”I Always Feel Dumb in Those Classes”: A Narrative Analysis of Women’s Computing Confidence

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Abstract

The lack of women in computer science is a decades old problem. Numerous studies have looked at contributing factors that lead to this problem, one of which is lack of self confidence in female students. Having less confidence than their male peers lead women to feel uncomfortable asking questions and speaking out in class, feel isolated in the field, and ultimately steer them away from computer science. The purpose of this study is to understand how women’s computing confidence is shaped by their experiences in introductory computer science courses and to understand how their experiences lead to negative attitudes towards computer science.

To answer these questions, this study uses a narrative analysis approach. Four female, non-computer science students at a large public university were interviewed, using a semi-structured protocol. Interviews were then qualitatively coded using thematic analysis, and analyzed using the theoretical frameworks of self-efficacy and self-concept. Results show that while participants were highly successful in their course (reporting a high mark in the class) and had relatively high self-efficacy when discussing specific programming problems, they lacked computing self-concept in whether or not they were good at programming in general. Some participants directly said they were not good at coding, while others noted that they knew they could be successful but then used unconfident language such as stating they often asked ‘stupid questions’ or believed they were only successful due to the help of instructors and TAs. Results also show a common theme in which most participants believed that if they had to work hard in the course, then they were not good at computer science.

Understanding how women grapple with self-confidence even while being highly successful in computing courses is needed to better understand how to create environments that are welcoming and inclusive of women. While self-efficacy can be built through mastery experiences, this study suggests that mastery experiences are not enough to build general computing self-concept. Since a lack of computing confidence in women can cause negative attitudes towards the field of computer science, future work should focus on ways in which this confidence can be increased so as to try and minimize the number of women avoiding or leaving the field of computer science.

1. Introduction

The gender gap in computer science is not a new problem. For over two and a half decades, women have earned less than 25% of bachelors degrees in computer science [1]. Diversity inequities such as this are a problem because they lead to computer science based innovations that are biased, like voice recognition software that cannot recognize female voices [2]. They also take power away from an already marginalized group. Technology is so ingrained in our society that computing related jobs are viewed as prestigious for their high paying salaries [3]. When so few women have access to these jobs, they lose the socionomic power that goes with them. And these biases are more of a problem now than ever, given the current state of artificial intelligence in our society. Experts in the field argue that a lack of diversity in artificial intelligence is not only a social or cultural concern, but is a life or death safety problem [4].

Another problem is that the few women who do stay in the field face negative experiences in the workplace and the classroom. At some point in time, most women will face an instance of sexism [5], such as having to prove oneself before receiving help, having colleagues mansplain concepts, face outright discriminatory comments by professors and peers, or be forced to work in a gendered, chilly, microclimate [6]. Furthermore, the stereotyped computer scientist is a 'nerdy' white male [7], which is in contrast to women's identity and sense of self. As a result, those who stay in the field are forced to either change their identity to fit, or feel isolated from the field in which they operate.

Researchers have noticed that women tend to self-select out of the field of computer science [8], and prior literature has focused on identifying what causes this self-selection decision. Factors such as lacking a sense of belonging [9], feelings of alienation [10], low self-efficacy and interest [11], facing an unwelcoming environment [12], facing a masculine culture in the field [13], underrepresentation and lack of role models [6] [14], facing microaggressions and harassment [15], lacking prior experience [16][17], and facing a difficult workload [12] all play a role in women deciding to leave the field. Of this list of factors, self-efficacy has been heavily studied. Multiple studies have found that women have lower computing self-efficacy than men, in high school [18] [19], undergraduate courses [11][18][20], and industry [21]. Self-efficacy has also been tied to women's computer science interest [22] and performance [20]. And finally, self-efficacy has been linked to women's sense of belonging in the field [23].

Despite there being numerous studies that look at women's computing self-efficacy, few studies look at non-computer science majors. The purpose of this study is to address that gap and to understand how women's computing confidence is shaped by their experiences in introductory computer science courses and to understand how their experiences lead to negative attitudes towards computer science. It is important to look at non-computer science majors to better understand why individuals with high computing ability are choosing not to enter the field, as this group remains an untapped source when it comes to improving the representation of women in computing.

3. Theoretical Framework

Two theoretical frameworks are used for this study. The first is Bandura's self-efficacy [24]. Self-efficacy is defined as an individual's belief about their ability to accomplish a specific task. In essence, self-efficacy is one's confidence in their ability to be successful for a specific task. Higher self-efficacy has been shown to increase motivation to learn [25] and to improve performance in computing students [26]. It has been frequently used in computing diversity studies, whose findings show that women have lower self-efficacy than their male counterparts [11].

Self-efficacy can be improved in four ways [24]. First, having mastery experiences increases self-efficacy. This means that the more an individual is successful in performing a specific task, the more confident that they will be successful on another similar task. Second, having vicarious experiences has been shown to increase self-efficacy. Here, instead of the individual having the mastery experience themselves, they see someone they can relate to or share an identity with have a mastery experience, thus building their confidence that they too can be successful. Third, positive social persuasion can increase self-efficacy. When an individual is told by another that they have confidence in their ability, confidence can be increased. Fourth, more positive physiological and psychological states leads to higher self-efficacy. That is, when an individual is physically and mentally feeling well, they are more likely to have confidence in their ability to be successful.

The second theoretical framework is self-concept [27]. Self-concept is similar to self-efficacy, but while self-efficacy focuses on one's confidence to perform a specific task, self-concept deals with their overall confidence in their ability. In particular, this study looks at domain self-concept, defined as an individual's beliefs about their academic abilities or skills in a particular domain. Having high computing self-concept can be seen in statements such as, "I am good at programming", while having low computing self-concept is expressed with statements such as "It is hard for me to understand things in my computer science courses". While most studies of computer science students focus on self-efficacy, it has been shown that academic and domain self-concept are significant predictors of grades in undergraduate courses, while self-efficacy had mixed results [28]. Therefore, by looking at both self-efficacy and self-concept, we can get a better understanding of students' overall confidence.

4. Methods

Narrative analysis is the study of experiences as told through stories [29]. This methodology allows researchers to investigate experiences, where experiences are seen as a narrative phenomenon. In doing so, it allows experiences to be understood as relational, continuous, personal, and social, meaning that while experiences are personal, larger societal and cultural influences shape the person's experience. This was an appropriate methodology for our study because it allowed us to understand our participants' experiences as it relates to their sense of self but also the world and context in which they lived it.

4.1. Participants and Sampling

During spring and fall semester in 2023, all students enrolled in an introductory computing course for non-computer science majors at a large public university were sent a survey via email. This survey asked them for demographic information, including their major, and whether or not they would be willing to interview for a $20 Amazon gift card. Four students identifying as female were chosen for interviews based on their high performance in the course. All participants reported receiving a high grade in the course. Table 1 shows the participant demographic information breakdown.

Table 1. *Participant Demographics*

	Major	**Class standing when taking course**	**Race/Ethnicity**
Participant 1	Smart and Sustainable Cities	Junior	White
Participant 2	Smart and Sustainable Cities	N/A	White
Participant 3	Statistics and Psychology	Freshman	White
Participant 4	Business and Information Technology	Sophomore	White

4.2. Data Collection and Analysis

To answer our research question, semi-structured interviews were conducted with our participants over Zoom. These interviews lasted approximately thirty minutes and contained questions about participants' experiences in their computer science courses, their future plans, and their experiences with the computer science community. Interviews were recorded using Zoom after receiving participant consent and then transcribed using Zoom automated transcription tool. The auto-generated interview texts were reviewed and corrected by the research team for clarity.

To analyze interviews, thematic analysis was used. Thematic analysis is a method to identify and analyze patterns in qualitative data, and allows for themes to emerge from the data [30]. It is widely used in qualitative research, and is not bounded by a priori codes from known theories. Instead, theoretical frameworks were applied after analysis to contextualize and make sense of the themes that emerged.

5. Results

During data analysis, four major themes emerged from the data. First, there was a wide variety of experiences that influenced participant's self-efficacy and self-concept. Second, most participants made comments that showed high self-efficacy. Third, despite showing high self-efficacy, most participants used negative language that showed low computing self-concept. And fourth, a few participants seemed to hold the belief that needing to work hard in their coding class meant that they were not good at coding. Each of these themes is further discussed and unpacked below.

5.1. Experiences Influencing Self-Efficacy and Self-Concept

When discussing what influenced their self-efficacy and self-concept, participants mainly discussed what in their classes made the material easy, harder, less confusing, or more confusing. Assignments, course setup and content, and professor behavior and teaching styles were the main contributing factors that influenced participant's confidence. And these factors were both positive and negative influencers.

For positive influences, participants noted that having to apply knowledge learned from readings and lectures to specific assignments helped to clear up the content information. And noted especially when this was core material, it made the rest of the course easier. They also discussed that having a textbook made it easy to turn back and review prior information, and that this was very helpful in their ability to learn course content. One participant who took two computing courses noted that one class without a textbook felt less guided which made it easier to feel like you were falling through the cracks. Finally, participants stated that when the instructor had them code along with them in class compared to just doing it himself, it was easier to process and understand the material.

For negative influences, participants first discussed the content pieces that were difficult for them. They discussed how they were feeling good and things were making sense in the beginning of the course, but loops and iterations, as well as scaling to work with large amounts of data became confusing. They noted feeling lost in the course, especially when assignments were not well scaffolded. For example, participants noted that projects were the hardest part of the course due to their size relative to their other assignments. One participant stated, "We would have like after every week on Sunday, we would have these little Python activities we had to do that were like two lines long. But then we would have projects that were like 80 lines of code. It was just a lot". Finally, the professors and their behaviors played a role as well. One participant noted how the professor was not helpful in making the course easier because he only repeated what was in the assigned videos, but failed to provide any new information. Another participant noted that the professor's behavior directly decreased her self confidence because he assumed they knew material that she did not, which caused him to go too fast during lecture. This made the participant feel as though the course was very difficult, but gave her the perception that it was not for others in the course.

5.2. High Self-Efficacy

Most of the participants were confident in their ability to be successful on assignments in the course, or be successful in the course in general. All of our participants were high performing, and some participants commented that because they earned a high mark in the course, they clearly knew how to and could perform well on specific coding tasks. They also would talk about how the course was not difficult, stating that it was "not very demanding at all", that they "thought like all of the problems were like pretty easy", and that "[the exercises] were pretty simple". One participant noted that she was confident that she knew what she was doing when coding in R and Python, and that she had a "good grasp".

One participant showed signs of increased self-efficacy when describing how her perception had changed since taking the computing course. She realized that you do not need to be smart in order to be successful at programming. This participant was also good at distinguishing what tasks she was confident in and which she was not. She noted that she was confident in her understanding of concepts and how to use them, such as dictionaries, but that she was not confident and still confused on how some concepts worked on the back end, or behind the scenes.

5.3. Low Computing Self-Concept

Despite our participants showing signs of high self-efficacy, how they talked about their overall computing competence and confidence showed that most of them had low computing self-concept. Most of our participants used negative language when discussing their overall competence, or their skill level at coding. Students used words like ‘dumb’ or ‘inadequate’, as shown by statements such as, “I wish I could have learned more, but like I felt like I was inadequate to learn it”. These feelings contributed to a lack of confidence in asking questions, as one participant explained, “I was afraid of like asking the TA, [...] [but] they’re not going to judge me for being really dumb. Even though like sometimes I probably was”. Moreover, students expressed similar sentiments that CS was not for them or that they were not a true coder, stating, “I think it was just not something that I’m great at”. One participant noted that they felt guilty for their competence level because of how many questions she had to ask both to the instructor and TA. She stated, “I felt I was bothering him so much, [...] I felt like a nuisance because like I was taking TA time away from other kids”. And, despite recognizing that she was skilled at some aspects of computing, one participant stated, “but the stuff that I was good at was definitely not the type of code that would be used professionally”.

A lack of computing self-concept and confidence also stemmed from comparison to others. In fact, perception of others’ ability compared to self-ability caused one participant to drop one of her computing courses. She stated, “It would take I felt like it was taking me way longer than anyone else which also attributed to me dropping. Like I was like, I don’t like I feel like I just am not cut out for this”.

The third place where negative language around computing self-concept and confidence occurred was when participants discussed the need for help in the course. Participants noted that they spent up to three hours a week in office hours, and noted that they would not have been as successful if it weren’t for the help they received. This mindset and negative connotation with asking for help caused a decrease in their computing self-concept, with one participant explaining her decision not to continue taking computing courses as a result. She stated, “I was definitely relying on the TA’s for a lot of assistance. If that’s what’s happening in an intro course, I do not think I could be moving any further, successfully”.

While three of our four participants used negative language that showed signs of low self-concept, despite having high self-efficacy, one participant did not. This individual showed signs of high self-concept. This participant noted that she was not as bad at computing as she originally thought. Interestingly, this realization was a result of comparison to others, as she noted, “at least among my classmates, [...] a lot of it came a little bit easier to me than other people”, showing that comparison to others can be both a positive and negative influence of computing self-concept. But despite this participant showing signs of high self-concept, she also made excuses as to why she was successful, rather than owning her ability. When thinking about pursuing a computer science minor, she explained that based on her past experiences, she didn’t think she would fail, but commented that her previous courses were likely easier than other introductory computing courses she could have taken, attributing some of her success to the ease of the course over her skills. Finally, when thinking about her future success, she was uneasy. While she was confident in her coding ability, she was hesitant to identify as a computer programmer, stating, "I'm definitely not like CS". Again, comparing herself to others, she discussed her computer science friends' coding projects and how she has no idea what they are doing. And she wrestled with whether or not she felt confident in her ability to gain the knowledge that they have, saying, "I have no idea what they're doing. But it doesn't mean that I couldn't learn. But also like I don't know, my friends are now in like upper level stuff now, so maybe I couldn't".

5.4. Needing to Work Hard and the Perception of Being Not Good

The final theme that emerged from the data for two of our participants is the idea that having to work hard at something means that you are not good at it. Once again, these perceptions were caused by comparison to others. That is, our participants felt that they had to work harder than others in the course, and therefore were not as good at the content as their peers who did not work as hard. One participant stated, "I would go on and ask at least one question every assignment. And like based on that, that makes me feel like I was the only one struggling". While another participant noted, "It just wasn't for me, the work was not something that I felt was very intuitive for me, it took a lot of effort. [...] There were definitely people who had taken comp sci classes in high school that it seemed as though they breezed through the material. That was not the case for me".

6. Discussion and Implications

Our results indicate that women's confidence in computing is complicated. They can hold high self-efficacy beliefs about their ability to successfully complete specific tasks, yet at the same time have low computing self-concept and not have confidence in their computing ability in general. In addition, our results support prior findings that having mastery experiences does lead to higher self-efficacy, as all of our participants earned high marks in the course and showed signs of high self-efficacy. However, our results also show that mastery experiences may not be enough to develop high computing self-concept. This is in contrast to prior literature that has found previous academic success to cause higher academic self-concept [31]. This finding has important implications for instructors, as this means they cannot assume that high performing students know they can be successful in the field. Female students may need additional support and encouragement about their abilities from their instructors in order to have the confidence to stay in computing.

Results also show that while there are many factors in the classroom that can influence self-efficacy and self-concept, a common influencer seen across participants is their self comparison to peers. Instructors of introductory computing courses should be cognizant of this phenomenon, as if not carefully managed, can cause women to leave the field. In order to mitigate negative effects of peer comparison, instructors can engage in discussions of why some individuals seem more successful than others, and contribute their success over others to learning strategies or previously acquired background knowledge rather than innate ability. Prior research has found that when students attribute their success to things they can change, such as study habits, over things they cannot, such as intelligence, they are more apt to handle failure [32].

7. Limitations

This study is not without limitations. One limitation is the small sample size, and its inability to generalize to the larger population. Another limitation is that our interviews are in retrospect. That is, participants were not currently enrolled in their computing courses when interviewed. This means that they had to remember their experiences and how they felt in these classes months later. As a result, their stories could be different from how they felt or exactly what happened during the course. Finally, our sample size was not racially/ethnically diverse. All of our participants identified as White, and as a result there was no discussion of intersectional identities at play. While our participants are a minority in the field based on their gender, they are not based on race/ethnicity. Based on other studies conducted in this space, it can be assumed that other factors would have been discussed had our participants been more racially/ethnically diverse.

8. Future Work

There are multiple areas that future work can focus on. First, our sample size was very small and limited to a specific institution. Further work can address this limitation by seeing if our results hold on a larger scale and in different contexts. Future work can also look to address the limitation of diversity in our sample to see how experiences differ across race. Second, future work should investigate what factors are the biggest influencers of computing self-concept, as mastery experience does not seem to be enough to improve it. Finally, researchers should investigate to what extent self-concept is a predictor of computer science major choice, and how this may vary across genders.

9. Conclusion

The purpose of this study was to understand how women's computing confidence is shaped by their experiences in introductory computer science courses and to understand how their experiences lead to negative attitudes towards computer science. Results showed that assignments, course setup and content, and professor behavior and teaching styles were the most common factors influencing their self-efficacy and self-concept, and that experiences with these factors had both positive and negative influences. Results also showed that while our participants showed signs of high self-efficacy, they had low senses of computing self-concept. And half of our participants seemed to believe that needing to work hard or ask for help meant they were bad at computing. This study has important implications for instructors, as it shows high performing female students may need unrealized additional support to improve their computing confidence, and that peer comparison, if left unchecked can have negative effects on their computing confidence.

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