimate for the scale.

Communal Goal Endorsement (Diekman et al., 2010)

How important is each of the following kinds of goals to you personally on a scale ranging from 1 (Not at All Important) to 7 (Extremely Important)?

1. Serving community
2. Working with people
3. Altruism
4. Helping others
5. Connecting with others
6. Serving humanity
7. Attending to others
8. Caring for others
9. Spirituality
10. Intimacy

Agentic Goal Endorsement (Diekman et al., 2010)

How important is each of the following kinds of goals to you personally on a scale ranging from 1 (Not at All Important) to 7 (Extremely Important)?

1. Power
2. Recognition
3. Achievement
4. Mastery
5. Self-promotion
6. Independence
7. Individualism
8. Status
9. Focus on the self
10. Success
11. Financial rewards
12. Self-direction
13. Demonstrating skill or competence
14. Competition

Field-Specific Ability Beliefs (Leslie et al., 2015; Meyer et al., 2015)

Please rate your level of agreement with the following statements on a 7-point scale (1 = Strongly Disagree to 7 = Strongly Agree).

1. Being an exceptional information technology professional requires a special aptitude that just can't be taught.
2. If you want to succeed in information technology, hard work alone just won't cut it; you need to have an innate gift or talent.
3. With the right amount of effort and dedication, anyone can become an exceptional information technology professional.
4. When it comes to information technology, the most important factors for success are motivation and sustained effort; raw ability is secondary.
5. To succeed in information technology you have to be a special kind of person; not just anyone can be successful in it.
6. People who are successful in information technology are very different from ordinary people.

Appendix D: Mean Difference Analyses Detailed Results

Expectancy-Value Theory

Path coefficients and R^2 values for the three mean difference expectancy-value models are presented in Figure D1. In terms of variance explained in both IT career pursuit and IT career value, as well as the strength of the relationships between constructs evidenced by beta coefficients, our technical learning self-efficacy measure seemed to outperform computer self-efficacy.

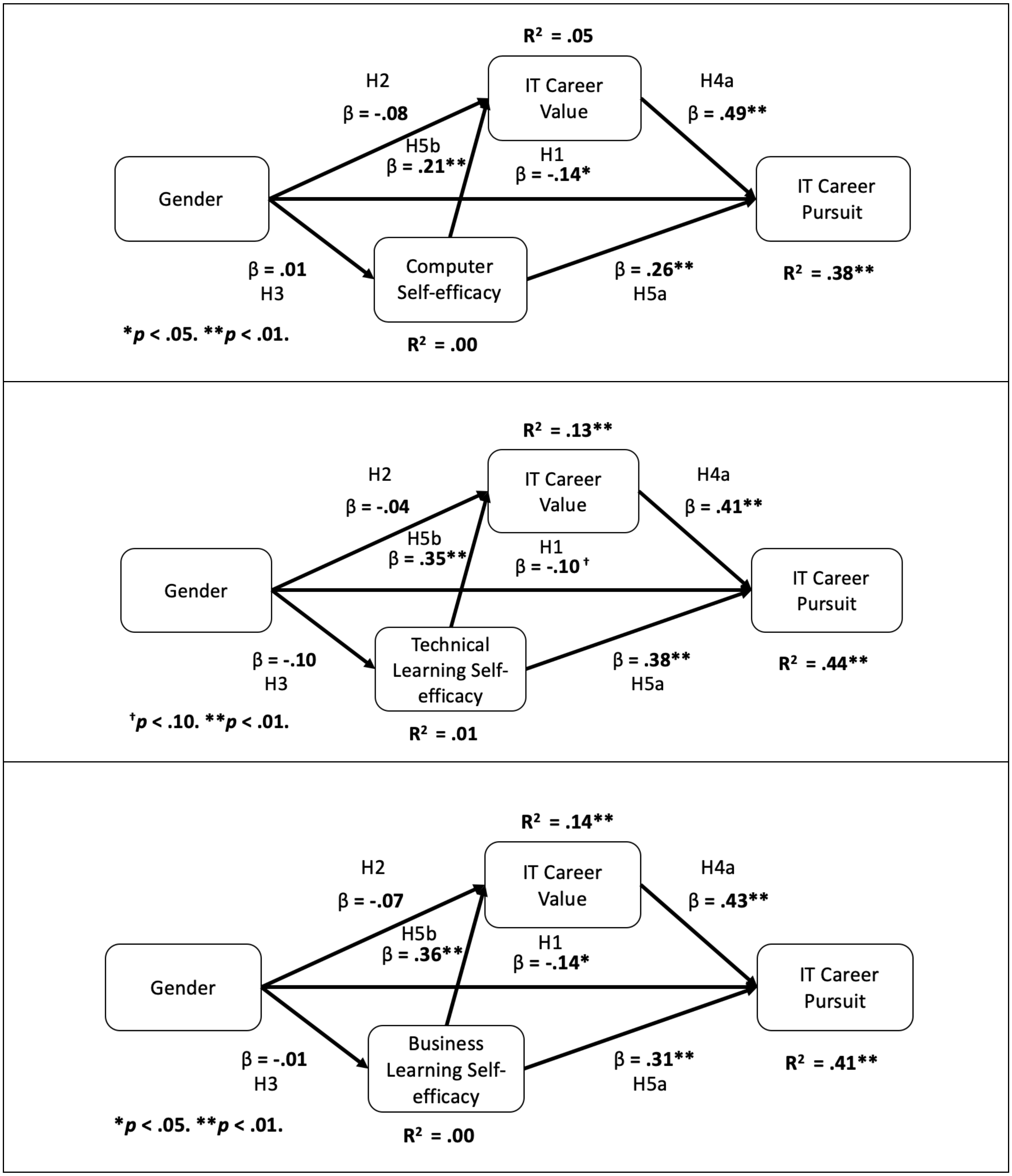

Figure D1. Expectancy-Value Theory Mean Difference Models

Results of the mediation analyses can be seen in Table D1. Because these models had two mediators, we tested each potential mediating path. Each indirect effect as well as the total effect from gender to IT career pursuit is included as well as percentile bootstrap confidence intervals. None of the indirect effects were significant, contrary to hypothesis H5c.

Table D1. Total and Indirect Effects of the Relationship Between Gender and IT Career Pursuit

Effect	**Standardized estimate (95% C.I.)**
Total effect	-.17 (-.30, -.03)
Indirect effects	
CSE	
IT career value	-.04 (-.10, .03)
CSE	.00 (-.03, .04)
CSE → IT career value	.00 (-.02, .02)
TLSE	
IT career value	-.02 (-.07, .04)
TLSE	-.04 (-.09, .01)
TLSE → IT career value	-.02 (-.04, .00)
BLSE	
IT career value	-.03 (-.09, .02)
BLSE	.00 (-.04, .04)
BLSE → IT career value	.00 (-.03, .02)
Note: IT career value = interest in the field of information technology; CSE = Computer self-efficacy; TLSE = Technical learning self-efficacy; BLSE = Business learning self-efficacy. Gender was dummy coded with men coded as 0 and women coded as 1. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.	

Role Congruity Theory

Path coefficients and R^2 values for the role congruity theory mean difference multiple mediation model can be seen in Figure D2. The R^2 for IT career pursuit in this model was 0.17. Gender only explained about 2% of the variance in communal goals and 1% of the variance in agentic goals. After considering communal and agentic goals, gender was still significantly related to IT career pursuit, b = -0.21, z = -3.20, $p < 0.01$.

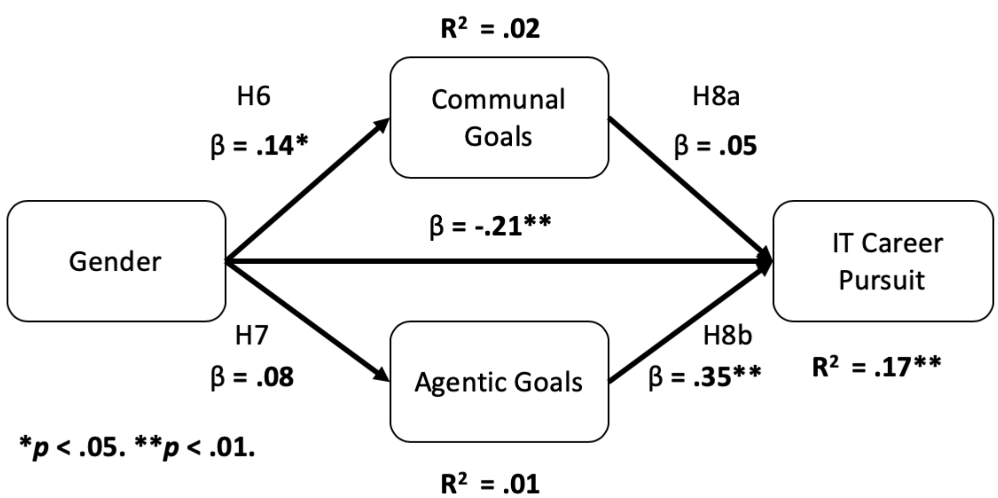

Figure D2. Mean Difference Model for Role Congruity Theory

Indirect effects for this model as well as the total effect can be seen in Table D2. The associated percentile bootstrap confidence intervals are also displayed.

Table D2. Role Congruity Theory: Total and Indirect Effects of the Relationship Between Gender and IT Career Pursuit

Effect	Standardized estimate (95% C.I.)
Total effect	-.17 (-.30, -.03)
Indirect effects	
Communal goals	.01 (-.02, .04)
Agentic goals	.03 (-.02, .08)
Note: Gender was dummy coded with men coded as 0 and women coded as 1. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.	

Field-Specific Ability Beliefs Theory Models

Path coefficients and R^2 values for the field-specific ability beliefs mediation model can be seen in Figure D3. The R^2 for IT career pursuit is 0.10. Gender only explained about 2% of the variance in field-specific ability beliefs, but the relationship between gender and field-specific ability beliefs was statistically significant, b = -0.21, z = 2.32, p = 0.02.

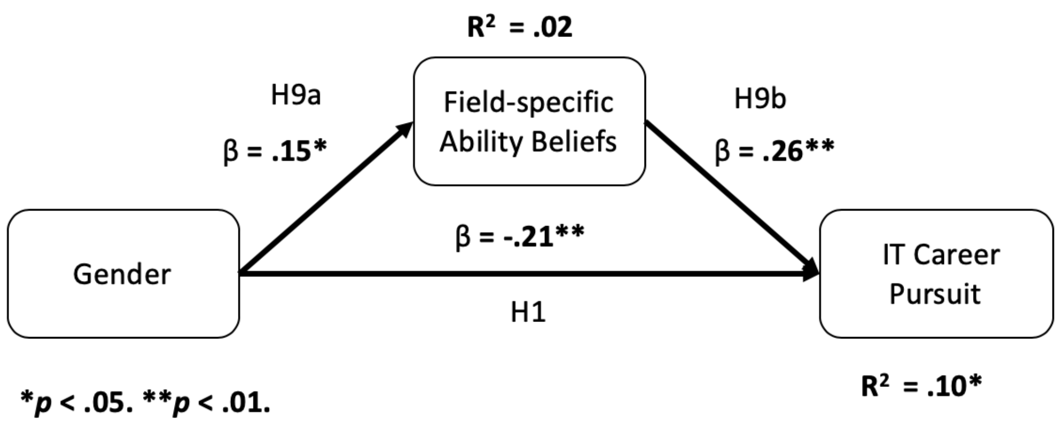

Figure D3. Mean Difference Model for Field-specific Ability Beliefs Theory

The analysis of field-specific ability beliefs mediating the relationship between gender and IT career pursuit can be seen in Table D3.

Table D3. Field-Specific Ability Beliefs Theory: Total and Indirect Effects of the Relationship Between Gender and IT Career Pursuit

Effect	Standardized estimate (95% C.I.)
Total Effect	-.17 (-.30, -.03)
Indirect effect	
Field-specific ability beliefs	.04 (.01, .09)
Note: Gender was dummy coded with men coded as 0 and women coded as 1. Confidence intervals were calculated using the percentile bootstrap method with 5,000 draws.	

About the Authors

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