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Women in Analytics: Exploring A Potential Path to Increase Female Participation in Computing Careers

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Abstract

The underrepresentation of women in computing has long been recognized as a problem. Despite many resources being applied to this issue, the representation of women in computing in the United States has been on the decline for the past four decades. In this work, we explore gender and negative stereotypes about data analytics, an application area of computer work that possesses a number of features that previous research identified as being more attractive to women. We conducted a survey of students at the University of Wisconsin-Whitewater comparing their impressions of computing and analytics professionals, and we found that they held fewer negative and gender stereotypes about analytics professionals than computing professionals. We suggest possible changes that could be incorporated into curriculum and future areas of research to bolster female students' interest in computing careers.

Keywords: women in computing, women in analytics, technology careers, broadening participation in computing

Introduction

The underrepresentation of women in technology has been recognized for the past few decades. This phenomenon has been the focus of many industry, non-profit, and academic efforts to reverse this trend. Despite these initiatives, the gap stubbornly persists. In 2019, only 21% of CS undergraduate degrees earned in the US were awarded to women (NCWIT, 2020). Research indicates that this disparity is likely due to stereotypes around computing careers and who is likely to be a computing professional. Women often encounter stereotypes that erode their sense of efficacy in computing professions (Cheryan et al., 2009). Furthermore, other research suggests that women lack a sense of belonging, which may explain why some women opt out of the field (Sax et al., 2018). A study by Diekman et al. (2010) found that STEM careers are perceived as inhibiting communal goals (e.g. working with or helping other people). According to Martell, Lane, & Emrich (1996), even small effects of communal motivation could lead to women opting out of STEM careers, especially if such small effects accumulated over time.

A variety of interventions have been deployed in an effort to combat these issues. In addition to industry diversity initiatives, academics have researched the impact of summer camps (Webb and Ronson, 2011; Outlay et al., 2017) and classroom factors (Sax et al., 2018). Other works suggest that a shift in the way we think about computer careers may have a positive impact on this issue. For example, much of the research in this area focuses on students in America or other western societies. However, research on societies across the globe suggest that this phenomenon is not universal (Adya and Kaiser, 2005; Mellström, 2009; Sien et al., 2014). Further, other researchers have suggested that a shift in what we consider to be computer work or computer workers may provide a fuller picture of what it means to work in computing (Vitores & Gil-Juárez, 2016).

In this paper, we take a broader view of computer work by focusing on data analytics. Although analytics is a technical discipline, its focus on interdisciplinary applications and emphasis on the effective communication of discovered knowledge differentiates it from other technical areas of study, such as computer science. Thus, analytics content may be a way to encourage more female representation in computing careers overall by providing a more attractive introduction. Further, there tends to be overlap in curriculum between analytics and other computing professions, such as Information Technology or Computer Science. Greater female interest in analytics could have a positive impact on their perception of those related majors. We administered a survey on gender and negative stereotypes to students enrolled in data analytics courses at a the University of Wisconsin-Whitewater to explore how data analytics is perceived as opposed to more traditional computer professions.

Literature Review

The gender disparity in computing and technology is well known and well-studied. Despite the attention of industry, governments, non-profits, and academics, the gender gap stubbornly persists. Female representation in computer science peaked in 1980 with women representing 44% of degree earners, but has been on the decline for most of the past four decades (Sax et al., 2017). In 2015, a study found that only 1.7% of female freshman respondents intended to major in Computer Science, as opposed to 6.3% of their male peers (Egan, 2015). Further, in 2019, only 21% of those awarded CS undergraduate degrees were women (NCWIT, 2020).

Gender roles and Societal Influence

Gender roles and societal influence are frequently identified as contributing factors the dearth of women in computing (Huffman et al., 2013). Young girls often adopt the belief that tech careers are “men’s work” early in their education (Ramsey and McCorduck, 2005), and this attitude can present a significant barrier to women pursuing the profession (Bock et al., 2013). Further, the image of the IT profession as being boring, nerdy, and socially isolated elevates the challenge even further (ACM, 2009). A 2009 study of college-bound girls and boys showed that slightly more than a third of girls (35%) rated IT as a good major or a very good major. The same study reported that 74% of boys rated IT as a good major or a very good major (ACM, 2009). According to a study by Buzzetto-More (2010), many women students reported that they had not studied computers or programming in high school or were exposed to IT careers. In addition, many of them were discouraged from pursuing an IT-related career. A study by Master et. al. (2015) reported that girls exposed to classes that did not perpetuate negative stereotypes of IT had significantly more interest in enrolling in computer courses (Master et. al., 2015). The result of persistent negative perceptions is a shortage of women in IT majors in college and in IT careers.

Some prior works investigate the differences in societal factors on career choice among different cultures. Hill et al. 2010 found that cultural factors in the U.S. negatively impact how girls perceive their abilities in math, science, and engineering. Gender bias in IT careers is also prevalent in countries other than the US. A study by Vekiri and Chornaki (2008) reports that Greek boys perceived more support for their interests in use of computers than their female counterparts. Furthermore, parental encouragement and expectations were strong predictors of self-efficacy. In Brazil, the gender gap continues to widen, and women view computer science as a field that is dominated by men (Holanda et al., 2020). Contrarily, in some countries the situation is quite the opposite (Adya and Kaiser, 2005; Mellstrom, 2009). For example, Malaysian girls tended to have positive attitudes towards technology related careers (Sien et.al, 2014). In India, the beliefs about women's incompetency in mathematics or notions of differences in intrinsic intellectual ability do not seem to occur in socio-cultural context (Mukhopadhyay, 2009). Gender does not play any role in acquiring mathematical and problem-solving skills for education in computer-related fields (Varma, 2011). Still, there are less women than men in doctoral education in STEM fields.

"Leaky Pipeline" and Interventions

Many prior works focus on the "leaky pipeline" of women in computing and interventions to retain women throughout their academic careers. However, Vitores & Gil Gil-Juárez (2016) assert that researchers ought to look at the problem more broadly. Specifically, they suggest researchers focus on highlighting a variety of additional research landscapes, including broadening the definition of computing work to include interdisciplinary or intersectional domains. Other works focusing on the leaky pipeline have also found evidence to support the importance of looking at more interdisciplinary computing work. Outlay et al. (2017) found that middle school girls had a greater interest in interdisciplinary computing work (e.g. creating and editing digital videos and music, computer graphics and media) than pure computing (e.g. computer science, computer programming). Kahn & Luxton-Reilly (2016) posit that much of the way computer science is stereotyped (e.g. a male-oriented discipline with little social interaction) alienates females students, and argues that computing courses should incorporate socially relevant examples and exercises to combat this. Further, Margolis and Fisher (2002) found that even women interested in computer science find it more meaningful if the domain is interdisciplinary.

Importance of Human Interaction

The perception that computing careers are more technical rather than people-oriented impacts recruitment efforts. Papastergiou (2008) found that many students chose not to study computer science because they preferred more human interaction. They found that this view is pronounced among female students, with male students more likely to view computer science as human oriented than female students. It may be that this influences female students to select majors with a greater perceived social impact (Buckley, 2009).

In this study, we build on these prior works by investigating attitudes towards an interdisciplinary technology field: data analytics. Data analytics incorporates elements of traditional computing disciplines (e.g. computer programming, databases, artificial intelligence) with technical communication (e.g. storytelling, visualizations) and apply these techniques to a variety of domains. Data science and data analytics are related; however, data science is differentiated by a greater focus on the technical aspects. Similar to other computing domains, data science suffers from a gender imbalance, with women represented only 15-22% of data scientists (Duranton et al., 2020). However, by focusing on a domain such as data analytics that has many socially oriented and interdisciplinary aspects, it may be a fruitful avenue to attract greater female representation.

Methodology

In this study, we evaluated the differences in negative and gender stereotypes of those in computing careers and analytics careers. In this section, we will discuss our Instrument/Survey, Subjects and Procedure, and Data Analysis.

Instrument/Survey

To gather our data, we distributed an anonymous survey to students enrolled in analytics courses. The surveys consisted of demographic questions, as well as questions we adapted from prior studies designed to measure stereotypes of computer workers (Web and Rosson, 2011; Outlay et al., 2017). These consisted of 7-point Likert type questions (Table 1) where respondents could indicate the degree to which they agreed or disagreed with common negative and gender stereotypes of computer workers. The same questions were then adapted to refer to analytics workers. We obtained IRB approval prior to conducting our survey.

Research question 1: *Are negative stereotypes about analytics professionals as prevalent as those about computing professionals?*

Research question 2*: Are gender stereotypes about analytics professionals as prevalent as those about computing professionals?*

Subjects and Procedure

We used a convenience sample of students (N=70) enrolled in at least one data analytics course at the University of Wisconsin-Whitewater. Of those respondents, 16 were undergraduates and 54 were graduate students. Respondents were 52.86% male, 42.86% female, and 2.86% declined to specify a gender, while 75.71% identified as White/non-Hispanic, 12.86% Hispanic, 5.71% Asian or Pacific Islander, 2.86% black/non-Hispanic, and 1.42% other. A minority of our respondents identified as first-generation college students (25.71%).

To gather our data, we distributed an anonymous survey to students enrolled in an undergraduate and a graduate analytics course. Students were invited to complete the survey and were awarded a small amount of extra credit for their participation. The survey was open for several days, and students were allowed to take it at a time and location of their choosing.

Data Analysis

After the survey period ended, results were compiled and analyzed. Our instrument exhibited a good level of reliability, with a Cronbach's Alpha of .8290. As we wanted to compare particular negative and stereotypes about computing professionals as opposed to analytics professionals, we compared responses for each category both for the entire cohort as well as the responses broken out by gender. Statistical significance was established using a t-test.

Results

In this section, we present our results followed by our findings for each of our research questions. Table 1 shows the aggregate responses to the survey, with 1 being strong agreement with the statements and 7 being strong disagreement. A number of statistically significant differences were found between how respondents viewed computing professionals and analytics professionals.

We found that respondents were more likely to disagree with negative stereotypes about computer professionals as opposed to analytics professionals. Respondents disagreed more strongly that analytics professionals are technology geeks (computing professionals: 4.51; analytics professionals: 5.17) and they were less likely to think about computer geeks when thinking about analytics professionals (computing professionals: 4.96; analytics professionals: 5.55). Respondents also felt that the analytics profession was less dominated by men (computing professionals: 4.33; analytics professionals: 5.06), and disagreed more strongly that men were more likely to pursue analytics professions than women (computing professionals: 5.32; analytics professionals: 5.64). This suggests that the answer to our second research question is that gender stereotypes about analytics professionals are less prevalent than those about computing professionals.

Table 1: Results of survey on negative stereotypes and gender stereotypes, with 1: Strongly agree to 7: Strongly Disagree (* p<=0.05; ** p<=0.01)

	Computing	Analytics	Diff.
[Computing | Analytics] professionals tend to be nerds.	5.30	5.17	0.13
[Computing | Analytics] professionals tend to be technology geeks.	4.51	5.17	**-0.67****
When I think about [computer | analytics] professionals, I think about computer geeks.	4.96	5.55	**-0.59****
The [computer | analytics] profession is dominated by men.	4.33	5.06	**-0.72****
Men, rather than women, typically pursue careers in [computers | analytics].	5.32	5.64	**-0.32***
[Computer | Analytics] professionals tend to be intelligent.	3.29	3.39	-0.10
[Computer | Analytics] professionals tend to have good problem-solving skills.	3.29	3.35	-0.06
[Computer | Analytics] professionals tend to be willing to keep up with technology.	3.42	3.70	**-0.28***
[Computer | Analytics] professionals tend to have good managerial skills	4.99	4.41	**0.58****
[Computer | Analytics] professionals tend to have good communication skills.	5.14	4.28	**0.87****
[Computer | Analytics] professionals tend to have good people skills.	4.97	4.54	**0.43***
[Computer | Analytics] professionals do a lot of programming.	4.22	4.61	**-0.39****
[Computer | Analytics] professionals tend to have a strong background in math and science.	4.48	4.14	**0.33***

Respondents also indicated that certain people oriented soft-skills were more important for analytics professionals than for computer professionals. Respondents felt analytics professionals were more likely to have strong managerial skills (computing professionals: 4.99; analytics professionals: 4.41). Interestingly, there was no significant difference between perceptions in certain positive stereotypes, specifically high intelligence and strong problem-solving skills. This lends support for our first research question in that there are fewer negative stereotypes about analytics professionals being more technology than people oriented.
We then analyzed our respondents results by gender, as shown in Table 2. While many of the items did not have significant differences in how stereotypes were perceived, some did. Men disagreed more strongly with the negative stereotypes associating analytics professionals with computer geeks and the profession as being dominated by men. Women disagreed more with analytics professionals needing to keep up with

technology and having to do a lot of programming. Women agreed more strongly than men that analytics professionals need strong people skills.

Table 2: Differences in perceived negative stereotypes and gender stereotypes by gender (* p<=0.05; ** p<=0.01)

Responses for men	Computing	Analytics	Diff.
When I think about [computer | analytics] professionals, I think about computer geeks.	4.78	4.59	-0.79**
The [computer | analytics] profession is dominated by men.	4.24	5.14	-0.89**
[Computer | Analytics] professionals tend to be willing to keep up with technology.	3.51	3.54	-0.03
[Computer | Analytics] professionals tend to have good people skills.	4.62	4.27	0.35
[Computer | Analytics] professionals do a lot of programming.	4.08	4.35	-0.27
Responses for women	**Computing**	**Analytics**	**Diff.**
When I think about [computer | analytics] professionals, I think about computer geeks.	5.20	5.63	-0.43**
The [computer | analytics] profession is dominated by men.	4.40	4.90	-0.50*
[Computer | Analytics] professionals tend to be willing to keep up with technology.	3.33	3.90	-0.57**
[Computer | Analytics] professionals tend to have good people skills.	5.37	4.77	0.60**
[Computer | Analytics] professionals do a lot of programming.	4.43	4.97	-0.53**

Discussion

In this paper, we conducted a survey of analytics students to investigate the prevalence of negative and gender stereotypes about analytics professionals as opposed to computing professionals. Specifically,

Research question 1: *Are negative stereotypes about analytics professionals as prevalent as those about computing professionals?*

We found that overall, negative stereotypes about analytics professionals were less prevalent. They were less likely to ascribe the moniker of "geeky". They also were more likely to perceive soft skills as being important for analytics professionals than computer professionals. Based on prior literature, these features are more attractive to female students.

Research question 2: *Are gender stereotypes about analytics professionals as prevalent as those about computing professionals?*

Our results indicate that respondents were less likely to perceive gender stereotypes about analytics professionals than computer professionals. This may be an important key to helping female students picture themselves as analytics professionals, as prior work has found this perception to be a significant barrier preventing women from pursuing computer careers (Bock et al. 2013).

If analytics is a subset of the general computing and IT field, why does the perception of analytics seem to be more positive? Why is the analytics profession viewed as less geeky, more social, more managerial-focused, and more desirable? We posit that the results stem from three possible explanations at three levels: perceptual, cognitive, and social. These explanations are not mutually exclusive and can co-exist and impact the decision to study in the computing and analytics field simultaneously or none at all. We discuss each possible explanation and offer paths for future research in this domain.

Perceptual Explanation

Living at a time when people of all ages need to process a plethora of information daily (Bawden & Robinson, 2020), individuals attempt to avoid or reduce information overload by using shortcuts in their decision-making (Nathaniel, 2022). Thus, titles and keywords have become their saviors. For instance, most people don't read the news itself but rather read only the headline (Van der Meer et al., 2020; Xie, 2019). Combining the existing stereotypes about women and computing (Vitores & Gil-Juárez, 2016) with daily attempts to reduce cognitive overload by relying on keywords, headlines, and titles can explain the ever-stagnant growth of women in computing and the bigger popularity of the analytics field. It is possible that many will only judge choices, items, and fields of study primarily based on the words used to describe those fields.

For this reason, appearances matter. Using the right word or phrase should not only be a marketing priority but also crucial in any communication. In other words, degree titles, major benefits, and other descriptors must be updated to words the current climate perceives more positively. This is somewhat analogous to corporations and media using constantly outdating certain words and using "politically correct words" instead to be more inclusive and neutral to everyone (e.g., artificial instead of man-made) (Ehlion, 2022). Similarly, in the context of women and computing, one stream of research can investigate which words are neutral or positively perceived by the targeted audience. Survey and focus group studies can be conducted to understand a) what qualities and attributes women are after in a major, b) understand which keywords trigger negative perceptions in their mind, c) investigate new keywords based on the results of (a) and (b).

Cognitive Explanation

The second explanation behind the results can be due to real deficiencies in the computing fields. This is where the issue is not merely surface level concerning using the right words. Rather, this reason deals with computing majors' actual content and offers. Under this explanation, it is assumed that the person has deliberated on their decision and has not mainly relied upon their perception to make a decision. Selecting a field of study and career is a personal choice. Although there are similarities to what all genders value in studies and careers, there are notable differences. For example, for women, a career that helps society and offers more time flexibility to be with family is more important than for men (Pew Research, 2013). Additionally, certain subjects, such as math, create more anxiety in women to the point that "math anxiety" is highlighted as a barrier to entry (AAUW, 2020).

Per this potential reason, the female students may astutely have investigated their options and found that computing doesn't have the desirable qualities they are after (e.g., helping society) and, worse, has attributes such as math, which can be anxiety-inducing. To address this potential cause, colleges must update their degree content and offer more support. This does not mean the colleges should start offering courses that are only desirable to students, ignoring market demands. Rather, the goal is updating the course materials based on the workplace expectations and present them in a way that is more engaging considering the student population, for example by using more examples of women in business, having additional women guest speakers, and intentional diversifying the methods of delivery and networking events. As another example, they should offer more courses and support for more anxiety-inducing topics. This can be beneficial for students of all genders. They should also highlight and discuss the benefits of careers in computing, which resonates more with women. We note these suggestions based on what has been done thus far. However, there is room for future researchers to understand what values female students have in the current age. Surveys and experiments to compare the status quo program curriculum with a novel curriculum that includes content and discussion of values important to women can be an exciting domain of future work.

Social Explanation

The final explanation can be attributed to the representation of women in general in the computing field. If we were to ask a focus group to imagine a person who works in IT or computing, chances are most will describe a man with glasses. When the media has historically depicted people in computing as men, when educational systems from early grades to universities do not attempt to highlight women in computing in history, and when most of the women in prior generations have not entered a career in computing (AAUW, 2020), it is no surprise that many current female students don't wish to enter the field of computing. People observe the world around them to make decisions and use others as role models. When they don't exist, it may feel risky to do something that others haven't. Considering most people, particularly women at younger ages, are more risk-averse (Jianakoplos & Bernasek, 1998), it is understandable why many wouldn't enter the field of computing. This also explains why analytics is more popular because it is novel in the eyes of many. Unlike computing and IT, society has not set expectations and established stereotypes.

Per this explanation, a social movement is required to push women's growth in the computing field. Accordingly, among all three possible explanations offered, this is the hardest to achieve as a change will only everyone from media to existing establishments, men, women, and other groups work together to make the societal shift. As for researchers, they can investigate how much societal reasons influence the decision-making of female college students. There's no denying that society's perception influences a person's perception. However, the degree of this influence can be worth investigating. For example, researchers can identify various societal factors, test their association as antecedents with perceptual factors, and see how both impact decision-making to study various computing majors.

Limitations

There are three main limitations to this study. First, despite the diversity in respondents (both gender and race), all respondents are roughly around the same age. As people age, perceptions will change and grow. Thus, the use of the convenience sample in this case poses an inherent limitation. Additionally, as with any student population from one location, it is possible the students' perceptions are influenced by their environment. While we cannot say that for certain, it is nonetheless a limitation to the findings. Finally, the methodology used in the study was not developed to find causation or establish association. Instead, to observe the existing perceptions of the students. We accepted the limitation in this stage as the study was designed to observe the existing perceptions. However, future work can further expand on these observations through more complex methodologies.

Future Research

Future studies can further improve upon the study's sample size, including students from various majors and expanding the study to middle school and high school. Table 3 summarizes future paths for the research.

Table 3 – Summary of Potential Explanations, Possible Solutions, and Future Research

Explanation	Description	Possible Solution	Future Research
Outdated descriptors **(Perceptual)**	Students are dissuaded by words, titles, keywords due to existing stereotypes	Change the degree titles, keywords, and description to something that while relevant to workplace requirement, is new and positively perceived	Conduct surveys, focus groups to understand the right words to use for computing majors and what qualities are female students are after
Outdated Content **(Cognitive)**	Students are dissuaded by the content of the major	Update the course requirement, add additional materials that desirable to female students	Conduct experiments, A/B testing between a status quo program curriculum with modified curriculum which has integrated the most desirable qualities
Outdated Culture **(Social)**	Students are dissuaded by how society/culture view computing field	Require a cultural movement at all levels	Research can investigate how societal views impact students' decision in pursuing computing

Conclusion

With the decline in participation and representation of women in computing, the current study set out to discover the perceptions of the students regarding this topic. In particular, we surveyed students on negative stereotypes and gender stereotypes with respect to computing fields. We additionally asked students about their perceptions of analytics and compared the results with those from computing. We observed that both negative and gender stereotypes are present more strongly among women. Not only do they perceive computing as a more male-friendly, but they also perceive it as geekier, more tech-oriented, and less social than analytics. While we argue that the causes can be merely based on respondents' perceptions, both cognitive and social reasons could be behind such negative and gender stereotypes. As we move towards a future where technology will dominate all industries, it is crucial to understand the hesitancy that women may have to join the computing field and try to address those reasons because lack of women representation in computing will not only create unhealthy power dynamics in the workplace but may also hinder women from fully realizing their potential (in particular if their hesitancy is due to social or perceptual views) and prevent them from contributing to the future where technology and computing will be the most prevalent and influential career choices. Further, these insights can be leveraged in future research to determine if additional analytics exposure or related interventions can provide a more positive introduction to other computing careers, such as Information Technology or Computer Science.

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References

AAUW. (2020). The STEM Gap: Women and Girls in Science, Technology, Engineering and Mathematics. https://www.aauw.org/resources/research/the-stem-gap/

Adya, M., & Kaiser, K. M. (2005). Early determinants of women in the IT workforce: a model of girls' career choices. Information Technology & People, 18(3), 230-259.

Bawden, D., & Robinson, L. (2020). Information overload: An overview.

Bock, S. J., Taylor, L. J., Phillips, Z. E., & Sun, W. (2013). Women and minorities in computer science majors: Results on barriers from interviews and a survey. Issues in Information Systems, 14(1), 143-152.

Buckley, M. (2009). Viewpoint Computing as social science. Communications of the ACM, 52(4), 29-30.

Cheryan, S., Plaut, V. C., Davies, P. G., & Steele, C. M. (2009). Ambient belonging: how stereotypical cues impact gender participation in computer science. Journal of personality and social psychology, 97(6), 1045.

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.

Duranton, S., Erlebach, J., Brégé, C., Danziger, J., Gallego, A. and Pauly M. (2020). What's Keeping Women Out of Data Science? BCG Global. https://www.bcg.com/publications/2020/what-keeps-women-out-data-science

Eagan, K., Stolzenberg, E. B., Ramirez, J. J., Aragon, M. C., Suchard, M. R., & Hurtado, S. (2014). The American freshman: National norms fall 2014. Los Angeles: Higher Education Research Institute, UCLA, 36.

Ehlion. (2022). What is Politically Correct language?

Gupta, N. (2012). Women undergraduates in engineering education in India, A study of growing women's participation. Gender, Technology and Development, 62(2), 153–176. https://doi.org/10.1177/097185241201600202

Hill, C., Corbett, C., & St Rose, A. (2010). Why so few? Women in science, technology, engineering, and mathematics. American Association of University Women. 1111 Sixteenth Street NW, Washington, DC 20036.

Holanda, M., Mourao, R. N., von Borries, G., Ramos, G. N., Araujo, A., & Walter, M. E. (2020, October). What do female students in middle and high schools think about computer science majors in Brasilia, Brazil? A survey in 2011 and 2019. In 2020 IEEE Frontiers in Education Conference (FIE) (pp. 1-7). IEEE.

Huffman, A. H., Whetten, J., & Huffman, W. H. (2013). Using technology in higher education: The influence of gender roles on technology self-efficacy. Computers in Human Behavior, 29(4), 1779-1786.

Jianakoplos, N. A., & Bernasek, A. (1998). Are women more risk averse? Economic Inquiry, 36(4), 620–630.

Khan, N. Z., & Luxton-Reilly, A. (2016, February). Is computing for social good the solution to closing the gender gap in computer science?. In Proceedings of the Australasian Computer Science Week Multiconference (pp. 1-5).

Margolis, J., & Fisher, A. (2002). Unlocking the clubhouse: Women in computing. MIT press.

Martell, R.F., Lane, D.M., & Emrich, C. (1996). "Male-female differences: A computer simulation. American Psychologist," 51, pp. 157–158.

Mellström, U. (2009). The intersection of gender, race and cultural boundaries, or why is computer science in Malaysia dominated by women?. Social studies of science, 39(6), 885-907.

Nathaniel, K.-A. (2022). Mental Shortcuts. The Routledge Handbook of Social Work Field Education in the Global South, 313.

N. C. for Women and I. T. (NCWIT). (2020) NCWIT Scorecard: The Status of Women in Computing. [Online]. https://ncwit.org/resource/scorecard/

Outlay, C. N., Platt, A. J., & Conroy, K. (2017). Getting IT together: A longitudinal look at linking girls' interest in IT careers to lessons taught in middle school camps. ACM Transactions on Computing Education (TOCE), 17(4), 1-17.

Papastergiou, M. (2008). Are computer science and information technology still masculine fields? High school students' perceptions and career choices. Computers & education, 51(2), 594-608.

Pew Research. (2013). What Men, Women Value in a Job. https://www.pewresearch.org/social-trends/2013/12/11/chapter-3-what-men-women-value-in-a-job/

Ramsey, N. and McCorduck, P. 2005. Where are the women in information technology? Report of literature search and interviews. Prepared for the National Center for Women & Information Technology. www.pamelamc.com/html/where_are_the_women_in_it.html.

Sax, L. J., Blaney, J. M., Lehman, K. J., Rodriguez, S. L., George, K. L., & Zavala, C. (2018). Sense of Belonging in Computing: The Role of Introductory Courses for Women and Underrepresented Minority Students. Social Sciences, 7(8), 122.

Sax, L. J., Lehman, K. J., Jacobs, J. A., Kanny, M. A., Lim, G., Monje-Paulson, L., & Zimmerman, H. B. (2017). Anatomy of an enduring gender gap: The evolution of women's participation in computer science. The Journal of Higher Education, 88(2), 258-293.

Sien, V. Y., Mui, G. Y., Tee, E. Y. J., & Singh, D. (2014, May). Perceptions of Malaysian female school children towards higher education in information technology. In Proceedings of the 52nd ACM conference on Computers and people research (pp. 97-104).

Van der Meer, T. G., Hameleers, M., & Kroon, A. C. (2020). Crafting our own biased media diets: The effects of confirmation, source, and negativity bias on selective attendance to online news. Mass Communication and Society, 23(6), 937–967.

Varma, R. (2011). Indian women and mathematics for computer science. IEEE Technology and Society Magazine, 30(1), 39–46. https://doi.org/10.1109/mts.2011.940294

Vitores, A., & Gil-Juárez, A. (2016). The trouble with 'women in computing': a critical examination of the deployment of research on the gender gap in computer science. Journal of Gender Studies, 25(6), 666-680.

Webb, H. C. and Rosson, M. B. 2011. Exploring careers while learning Alice 3D: A summer camp for middle school girls. In Proceedings of the 42nd ACM Technical Symposium on Computer Science Education. ACM, 377–382. Proceedings of the 42nd ACM Technical Symposium on Computer Science Education. ACM, 377–382

Xie, W. (2019). An analysis of fragmented reading and its social impact on college students in the era of new media. Journal of Contemporary Educational Research, 3(3), 33–37.