A Qualitative Approach to Understanding Computing Self-Efficacy Development Among Girls of Color

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***Abstract*—Research on increasing diversity in computing requires focused investigations of how girls of color develop their self-efficacy beliefs. Measures of self-efficacy are commonly collected using validated survey instruments that require self-reporting. In this paper, we present an observational protocol based on Bandura's four sources of efficacy beliefs that can be used in conjunction with existing surveys to capture qualitative data on how computing self-efficacy beliefs develop. We present the observational protocol as a complementary instrument that can be used alone or in conjunction with validated surveys to capture learners' observable behaviors as they learn new computing knowledge and skills.**

***Index Terms*—self efficacy, girls of color, computing identity, qualitative research, participant observation**

I. Introduction

Research on broadening participation in computing requires focused investigations of how girls of color develop computing self-efficacy beliefs. Data related to computing self-efficacy is commonly collected using validated survey instruments that are informed by Bandura's four sources of efficacy beliefs [1], [2]. While these validated survey instruments have increased our understanding of computing self-efficacy as a construct, they are also limited to psychometric scales that rely on participant self-reporting. Using instruments that rely on participant self-reporting have significant limitations for studies that measure self-efficacy beliefs among girls of color, including the susceptibility of acquiescence bias and evidence that girls of color tend to report lower levels of self-efficacy in STEM, regardless of their actual abilities [3], [4]. In this work-in-progress paper, we present a qualitative observational protocol for collecting data on observable behaviors exhibited while girls of color learn new computing knowledge and skills.

We developed the observational protocol as a complementary instrument that can be used alone or in conjunction with surveys to capture rich qualitative data on how computing self-efficacy beliefs manifest. The observational protocol aligns with Bandura's four sources of efficacy beliefs and provides guiding questions that correspond with each source. We believe that conceptually grounding our observational protocol on Bandura's four sources of efficacy beliefs allows other researchers to pair our protocol with existing survey instruments to gain a more nuanced understanding of how girls of color, and potentially a broader group of learners, develop self-efficacy beliefs.

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II. Theoretical Grounding

To guide the data collection of observable behaviors related to computing self-efficacy, we theoretically grounded the observation categories in Bandura's four sources of efficacy beliefs. Self-efficacy is defined as one's beliefs about their capabilities to execute behaviors necessary to produce specific performance attainments such as achieving goals or completing tasks [1]. We conducted a literature review on the concept of self-efficacy, including general self-efficacy [1], [5], [6], computing self-efficacy [7], [8], [28], programming self-efficacy [29] and other related noncognitive constructs such as motivation and confidence [26], [27]. The analysis of the literature focused on developing a working definition, identifying existing instruments for measuring self-efficacy, and understanding the impacts of self-efficacy on academic achievement, sense of belonging, and career trajectories. Given our focus on girls of color, we also identified self-efficacy studies that aimed to improve self-efficacy beliefs among gender, racial, and ethnic minorities in computing and STEM more broadly [9]–[12].

According to the literature, learners with higher measures of perceived self-efficacy are more likely to demonstrate persistence and self-regulation when working toward academic goals [13], [14]. Based on the positive association between self-efficacy beliefs and academic achievement, researchers also studied the relationship between learners' perceived self-efficacy and positive outcomes related to interest, persistence and achievement in computing. We refer to this as computing self-efficacy, which is a domain- specific measure of learners' beliefs in their ability to complete tasks using a computer [15]

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or generally use a computer to solve problems [16]. We also reviewed computer programming self-efficacy scales [17]–[19] but chose a working definition that focused on a broader set of observable behaviors related to problem solving with a computer and completing computing tasks.

Our work focuses on the development of computing self-efficacy among girls of color based on the relationship between perceived self-efficacy and academic performance among underrepresented students [20]. Girls of color persist in the face of racialized and gendered stereotypes that position them as lacking motivation, unable to master challenging STEM course content, and missing the social support necessary to fully participate in an academic culture [21]. By focusing on how girls of color develop computing self-efficacy, we contribute to research that works to debunk deficit-based explanations for why girls and women of color leave STEM disciplines, empirically disproving negative stereotypes about their interests, career goals, and academic abilities [22].

III. Observation Categories

Our analysis of the literature also showed that many of the survey instruments used to measure self-efficacy were based on Bandura's four sources of efficacy beliefs [1]. Given our aim of developing the observational protocol as a complementary instrument, we based our observation categories on the same four sources of efficacy beliefs: performance accomplishments, vicarious experiences, verbal persuasion, and emotional arousal. Drawing on these four sources, we created guiding questions that help researchers focus their observations. We define each observation category and present guiding questions for data collection below.

A. Performance Accomplishments

Performance accomplishments describes the experience of successfully accomplishing a similar task in the past. If learners have accomplishment experiences to draw on, they are more likely to judge themselves as capable when faced with a new challenge. **Guiding observation questions:**

- Do learners exhibit an affinity towards increasing complexity in the computing tasks they undertake?
- Do learners persist in the face of difficulty and repeated failure? i.e. debugging code, approaching code problems from different angles
- Do learners apply their new knowledge and take risks with new tasks? i.e. setting up another code project or trying out new ideas with a program design
- Do learners exhibit signs of increasing independence? i.e. using google to solve code bugs or working with other learners instead of an instructor
- Do learners express pride in finished work? i.e. showing off website design, sharing accomplishments with others

B. Vicarious Experiences

Vicarious experiences describes the experience of observing others perform a given task. If learners see that others are able to accomplish the task they face, they are more likely to believe in their own ability to succeed at that task as well. **Guiding observation questions:**

- Do learners spend time watching others perform tasks? i.e. engaging in code reviews
- Do learners express encouragement or discouragement if they see others doing well on a task they themselves have not mastered yet?
- Do learners ask for repeated demonstrations? Or look up examples on their own? i.e. watching YouTube videos or doing code tutorials
- How do learners look to others for guidance, such as peers and facilitators? i.e. Do they ask task-specific questions? Do they prefer a hands-on approach for troubleshooting or do they prefer to watch others troubleshoot?

C. Verbal Persuasion

Verbal persuasion describes the experience of being encouraged in your pursuit of a new challenge. If those around learners are affirming of their ability to perform well at an unfamiliar task, they are more likely to believe in their own abilities. **Guiding observation questions:**

- How do learners respond to verbal reinforcement from peers and facilitators? i.e. Do they shut down, continue on a coding task, or try again when solving an issue?
- What does the learners' self-talk sound like? i.e. Do they exhibit verbal signs of self-encouragement or self-beratement?
- Do learners seek verbal praise? If so, from whom?

D. Emotional Arousal

Emotional arousal describes the experience of the physical sensations of anxiety or anticipation that may cause discomfort and limit the ability to perform well in a new situation. **Guiding observation questions:**

- What physical manifestations of anxiety and frustration do learners exhibit while engaging in computing activities? i.e. nail biting, fidgeting
- What physical manifestations of confidence and exuberance do learners exhibit while engaging in computing activities? i.e. smiling or excitedly moving around
- What verbal manifestations of anxiety and frustration do learners exhibit while engaging in computing activities? i.e. saying phrases like "This is hard" or "I can't do this."
- What verbal manifestations of confidence and exuberance do learners exhibit while engaging in computing activities? i.e. saying phrases like "This is easy" or "I know how to do this"?

IV. Implementation

The protocol is designed to be implemented by researchers positioned as participant observers. Participant observation requires interacting with participants and contributing to the social milieu of the site, while also simultaneously collecting the data needed to examine a research topic. Given the dual role that researchers must fulfill as participant observers, we

suggest that the observational protocol be implemented by at least two researchers.

Our initial testing of the protocol revealed that self-efficacy beliefs often manifest in relation to other learners. Thus, we also suggest that researchers capture the interactional nature of self-efficacy development by assigning at least one researcher to collect data on how the observable behaviors manifest through group dynamics.

In our initial testing of the protocol, we were able to collect systematic field notes, audiovisual recordings of program activities, and photographs of participant-created artifacts such as journal entries, code sets, group projects, and expressive artwork. We also were able to collect observable behaviors such as the following:

- Self-talk: verbal expressions of self-doubt or confidence
- Questioning and answering: posing task-specific questions or providing answers to peers' questions
- Physical manifestations of anxiety and frustration: Nail biting, fidgeting, pushing projects away
- Audible manifestations of anxiety and frustration: sighing, groaning, verbal expressions of frustration
- Physical manifestations of persistence: Taking breaks and returning to a task
- Visual manifestations of task completion: Debugging code and successfully executing a program

We believe these types of observation data can triangulate survey results and provide nuance to survey responses. Since this protocol is still a work-in-progress, we do not have a formalized implementation guide to share. However, in the future work section, we specify the additional actions we are undertaking to refine this protocol.

V. Positionality

Patricia Garcia is an assistant professor who identifies as a Chicana first-generation college graduate. Her lived experiences as a racial and gender minority within STEM motivated her to develop efforts to broaden participation in computing among girls of color. Melissa Perez is a Tejana/x person and graduate student. Her personal experiences as a minoritized learner in computer science inform her efforts to broaden participation in computing. Tori Culler is a white woman and a first-generation college student. When co-developing the observational categories, she remained cognizant of how her own identities — particularly in terms of gender, race, and class — might impact her interpretation of the girls' observable behaviors.

VI. Discussion and Future Work

We present our observational protocol as a work-in-progress; thus, we discuss the future work we are undertaking to refine the protocol. Qualitative researchers have differing perspectives on whether validity and reliability are applicable measures for naturalistic research conducted in real-world settings, especially for research that aims to develop a contextual understanding of an issue and does not aim to measure or analyze causal relationships between variables [23]. Our observational protocol does not aim to measure or analyze causal relationships between sources of self-efficacy and observable behaviors. Instead, we present the protocol as a complementary tool to other quantitative methods that can help researchers capture observational data on how computing self-efficacy beliefs develop as a complex set of self-beliefs that may be expressed through observable behaviors.

While we do not offer statistical means for assessing validity or reliability, we are conducting future work to refine the protocol. We have conducted initial testing of the protocol in a 20-hour implementation of an informal computing program for girls of color, ages 13-17. We plan to further test the protocol in future iterations of the program at two sites, one in Texas and one in Michigan. We will implement the protocol two times at each site during 20-hour program implementations, totaling 80 hours of observation. Based on the results of those observations, we will refine the observable behaviors associated with each observation category to ensure that they continue to align with the corresponding source of influence and assess the usefulness of the guiding questions. We will also develop an implementation guidebook that can be used to train other researchers on how to use the protocol. The guidebook will include guidance on the minimum number of participant observers required to implement the protocol and to achieve researcher triangulation. It will also include sample quotes and behaviors from our data to illustrate how each source of influence may manifest. If the test observations confirm that collecting quantitative evidence, such as frequency counts of observed behaviors, is feasible and useful, we will refine the protocol to include those additional modes of data collection.

Finally, we will refine our data analysis procedure. Given the centrality of race and gender as identity markers for girls of color, the analysis of the observable behaviors will be informed by intersectional feminist frameworks [24], [25]. Grounded in Black Feminist epistemologies, intersectionality has served as a heuristic for understanding how intersecting social categorizations such as race, gender, and class structure power and produce marginalization. However, instead of focusing only on marginalization, the analysis of observation data will also explore how the intersections of race, gender, and age can function as sources of power and positively influence the educational trajectories of girls of color. Thus, our future analysis procedure will contextualize girls' observable behaviors in a historically grounded framework that considers their social position in and out of the classroom.

VII. Conclusion

Rather than assuming girls of color implicitly experience an increase in their computing self-efficacy beliefs through positive learning experiences, our protocol looks at the process of developing those beliefs explicitly and focuses on understanding the observable manifestations of those beliefs. The observational protocol has the potential to help researchers identify the unexpected ways that self-efficacy beliefs develop, especially when the girls' actions differ or conflict with the program's predetermined outcomes.

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