A. Overview and Objectives

The world is becoming increasingly reliant on digital technologies, which has resulted in enormous amounts of digital data being recorded, sorted, and analyzed. Data analytics are now used to decide whether people obtain employment, receive loans, or are convicted of a crime. While improving human efficiency and quality of life, such algorithms have also been shown to reinforce racial and gender discrimination at large scales (Noble, 2018). Moreover, the software that is used is largely unintelligible and inaccessible to the public (O'Neil, 2016). As big data algorithm usage and dependency become more ubiquitous, ***it will become critical for all young people, and in particular those from historically marginalized populations, to have a deep understanding of data science that empowers them to enact change in their communities.***

In contemporary data science, there has been a shift from small-scale data, such as data on 1,313 survivors on the Titanic, to large-scale data, such as 19 million tweets on Twitter that used the #metoo hashtag. This shift has resulted in a reliance on automated machines to collect human data, analyze patterns of behavior, and, in many cases, to make decisions for society at unprecedented scales (Kitchin, 2014). Recent changes in the way data are collected, made publicly available, and analyzed at larger scales suggests a reconsideration of how to educate the next generation of data literate citizens in digital technology production and consumption (Wise, 2020). Without a data science education that includes reflection on the social, ethical, and political consequences of data-based algorithmic decision-making, problematic assumptions are reproduced. These assumptions include that data are objective and independent of the thought systems that create them (Kitchin, 2014), that information is static and not subject to change or reinterpretation (Pangrazio & Selwyn, 2019), and that simply teaching knowledge and skills about data manipulation will spontaneously address inequities and promote social justice (Philip et al., 2013). Thus, a ***critical data science education*** is needed for young people to recognize, question, and take action against inequities in data practices and be aware of the ideological, historical, and political dimensions of data production and usage.

This proposed BCSER Individual Investigator Development project addresses this need by ***developing and implementing a critical data science education program in which middle school aged youth will engage with algorithm bias issues***. I and the research team will partner with community after-school centers in under-resourced upstate South Carolina communities and co-design a new program that is culturally-responsive and focuses on algorithm bias issues relevant and important to the community. The program will include activities, materials, and guides that will be available on the PI's research lab website. The ***research objective*** of this proposal is to measure and model how young people learn data science practices and how they make sense of the social, ethical, and political implications of big data algorithms after engaging in a critical data science educational program co-designed by community stakeholders and researchers. I posit that situating the critical data science education program in community-based participatory design research will support youth participants to (1) learn data science concepts/practices, (2) question the effects of digital technologies, and (2) uncover their and their communities' interests and values in empowering ways. This research will focus on the process of learning that occurs in a particular learning environment. While the project includes a design component to develop the learning environment, answering questions about the process and efficacy of the design is not the primary focus.

This project will advance my ***long-term career goals*** to conduct foundational research about how youth engage in critical data science practices and how to foster inclusive STEM learning. In particular, my research will: 1) provide empirical evidence of youth engaging in critical data science and their related feelings of empowerment; 2) develop a theoretical learning model of critical data science practices; and 3) ultimately empower community programs to broaden youth participation in STEM. While I have experience analyzing STEM learning in formal secondary education settings, I am new to community-based participatory design methodologies and designing informal STEM learning environments for middle school youth. The ***professional development objective*** of this proposal is to provide me training in participatory design methodology, particularly with and for middle school STEM informal education. This training will allow me to conduct research that aligns with the NSF's EHR directorate mission to advance theoretical understanding around STEM learning and learning environments, to broaden participation in STEM, and to develop a diverse, ethical, and well-prepared STEM workforce. Additionally, the proposed research will advance our understanding of how youth learn when engaged in community programs that promote ethical and culturally-responsive STEM programs which may ultimately motivate underrepresented youth to pursue STEM majors and careers (Estrada et al., 2016; Stevens et al., 2016).

B. BACKGROUND AND SIGNIFICANCE

B.1. The Need for Critical Data Science Education. In the digital age, people rely on digital technologies to navigate their lives. Such technologies collect, store, and analyze data to improve human efficiency and ultimately improve quality of life. For example, data analytics are now used to more accurately predict cancer patient outcomes, measure natural disaster damage using social media postings, and quantify traffic dynamics to reduce air pollution (*Data Science for Social Good*, 2014). However, such reliance on data algorithms can also be problematic (Chen & Quan-Haase, 2020). Widely used internet search algorithms that distribute knowledge to billions of people daily have been shown to reinforce racial and gender discrimination at large scales (Noble, 2018). A value-added model used to assess teacher performance was evaluated to be as accurate as a random-number generator (O'Neil, 2016). Government software has been used to extrapolate data that preemptively criminalized the actions of low-income populations (Eubanks, 2018). Such algorithms are further marginalizing those who are from non-dominant populations, including women, people of color, and those who live in poverty. Without a data science education that includes reflection on the social and ethical consequences of data-based algorithmic decision-making, future generations will continue in this harmful tradition of technology development and consumption without a critical lens. Moreover, youth from non-dominant populations will continue to be oppressed by such technologies, not have a representative voice in the development of future digital technologies, and not have opportunities for employment in sectors that are increasingly depending on data science. Thus, for young people to participate in a digitally reliant society, a robust ***critical data science education*** is essential for all.

B2. Current Research and Existing Gaps in Critical Data Science Education. Although the practice of data science is not new, the ways in which data are analyzed, accessed, and used has changed dramatically in the last few decades. The internet and networked systems now allow a wider range of people to access and interact with data. Moreover, advances in computation allow for more sophisticated analyses at large scales. Such advances and broad usage of computational statistics and data analytics has resulted in a reliance on automated machines to collect human data, analyze patterns of behavior, and, in many cases, to make decisions for society at unprecedented scales. For example, in London there is a need to understand how traffic disruptions affect traffic congestion and how such congestion affects vehicle emissions and air quality. Obtaining traffic statistics requires high-cost manual labor and routinely underestimates emissions from vehicles. Thus, the City of London and its partners created an open-source algorithm that processes traffic video data and extracts descriptive statistics, such as the type of vehicle and the number of times each vehicle stops and starts. This algorithm has improved emissions model predictions, enabled more accurate evaluation of the impact of future transport initiatives, and provided an understanding of road closure impacts and traffic optimization to reduce congestion (*Data Science for Social Good*, 2014). This is one example of the many ways data analytics are used to collect human data, analyze patterns of behavior, and make large-scale decisions.

Relatedly, research on how to best prepare learners to work with data analytics and engage in evidence-based thinking has been ongoing. However, recent changes in the way data are collected, accessed, and analyzed as described above requires a reconsideration of data science education and how to educate the next generation of data literate citizens (Finzer, 2013; Wise, 2020). Data literate citizens should be able to engage effectively and critically with data and data-informed processes involved in everyday life. Wolff and colleagues (2017, p. 23) argue that data literacy is the ability to engage in inquiry with large and small datasets and involves the abilities to "select, clean, analyze, visualize, critique, and interpret data, as well as to communicate from data and to use data as part of a design process." Recent studies have shown that fundamental core concepts and practices for contemporary data education include developing data collection protocols and being active producers of data (Hardy et al., 2020), using large-scale data sets to create visualizations and tell data stories (Jiang & Kahn, 2019), connecting existing datasets with personal experience and beliefs (Van Wart et al., 2020), understanding a level of computational and statistical knowledge (Wilkerson & Polman, 2020), and making and questioning inferences, generalizations, conclusions, and action based on data analytics (Rubin, 2020).

Integrating social, ethical, and political dimensions into data science education, Hauea and colleagues studied how youth between the ages of 11 - 15 engaged in critical data literacies in a social media context. The results detailed five emerging themes on youth perspectives: data collection and retention have privacy implications, data analysis requires skepticism and interpretation, data can come with assumptions and hidden decisions, data-driven algorithms cause exclusion, and measuring and reporting on data can affect the system that created the data. Their findings suggest that young teens can engage in discovery, critique, and inquiry around implications of digital data collection and usage and many of the concerns raised reflected existing topics in broader social discourse. Hauea and colleagues' study aligns with Pangrazio and Selwyn's (2018) findings that teens who use social media have concerns over their personal data usage and often feel powerless navigating the complexities of algorithms, privacy settings, and "terms and conditions" agreements. Other studies have shown that feelings of empowerment are important for critical data science education, and programs that focus on existing problems in students' personal lives and communities can empower them to create change (Bhargava et al., 2015).

Studies with younger populations of children have shown that children do not have a clear understanding of how artificial intelligent (AI) technologies work and will tell toy robots personal information without realizing that the toy can record their conversations (McReynolds et al., 2017). For example, Ali and colleagues (2019) empirically examined how preteens engage with ethical issues around AI and machine learning. Their preliminary evaluation of 225 students revealed that children engaged with ethical AI concepts and identified the societal impacts of racist and biased algorithms. Theoretically, Philip and colleagues (2013) have proposed a framework on big data for democratic participation that consists of three categories of student objectives: content proficiency and discursive fluency (the ability to use language and tools of the discipline), motivated use of content (learners see themselves as users of data science and work towards greater justice and equity in society), and the politics of knowledge (learners know that data are political and address limitations/opportunities for particular populations). These three categories purposefully center topics of inequities, power, and ethics around data education.

This body of empirical and theoretical work demonstrates initial progress on critical data literacies research, but there is still a lack of consensus on critical data science education in terms of how youth develop critical data science knowledge and practices and how to design learning environments to support critical data science education (Wolff et al., 2019). In formal K-12 schooling, integrating contemporary data science education into curricula has been a challenge. Because data science is interdisciplinary, it is not clear how to integrate it into existing school subjects (Finzer, 2013). Furthermore, implementing data literacy requires updates to classroom technology and significant teacher training that includes a cross-disciplinary approach (van't Hooft et al., 2012).

Although formal schooling is unarguably a space for continuing data science education research, informal spaces are also rich spaces for research that are less bounded by institutional constraints. Informal learning environments such as museums, after-school programs, and online communities are engaging social spaces in which learners develop awareness, interest, motivation, competencies, and practices that can set them on a trajectory to learn more (National Research Council, 2009). Further, learners spend significantly more time in informal environments than formal, indicating a rich opportunity for researching learning (National Research Council, 2009). In informal learning spaces, activities tend to be self-directed, involve hands-on exploration, and in many situations, shifting children's attitudes and preconceptions is as important as technical and scientific knowledge development (Horn et al., 2009). Moreover, a combined tangible and computational system can promote participants to engage in cultural forms of literacy, learning, and play and invite them to construct their own understandings when engaging with the hybrid physical/digital system (Horn, 2018).

For this research proposal, the goal is to analyze learning in an after-school critical data science program for youth ages 11 - 14. In line with this critical perspective, the design of the program will involve all stakeholders, including researchers, counselors/mentors, parents, and youth.

B.3. Community-Based Participatory Design Research. To engage youth in critical data science that is culturally-relevant and aligned with their and their communities' interests and values, it is necessary to include youth, counselors, and parents/caring adults in the design of the educational program. The downside of not including youth input in the design of their educational experiences is the possibility of a mismatch between designers' intentions and learners' interpretations which can cause the learning environment to be used in a different way than intended (Elen & Lowyck, 1999). The sense of not being heard causes feelings of isolation and powerlessness, which contribute to disengagement from learning (Mitra, 2004; Smyth & Fasoli, 2007). Further, including parents and counselors in the design process can also improve learning and general well-being as they strongly influence young people's value systems (DiSalvo et al., 2011).

Participatory design research is similar to co-design efforts (Penuel et al., 2007) and researcher-practitioner partnerships (Coburn & Penuel, 2016) in that it involves the collaborative design of a learning environment in contrast to the environment being designed solely by researchers. However, participatory design also attends to the political and oppressive issues around learning, particularly the power dynamics between researchers and research participants (Bang & Vossoughi, 2016). Importantly, participatory design advances fundamental research about learning and development by examining how knowledge is generated and by whom and includes all stakeholders. In this project, I will employ a community-based (Bang, 2015) participatory design research approach that includes the research team, counselors/mentors from the after-school program at the community center, parents, members of the community center, and youth. I anticipate that participatory design involves complex social interactions and competing interests, scientific cultures, and value systems. To reflect critically on these complexities and ensure a rigorous design process, the research team will rely on Frauenberger and colleagues' (2015) framework consisting of four lenses of inquiry: epistemology, values, stakeholders, and outcomes. Such inquiries include: What are the kinds of knowledge constructed? To what degree can we trust the knowledge? What are the conflicts and dilemmas arising from values? How do values change in the process? Who owns outcomes? How sustainable are outcomes?

Similar to DiSalvo and colleagues' (2017) work, the participatory activities for children in this project may not directly involve the design of the program but instead focus on developing a shared vocabulary, reflecting on existing practices, and speculating about the future. The goals are to "develop a relationship with the [children], understand their perspectives on school and education, and find ways to design learning experiences with them that would meet their values, beyond what they found interesting or fun, to include what was important to them, as well as to their families, peers, and community." For example, in DiSalvo's study, one activity involved 10 male and female teens in an after-school program creating advertisements to encourage young people to stay in school. The researchers learned that a core value associated with lifelong education was economic independence. Based upon this finding and others, the researchers developed a program that not only leveraged the participants' interest in games, but one that also directly addressed participants' desire for economic stability by offering game testing jobs (DiSalvo et al., 2013).

Thus, the expectation for this proposed research is that situating a critical data science education program in community-based participatory design research will support youth participants (1) to learn data science concepts/practices, (2) question the effects of digital technologies, and (2) uncover their and their communities' interests and values in empowering ways.

B.4. Learning Theory and Evaluation.

B.4.1 Epistemic Frame Theory. To evaluate the learning that occurs in the critical data science education program, I draw on sociocultural learning theories that characterize learning as complex and situated combinations of ways of knowing, doing, and being (Lave & Wenger, 1991; Wertsch, 1991). Specifically, this work is grounded in *epistemic frame theory*, which models learning as connections across both cognitive and social elements such as knowledge, skills, values, and epistemologies (Shaffer, 2006). More specifically, "epistemic frames are a form of… knowing where to begin looking and asking questions, knowing what constitutes appropriate evidence to consider or information to assess, knowing how to go about gathering that evidence, and knowing when to draw a conclusion and/or move on to a different issue" (Shaffer, 2004). This theory allows for an analysis of critical data science learning in terms of the individual and the social context simultaneously as a complex system. In this way, we can model how learners are connecting across their own personal knowledge, practices, values, and epistemologies and those of critical data science as they interact with the program.

B.4.2 Quantitative Ethnography. To measure the connections learners make, I will use *quantitative ethnography*, a novel methodology that integrates qualitative and quantitative analyses (Shaffer, 2017). This methodology brings together ethnography and the tools of statistics to create deep meaning from large datasets. The statistical analyses allow for discovering unexpected patterns in large datasets and measuring the strength of relationships among variables. The ethnographic analyses allow for interpreting meanings behind what learners are doing and saying in order to tell their stories. Through quantitative ethnography, the power of computation and the power of human interpretation are leveraged to reveal meaningful results about the process of learning. From an ethnographic perspective, data that is collected from learners can be referred to as small-d discourse—ways of acting and interacting in the world that we observe from individuals (Gee, 2011). Using quantitative ethnography, discourse can be computationally analyzed to understand broader patterns of interactions that can be attributed to a group culture. These patterns of discourse are known as big-D Discourse and are ways of "talking, listening, writing, reading, acting, interacting, believing, valuing and feeling (and using various objects, symbols, images, tools, and technologies)" that are unique to a particular group of people who share common ways of being and thinking in the world.

In this project, the research team will collect small-d learner discourse data from audio and video data and learners' digital and non-digital artifacts, which will be in the form of presentable media, such as a poster, an interactive website, video, or programming code to create databases of the specific things that learners say and do. We will then use two quantitative ethnography tools, nCoder and Epistemic Network Analysis (see below) to infer and make meaning of the discourse data to understand the broader big-D Discourses of critical data science learning.

B.4.3 nCoder. To analyze discourse data and learner artifacts, we will use grounded, qualitative coding methods to identify data sciences practices and social, ethical, and political technology issues. However, because the datasets will contain large amounts of data, it will be difficult to identify and code all the themes by hand. In turn, we will use nCoder, a learning analytics platform for developing and automating coding schemes (Cai et al., 2019; Shaffer et al., 2015). The nCoder assists researchers by providing a user-friendly interface for developing sophisticated keyword lists that automate the hand-coding process. To validate the automated process, the data coded by the algorithm is compared to data coded by human raters and inter-rater reliability is measured. In addition to providing a usable platform to develop codes and test inter-rater reliability, the nCoder provides a statistic, rho, that functions like a p-value. If rho is less than .05, then the results from the sample which was coded can be generalized to the larger dataset (Eagan et al., 2017; Shaffer, 2017).

B.4.4 Epistemic Network Analysis. To analyze the coded data, we will use Epistemic Network Analysis (ENA), a tool that measures and visualizes connections among codes in data (Shaffer, 2017; Shaffer & Ruis, 2017). ENA measures when and how often learners make links between domain-relevant elements during their work, which in this case would be links among data science practices and ethical/social issues. ENA identifies the co-occurrences of coded elements and represents them in weighted network models. When a learner repeatedly makes a link between elements over time, the weight of the link between those elements is greater. Furthermore, ENA enables researchers to compare networks both visually and through summary statistics that reflect the weighted structure of connections. Thus, researchers can use ENA to model discourse networks and quantitatively compare the discourse networks of individuals and groups of people in a variety of domains (Arastoopour et al., 2014; Arastoopour & Shaffer, 2013; Nash & Shaffer, 2011). These affordances also allow researchers to make claims about assessing knowledge development (Arastoopour et al., 2016).

B.5. Pilot Study on Critical Data Science Education and Quantitative Ethnography. In Spring 2019, I and a graduate student researcher at Northwestern University developed and instructed a data science extra-curricular program and used quantitative ethnography to evaluate learning. The course was titled "Data Detectives," and took place on six consecutive Saturdays for 2.5 hours each day. The first half of the course was an introduction to data visualizations, statistical concepts, and the statistical programming language R. In the last half of the course students completed a final project by analyzing a chosen dataset using R. Students presented their projects in an expo-style format in which parents and family were invited to attend. The learning goals of this course were to (1) learn to use programming and statistics as tools to analyze, visualize, and make claims about data and (2) reflect on the social and ethical implications of algorithm bias.

B.5.1. Design of Data Detectives. In the course, students engaged in four algorithm bias activities. The first activity was an introductory discussion about algorithm usage. One instructor displayed her Amazon home page and discussed the usage of Amazon algorithms for customers. Students were asked to define algorithms in this context and shared personal experiences with Amazon. The second activity was an embodied version of an algorithm that simulated Amazon's biased hiring algorithm that discriminated against women applicants. Students each received a card that simulated a resume and gathered in the center of the room. One instructor personified the algorithm by announcing the step-by-step procedures and revealed which resume characteristics scored a positive or negative score. Students stepped forward if their characteristics scored positively and backwards if their characteristic scored negatively. After three rounds, the instructor announced the top three candidates with the highest scores. Students were then asked to flip over their resumes to uncover their assigned genders (limited to man or woman) and discovered that men had positive scores and women had negative scores. Students were then asked to compare resumes and discuss the results. In the third activity, students watched a video about algorithm bias, which included discrimination issues with facial and photo recognition technology, and then engaged in a discussion. In the fourth and final activity, students reviewed the prior activities and discussions. Then, in small groups, they used Google image search to evaluate potentially biased searches and discussed their results in a large group.

B.5.2. Data Analysis. The following analysis focused on the fourth and final algorithm bias activity and discussion in the course. In this activity, students conducted Google image searches in small groups to investigate gender and racial discrimination in the results. Afterwards, the instructors led the 12 students (all males with prior programming experience, ages 11 – 13) through a discussion about the images. We segmented the conversation into 72 lines of turns of talk and then coded the data. We adapted the Philip et al.'s (2013) framework for learning about big data for demographic participation to develop a coding scheme (Table 1). The coded data was analyzed using ENA and networks were created for each participant. Co-occurrences between codes were measured using a *sliding window model* (Siebert-Evenstone et al., 2017), in which a window size of 4 lines of talk was used to count co-occurrences of codes within one person's line and the recent temporal context of the conversation up to 3 lines before their line.

Table 1. Coding Scheme for Data Detectives Group Discussion About Google Search Algorithm Bias. Adapted from Philip et al.'s three categories for learning about big data for demographic participation.

Content/Discursive Fluency	Motivated Use of Content	Politics of Knowledge
Algorithms Defining, referring to, or providing examples of general algorithms or rules	Social Justice Referring to algorithms, user interface, and machine learning concepts to work towards greater justice and equity in society	Gender Bias Referring to the limitations of algorithms in terms of marginalizing or obscuring perspectives of women or non-binary gender populations
User Interface Referring to existing or new user interface design	Algorithm Accuracy Referring to designing algorithms such that the results represent current existing social situations	Racial Bias Referring to how algorithms marginalize, obscure perspectives, or do not address the needs of people of color (in this discussion, referring to Black or Asian populations)
Machine Learning Referring to training/test datasets or algorithms created based on previous data	Personal Effect Referring to how algorithms effect their personal lives or of their communities	Posing Dilemmas Posing a paradox, dilemma, or difficult question related to social, ethical, and political issues in data science

B.5.3. Results. Based on the course of events, we separated the conversation into four key events: (1) Students' collective observations and sense-making, (2) Ted's posed dilemma, (3) Alexander's design question, and (4) Pat's story, and focused on the discourse networks of Ted, Alexander, and Pat. At the start of the activity, students freely investigated Google image search for algorithm bias in teams of four. The instructor initiated a discussion and Ted, one of the key players in the conversation, introduced race and gender issues by stating "So first of all besides Steve Harvey, 'game show hosts' are a bunch of *(hesitates)*, I mean, old White dudes. And if you look at 'nurse,' there's a bunch of women and a majority of them are White and if you look up 'doctor,' there's a few girls, but it's mostly men." Initially, he hesitated to describe the race and gender of the people in the image search and chose to use the word "dudes" to add comedic relief. As the discussion progressed, Ted used "men" in place of "dudes," seemingly more comfortable in the discussion. He continued to describe the inequities in gender when searching for athletes. Other students joined the discussion, noticing that there were more men than women in the image search for basketball and tennis.

After some time, Ted posed a question to the group: "Well, here is the question: Would you rather have accurate results when you Google physics professor and it's all old, White men or would you rather have it be very diverse but that's not the majority of physics professors. I don't really know, but if they are mostly old White men, would you want the results to be not accurate when you Google that, you get different—So that's the question: *would you rather have it be accurate or would you rather have it be diverse?*" Ted's question powerfully framed the remaining discussion as a dichotomy between "accuracy" and "diversity."

Replying to Ted's questions, another student suggested a redesign of Google's search algorithm that offered the user a choice between displaying results that were diverse and results that were based on existing data. Building on this suggestion, Alexander shared a concern about which search results would require such an option: "Let's say we ask for doctor and try and balance it out. But how's it supposed to know what topics don't need balancing out? Because like if you say give me a red apple, that would totally ruin the results by saying something like that… it wouldn't make the results mean anything." Alexander's main question was which algorithms should we change to make more diverse and which algorithms should we change to make more accurate? He claimed that the algorithm would not know which topics to appropriately diversify. He chose an inanimate example of searching for a red apple and argued diversifying such image results would be meaningless. The conversation then shifted to algorithms with bias that impacted people and the students contributed examples outside the scope of the Google image search algorithm. For example, Pat, an Asian-American male, shared this story: “So a while ago, the iPhone X, the face recognition, so this kid, he was Chinese, his mom said the face recognition was for her face but when he put it up to his face, it recognized him and said they were the same thing.” In response, another student, expressed “That’s messed up,” indicating that the situation was unsettling or, potentially, unjust. This student later added, “But no matter how much data you have, there’s probably always going to be some bias because there might be a little bit more of this or that but if you use more even data, then there will be a smaller bias than if the data had a majority of *(hesitates)* White people or tall people or short or stuff like that.” He claimed that training data will always contain bias, no matter how much data are used. However, he acknowledged that the use of a dataset that includes a variety of people may reduce bias and the consequences associated with biased data. He used a racial term (“White”) but hesitated before using the term and quickly added other non-racial descriptive categories (“tall people or short or stuff like that,”), potentially because of his discomfort discussing race.

The ENA results display summary visualizations of each key student’s contributions to the conversation in terms of a discourse network (Figure 1). The networks revealed that students made connections across the three categories of content/discursive fluency, motivated use of content, and politics of knowledge, but did so in different ways. Pat focused on racial bias and social justice, Alexander focused on the structure of the algorithms and machine learning concepts, and Ted had an overall balanced network.

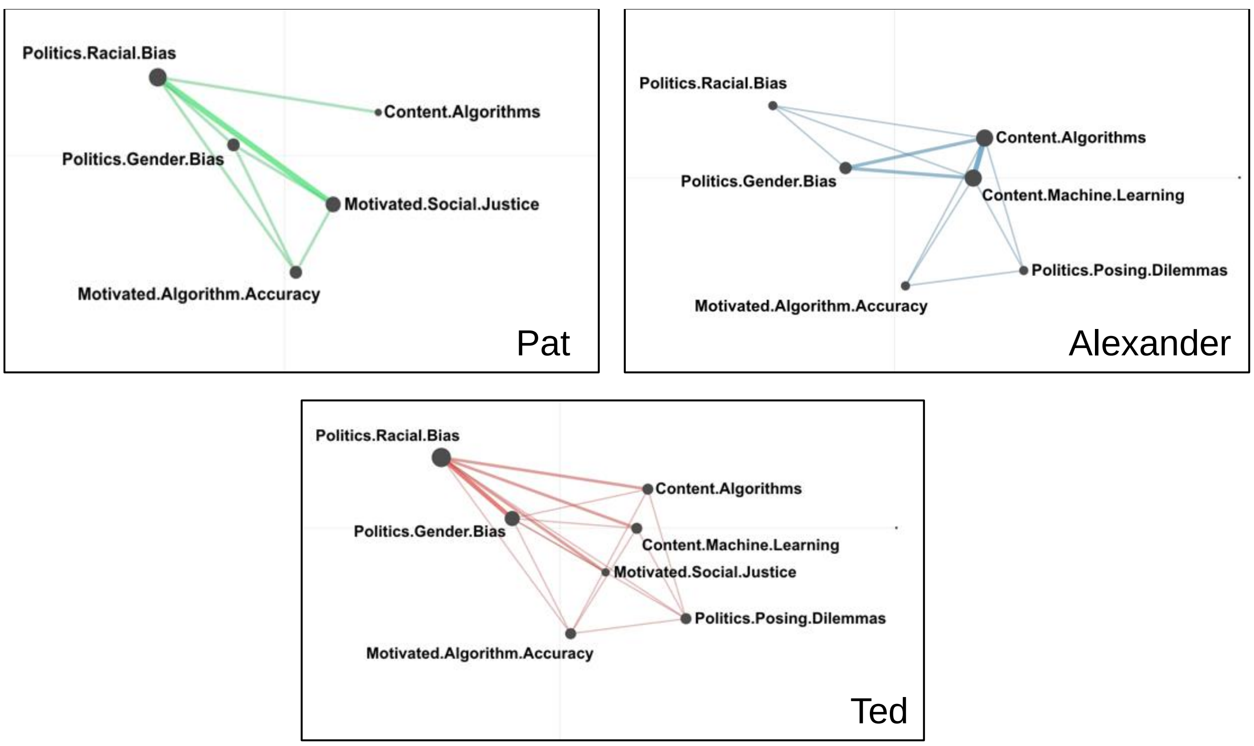

Figure 1. Discourse networks for three key students: Pat (green, focus on racial bias and social justice), Alexander (blue, focus on machine learning and algorithms), and Ted (red, overall distributed network)

The quantitative ethnography analysis of the classroom discussion suggests students engaged in all three categories of the big data for democracy framework: content/discursive fluency, motivated use of content, and politics of knowledge. For example, students navigated their own Google image searches, choosing to search for athletes and doctors to investigate racial/gender discrimination and offered design suggestions to work towards social justice. Although they were visibly uncomfortable discussing race at times, students showed an understanding that algorithms are political, questioned the use of algorithmic results and usage, and engaged in complex, ethical dilemmas that are currently being discussed in the broader world. The implications of this initial work are that through structured activities, youth can engage in complex, ethical big data dilemmas that are part of a broader social conversation. This initial pilot study serves as the foundation for this proposal to (1) broaden investigations of how diverse populations of students make sense of algorithm bias and how they relate such issues to their own personal lives and of those in their communities, (2) develop more robust learning frameworks to inform future teaching and learning in areas of critical data literacies and learning, and (3) broaden participation of youth in critical data literacies and computing education.

C. RESEARCH PLAN

C.1. Project Development and Implementation. According to the IES-NSF Common Guidelines for Education Research and Development, this proposed project is classified as *foundational research* and investigates the development of learners' knowledge, practices, and feelings of empowerment towards enacting change in their communities in the context of critical data science learning. The aim of this research is to contribute to our understanding of how middle school aged youth make sense of social, ethical, and political algorithm bias issues when engaging in data science practices and to develop a theoretical model for critical data science learning in the context of informal learning environments. This theoretical approach will be grounded in existing sociocultural theories and epistemic frame theory and will model critical data science learning as a dynamic connected web of knowledge, practices, values, and epistemologies. This research will focus on the process of learning that occurs in a particular informal learning environment. While the project includes a design component to develop the learning environment, answering questions about the process and efficacy of the design is not the primary focus. Thus, to support the research aims of answering questions around learning processes, the research team will design and implement a critical data science (CDS) after-school program.

C.1.2. Research Sites and Community/Youth Demographics. For this project, the research team will partner with the YMCA of Greenville, South Carolina. The YMCA of Greenville offers an after-school program at 5 branches for primary and middle school aged youth between the ages of 5 – 14. Collectively, the sites serve 40 elementary schools and 19 middle schools. During the after-school program, youth participate in one hour of physical activity and one hour of homework assistance daily. The after-school program also offers a one-hour enrichment session to "enhance the overall exposure to a balanced curriculum" (*After School | YMCA of Greenville*, 2020). The CDS program will be implemented during this enrichment time for 4 – 6 consecutive weeks with a subsection of youth who are between the ages of 11 – 14 and attend middle school. For the implementation, we anticipate a total sample size of 110 middle school aged youth. In the city of Greenville, South Carolina, 65% of the population is White, 25% is African American (which is higher than the national average of 12%), 5% is Hispanic or Latinx, and 5% are other races or mixed. Further, 15.3% of people live below the poverty line which is higher than the national average of 13.1% (US Census Bureau 2018), and 50% of Greenville county middle school students qualify for free or reduced-price lunch (Greenville County Schools, 2019). The YMCA of Greenville estimates that 65% of participants in the after-school program are youth of color.

C.1.1. Design of the CDS Program. The project will span two years. In year 1, the research team will use community-based participatory design to develop and design the CDS program. In year 2, the research team will implement CDS, collect data, and conduct analyses to answer research questions. As suggested by Könings and colleagues (2014), participatory design in practice often occurs in separate pairs of interactions. In turn, the structure of our participatory design will include meetings in which researchers meet independently with YMCA mentors/counselors, parents, and youth. The design activities will be based on prior work from the Data Detectives pilot study conducted at Northwestern University (see section B.5.3 for results), MIT's AI + Ethics Curriculum for Middle School (Payne, 2019), and the *Glitch Game Testers* project (DiSalvo et al., 2013). The table below outlines the description of example activities for each meeting.

Participants	Example Design Activities	Desired Outcomes
Researchers and Children (Middle school aged youth in YMCA after-school program)	1) Researchers and children co-develop questions about digital technologies and artificial intelligence. Youth interview each other in pairs using digital cameras. Then, youth watch videos of other pairs and reflect. 2) Embodied algorithm activity in which youth role-play as inputs to an algorithm with embedded biases. Youth reflect on algorithm output, efficacy of the activity, and potential future activities for the curriculum.	Researchers: understanding of student values around algorithm bias and everyday use of digital technologies, understanding of the political and social issues children face in their communities (both individually and more broadly), identifying culturally-relevant ways of teaching and learning Children: awareness of algorithm bias, reflection on the political and social issues in their communities, contribution in terms of topics or activities to future design of the CDS program.
Researchers and Adults (YMCA counselors/mentors, parents, members of the community)	1) Researchers and adults watch short video clip on algorithm bias and engage in structured dialogue to reflect on algorithm bias issues. 2) Adults engage in a structured activity with a Google AI experiment (https://experiments.withgoogle.com/collection/ai) and on ethical concerns. This activity promotes further discussion into ethical concerns with technologies.	Researchers: understanding of parent values and concerns around algorithm bias, parent's everyday use of digital technologies and perspectives on children's use, understanding of the political and social issues adults face in their communities (both individually and more broadly) Adults: awareness of algorithm bias issues, reflection on the political and social issues in their communities, contribution in terms of topics and activities to the future design of the CDS program

Data will be collected from the participatory design activities in the form of audio and video recorded interactions. The research team will review this data and use it for the basis of the design and development of the CDS program which will be implemented in year 2. The details of the activities will be dependent on the results of the participatory design activities and what the research team discovers about the communities' values. However, the core components of CDS will include:

Social/Ethical/Political Data Science Issues. The CDS program will incorporate activities and discussions around pressing social, ethical, and political issues in big data algorithms. Such issues include racial/gender biased search algorithms, inaccurate or inappropriate suggestions from YouTube video suggestion algorithms, the use of limited training datasets for facial recognition technologies, and how facial/video recognition data are commoditized and used by companies and law enforcement agencies. The issues that will be chosen for youth to explore will be presented as dilemmas, be open-ended, and exist as a topic in the broader social discourse. The specific contexts of such issues will be determined from the results of the participatory design activities in order to maximize alignment with learners' interests and values.

Culturally-Relevant Teaching. We will employ culturally-relevant teaching strategies that align with the culture of the learners and the community (Ladson-Billings, 1995, 2014). For example, prior work from Nasir and colleagues (2008) showed vast differences in a group of African American male students' engagement within basketball and mathematics classrooms and concluded that particular structures of activities can promote or hinder learning and self-expression. However, we are careful not to imitate prior research and make broad generalizations based on the demographics of the participants in this study. Thus, the specific details of how to engage students and the details of the activities will be determined from the results of the participatory design activities.

Integration of Existing Frameworks for Data Science Learning. We will also align the activities with existing critical data literacies frameworks appropriate for informal learning, such as Philip et al.'s (2013) big data for democratic participation, Jiang & Kahn's (2019) ten sociotechnical practices for data wrangling, and Lee and Wilkerson's (2018) status report on data use in the digital age for middle and secondary students. It is possible and even likely that there will be conflicts with the community's discovered ways of knowing and doing and the ways that are outlined in existing knowledge frameworks. In the spirit of a critical education program, the CDS program will highlight such conflicts and invite students to reflect on existing tensions between dominant and non-dominant approaches in education. For this first implementation of CDS specified in year 2 of this proposal, the research team will co-facilitate with YMCA counselors. However, the long-term implementation plan beyond the scope of this proposal is for the YMCA personnel to be the facilitators, implementors, and core designers of this program in the future.

C.1.3. Research questions.

RQ1. While engaged in a participatory design-based critical data science program, how do learners develop data science knowledge, practices, values, and epistemologies?

RQ2. After participating in a participatory design-based critical data science program, to what extent do learners feel empowered to enact change in their communities regarding the generation, transformation, interpretation, and representation of data?

Based on prior work conducted in the pilot study, I hypothesize that (1) participants will connect across data science knowledge, practices, values, and epistemologies, **developing more connected discourse networks** as they progress through the program, (2) participants will engage in the program in various ways and thus, **results will show multiple trajectories of participation** as evident in participant discourse networks, and (3) participants will have **increased feelings of empowerment** to enact change in their communities after participation in the program.

C.1.4. Data Sources.

Learning Data. The research team will collect discourse data from students as they engage in activities in the form of audio and video recordings. We will also collect students' digital and non-digital artifacts which will be in the form of presentable media, such as a poster, an interactive website, video, or programming code. These data will be used to answer RQ1.

Surveys. Currently, no validated surveys exist that specifically measure feeling of empowerment to enact change in the context of data science, computing, or digital technologies. Thus, in this study, we will measure feelings of empowerment in several ways. First, we will administer pre-post surveys adapted from the 22-item Critical Consciousness Scale (Diemer et al., 2017) and the 17-item Sociopolitical Control Scale for Youth (Peterson et al., 2011) to measure political perceptions, civic engagement, and agency. Questions include asking Likert scale agreement levels on items such as, *Certain racial or ethnic groups have fewer chances to get ahead*, *All groups should be given an equal chance in life,* and *It is my responsibility to get involved and make things better for society*. Second, we will measure general attitudes towards the discipline of data science by adapting the Attitudes Towards Computing scale that consists of 19 items measuring computing confidence, enjoyment, perceived usefulness, motivation to succeed, and identity/belongingness (Wanzer et al., 2019). Third, we will add open-ended questions to the end of the administered surveys to collect qualitative data about learners' self-perceptions as agents of change in terms of the generation, transformation, interpretation, and representation of data. These questions include *What are examples of unfair or biased algorithms that affect you or people you care about?, What are your concerns with technology consumption and production?,* and *In your examples, who benefits from technology and who is harmed?*. These data will be used to answer RQ2.

C.1.5. Data Analyses.

Quantitative Ethnography. To answer RQ1, we will use two quantitative ethnography tools, nCoder and ENA. We will use a grounded analysis guided by existing data science education frameworks to uncover learners' emerging knowledge, practices, values, and epistemologies. Then, we will use nCoder to develop and validate automated coding schemes to code our large datasets of learner discourse and artifacts. To analyze the coded data, we will use ENA to model learners' developmental trajectories of learners' data science knowledge and practices by measuring the co-occurrences of these elements and modeling their relationships over time. We will also use the results from the surveys as a grouping variable for the ENA models to determine if there are relationships between learners' levels of feelings empowerment, attitudes towards computing, and their patterns of data science knowledge and practices.

Statistical Models. The research team will construct three linear mixed-effects (multi-level) models that nest participants within the 5 after-school sites. In the first model, the civic engagement post survey results will be the dependent variable and the independent variables will be the civic engagement pre survey results and participant demographic information (as covariates) and the 5 sites as grouping variables to determine if there are significant changes in learners' civic engagement and agency. In the second model, the attitudes towards computing post survey results will be the dependent variable and the independent variables will be the pre survey results and participant demographic information (as covariates) and the 5 sites as grouping variables to determine if there are significant changes in learners' attitudes. In the third combined model, the dependent variable will be changes (post – pre) in civic engagement and the independent variables will be changes (post – pre) in attitudes towards computing to determine if attitudes toward computing predict civic engagement at any or all of the 5 after-school sites. These models will be used to answer RQ2.

D. PROFESSIONAL DEVELOPMENT PLAN

D.1. Research Skills Training and Professional Development. To address research questions around critical data literacies in informal learning environments, I will need mentoring in three scholarly areas: participatory design for computing education, informal learning environments for middle school aged children, and modern quantitative ethnography methods. My graduate training focused on design-based research developing engineering virtual internships in which undergraduate students role-played as interns for a biomedical devices company. Similarly, my post-doc training focused on developing science curricula that integrated computational thinking for high school students in public schools. In both of these research projects, I and a team of researchers developed learning interventions for young adults with limited feedback from teachers, students, and stakeholders. This leaves me with a lack of knowledge on how to design learning environments using a more democratic participatory design approach that involves all stakeholders in the design of a computing educational program. Further, I require training on how to design informal STEM learning environments for younger populations outside of a traditional classroom. Regarding the analysis of learning data, I have had experience with quantitative ethnography in my graduate training at the University of Wisconsin with the Epistemic Analytics group. However, it has been four years since I have engaged in collaborations with the group and since then, quantitative ethnography methods have advanced significantly. To engage in the highest quality analysis, I will need access to the recent versions of the tools, guidance on using the most advanced methods, and feedback on my analyses.

This proposed project also provides opportunities for me to advance my professional development as a rising scholar in terms of developing my mentoring skills and receiving guidance on mapping out a long-term research agenda. As a first-year assistant professor in the learning sciences, I have had limited opportunities mentoring graduate students in STEM education. The learning sciences program at my institution was established five years ago and doctoral enrollment has increased dramatically in a short time. I am quickly becoming one of the core faculty to help shape the program. The program admits students with a variety of interests but has recently seen an increase of students at the intersection of STEM education and democratic/ethical design of learning environments. To best serve our students and to contribute to a robust learning science program and the learning sciences field overall, I need to broaden my expertise in STEM education to include informal learning, early and middle childhood education, and democratic participatory design and analysis methods. I am also engaged in inclusive mentoring and seek to support students who are from non-dominant populations. For example, I am a certified Clemson University LGBTQ+ ally and a member of the inclusion committee for the Society of Learning Analytics Research. As a result, I am approached by undergraduate and graduate students frequently to provide informal feedback, mentorship, or guidance. I would like to further develop my ability to mentor in STEM education research and particularly to support non-dominant populations in STEM education research and academia.

D.1.1 Feedback Sessions with Mentors. Three faculty members will provide mentoring on this project and each is an expert in the three scholarly areas related to the project detailed above. Each mentor will meet virtually with me and the graduate research assistant (GRA) two times during the stage of the project in which their expertise is needed. I will also travel once to each mentor's institution to meet with them and their research lab.

Betsy DiSalvo, Ph.D., Associate Professor, School of Interactive Computing, Georgia Institute of Technology, is a leading expert on the impact of cultural values on technology use and production. She will provide guidance and feedback on the community-based participatory design process.

Michael Horn, Ph.D., Associate Professor, School of Education and Social Policy, Northwestern University, is a leading expert on the uses of emerging technologies in diverse learning settings. He will provide guidance and feedback on the design of informal, culturally-relevant learning environments for youth.

David Williamson Shaffer, Ph.D., Vilas Distinguished Achievement Professor, School of Education, University of Wisconsin, is a leading expert in assessing complex and collaborative thinking skills. He is the founder of the quantitative ethnography methodology and developer of Epistemic Network Analysis and nCoder and will provide guidance and feedback on the quantitative ethnography analysis of learning data.

D.1.2 Developing Mentoring Skills. As this proposal would support two GRA's, I will have an opportunity to further develop my mentoring skills. The GRA's will be involved in all stages of the project: collecting data from participatory design activities, the design of the CDS program, collecting data from the CDS implementation, analyzing data using statistical models and quantitative ethnography, and attending mentoring meetings. I will also be receiving guidance from the mentors on how to best delegate tasks to the GRA's and support the GRA's research development and goals.

D.1.3 Advisory Board Meetings. All three mentors will also serve as an advisory board of experts. There will be two advisory board meetings (one per year, all held virtually). Advisory board meetings differ from individual mentoring meetings in that all faculty will meet with me and the GRA's to provide collective evaluation and feedback on the project. For the second meeting, the advisory board will also discuss a 5-year plan for my professional development and research trajectory.

D.1.4 Additional Professional Development Activities. I will attend conferences and workshops to connect with potential collaborators and deepen my theoretical understanding of STEM learning. I propose to attend the International Conference of the Learning Sciences (ICLS), American Education Research Association (AERA) Conference, the International Conference of Quantitative Ethnography (ICQE), the Educational Data Science Conference at Stanford University, CSforAll Summit, the Connected Learning Summit, and the ACEM SIGCSE (Association for Computing Machinery Special Interest Group in Computer Science Education). These conferences will also serve to disseminate the research findings. I will also target several research journals to publish findings including the *Journal of Learning Sciences*; *Learning, Media, & Technology*; and *Educational Researcher*.

D.1.5 Professional Development and Project Timeline. Below is a timeline for travel, project milestones, project deliverables, and professional development activities.

Timeframe and Travel	**Project Milestones**	**Project Deliverables**	**Professional Development Activities**
Aug 2020 – Dec 2020 Arastoopour Irgens → DiSalvo @ Georgia Tech	Participatory design activities conducted with all stakeholders Data collection in the form of interviews and observational data from activities Conduct qualitative analysis of participatory design activity data	Clear plan for the design of CDS program based on analysis of participatory design activities	Mentoring from DiSalvo for Arastoopour Irgens on the implementation of participatory design activities, the qualitative analysis of interview and observational data, and the use of results to design CDS program. This includes suggested readings and feedback on analysis and results.
Jan 2021 – Jul 2021 Arastoopour Irgens → Horn @ Northwestern	Design and development of the CDS Program Initial advisory board meeting (takes place virtually)	CDS Program materials	Mentoring from Horn for Arastoopour Irgens on the design of an after-school learning environment for youth ages 11-14. This includes suggested readings and feedback at multiple stages of the design process.
Aug 2021 – Oct 2021	Implementation of the CDS program at YMCA of Greenville after-school locations	Data collected in the form of interviews, pre-post surveys, observational data from implementation, and digital data from learning environment	
Nov 2021 – Mar 2022 Arastoopour Irgens → Williamson Shaffer @ Wisconsin	Analyze learning data with nCoder and Epistemic Network Analysis Analyze pre-post surveys through multilevel models	Results that answer research questions about youth learning and feelings of empowerment	Mentoring from Williamson Shaffer for Arastoopour Irgens on using Quantitative Ethnography for analyzing learning data. This includes feedback at multiple stages of the analysis process.

Apr 2022 – Jul 2022	Collaborative writing of manuscripts for publication Final advisory board meeting (takes place virtually)	Dissemination of research through conference and journal publications	Guidance from the advisory board on a 5-year plan to continue this line of research, including iterations and expansions of the CDS program, expanding research to include questions about the community-based participatory design process, and submitting an interdisciplinary EHR grant proposal.

E. INTELLECTUAL MERIT

This project integrates data science education research and sociocultural learning theories to build new theoretical understandings about the nature of data science learning in the context of pressing social, ethical, and political issues. The setting of a community-based after-school center offers a unique opportunity to co-design culturally-relevant STEM programs with community stakeholders, including the youth themselves. This approach will advance knowledge and understanding of how middle school aged youth engage in STEM practices in ways that are valued within their own cultures and within broader STEM communities. This project supports a long-term research program to develop theoretical sociocultural models of critical data science learning and more practically, how to successfully engage youth in community programs that promote ethical, culturally-responsive, and critical STEM learning.

F. BROADER IMPACTS

Although access to general data science programs are increasing across K-12 education, few programs exist that engage learners at an early age in data science education in which culturally-relevant social, ethical, and political issues are the focus. This project addresses this gap by developing a critical data science program for middle school aged youth in an after-school community center. This highly collaborative project involves the direct engagement of over 100 after-school counselors, parents, youth, researchers, and valued members of the community center to co-design and implement a critical data science education program. This broad reach exposes not only young people to data science learning and social/ethical issues within big data technologies but also counselors, parents, and other members in the community who choose to participate. Moreover, the majority of youth in this project are children of color and living in poverty—populations who are underserved and underrepresented in STEM. This project serves these youth by providing culturally-relevant experiences that may ultimately motivate underrepresented youth to pursue STEM majors and careers, thus broadening participation in STEM. Youth who are members of the dominant population in STEM will also be impacted by this program by viewing harmful traditions of technology development and consumption through a critical lens and being made aware of those who are widely marginalized by digital technologies. Broadly, because of the critical approach used in this STEM curriculum that centers social/ethical/political issues, this project contributes to the development of a diverse, ethical, and well-prepared STEM workforce. Further, materials for the data science digital learning environment will be made openly available and easily adaptable, potentially engaging hundreds more counselors and learners in the future. This project also enhances the career development and interdisciplinary expertise of the PI through mentoring from an advisory board. Implementation materials of the educational program will be publicly available, enabling other YMCA centers or informal/formal education venues to adapt as needed for instructional or research purposes. Research results will be disseminated through learning sciences and computing education journals and conference publications.

G. RESULTS FROM PRIOR NSF SUPPORT

There is no prior NSF support to report.