DESIGNING FOR HIGH SCHOOL STUDENTS' ETHICAL MATHEMATICS CONSCIOUSNESS IN AN INTRODUCTORY DATA SCIENCE COURSE

by

Jordan Trombly Register

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Approved by:

____
Dr. Michelle Stephan

____
Dr. David K. Pugalee

____
Dr. Luke Reinke

____
Dr. Chandra Subramaniam

____
Dr. Laurie Rubel

____
Dr. Robert Q. Berry III

ABSTRACT

JORDAN TROMBLY REGISTER. Designing for High School Students' Ethical Mathematics Consciousness in an Introductory Data Science Course. (Under the direction of DR. MICHELLE STEPHAN)

The increased reliance on Big Data Analytics (BDA) in society, politics, policy, and industry has catalyzed conversations related to the need for promoting ethical reasoning and decision-making in the mathematical sciences. While the majority of professional data scientists today come from privileged positions in society, those processed by the decisions made using data science are more often members of one or more marginalized social groups, translating into disproportionately negative outcomes for these individuals in society. Thus, it is argued that future citizens must develop an *ethical mathematics consciousness* (EMC) *that human beings do mathematics; thus, there are potential ethical dilemmas and implications of mathematical work which may affect entities at the individual, group, societal, and/or environmental level.* Drawing from this conjecture, the purpose of this Design-based research study was to develop a local instruction theory and materials that promote students' ethical mathematics consciousness in a high school Ethical Data Science (EDS) course grounded in a *feminist, relational ethic of caring* and *social response-ability*. Outputs include the identification of design heuristics, including the task structures, participation structures, and discursive moves that supported students' development of EMC and equitable participation in classroom activities, an initial curriculum for the EDS course, and a student-use protocol and corresponding analytic framework for making critically conscious ethical decisions in data science.

KEYWORDS: *Ethical Reasoning, Big Data Analytics, data science, Design-Based Research*

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DEDICATION

To *Blake, Max,* and *Tyler*, for having you in my life is my greatest privilege.

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LIST OF ABBREVIATIONS

AB - Asian Boy

AI - Artificial Intelligence

BDA - Big Data Analytics

BG - Black Girl

C1 – Component 1: Moral Issue

C2 – Component 2: Relevant Knowledge

C3 – Component 3: Proposed Solution

C4– Component 4: Moral Justification

C5– Component 5: Alternative Scenarios

C6– Component 6: Alternative Consequences

C7– Component 7: Alternative Solutions

C8– Component 8: Agency

CK - Common/Accepted Knowledge

CMC - Critical Mathematics Consciousness

CME - Critical Mathematics Education

Cons - Consequentialism

CSK - Computer Science Knowledge

CT - Critical Transitivity

DBR - Design-Based Research

Deon - Deontic

Dis - Disempowered

DS - Data Science

DSIS - Data Science in Society

DSK - Data Science Industry Knowledge

Dys - Dysconscious

EMC - Ethical Mathematics Consciousness

EOC - Ethic of Care

GPK - General Professional Knowledge

IB - Indian Boy

IG - Indian Girl

Int - Intransitive

K-12 - Kindergarten through 12th grade

MK - Mathematical Knowledge

MT - Moral Theories

PRINC - Mid Level Moral Principles

RME - Realistic Mathematics Education

Semi - Isolated or Systemic Semi-Transitive

SK - Statistical Knowledge

SPK - Sociopolitical Knowledge

SR - Social Responsibility

STEM - Science, Technology, Engineering, and Mathematics

WB - White Boy

WG - White Girl

CHAPTER 1: INTRODUCTION

The accumulation of data and lack of ethical guidance for managing the scale of personal information collected daily is arguably the greatest concern of the modern age (D'Ignazio et al., 2020) and has significant implications for education. Given the newfound desire to process such data, the lack of qualified data scientists available has positioned individuals with advanced statistical, computational, coding knowledge as a commodity for corporations globally. As a result, it has been estimated that the majority of the jobs that will be available to students in the near future do not exist, and that many of these jobs will be in the data science field (Darling-Hammond, 2015). Importantly, every element of data science, from collection to analysis to enactment, includes distinct mathematical and statistical reasoning and critical thinking skills, while coding procedures and languages (e.g., Python, C++, Java, etc.) are grounded in algorithmic and logic-based thinking (Matthews, 2019). As such, the responsibility for the development of a data science workforce lies, at least partially, within the mathematics education community.

Beyond developing a data literate workforce, the impetus for a data science education is intimately connected to the global influence of Big Data Analysis (BDA). The emergence of data science as a means to predict a myriad of outcomes and behaviors, as well as replicate human-created products (i.e., generative Artificial Intelligence (AI)) has led to its all-encompassing dispersion in society, influencing industry, politics, policy, and our everyday lives. The consequences of its use are significant for individuals, groups, ways of knowing, and ways of creating in society. In particular, the algorithms developed through data science methods are often used as decision-making tools for policymakers in society and eligibility systems for social programs (O'Neil, 2016). While advancements in healthcare, improved consumer experiences, increased productivity, and expedited design and development processes reflect some of the benefits of BDA, it has been argued that the societal costs of its use may disproportionately affect individuals from historically oppressed groups (Benjamin, 2019; D'Ignazio et al., 2020; Eubanks, 2019). In addition, those who are processed most often by Big Data are rarely those behind the development of the algorithms that make decisions for their lives (D'Ignazio et al., 2020). Even in cases where the algorithms are open to public use (as in generative AI tools, like ChatGPT), there are already concerns about who has access, not only to the tools themselves, but to the knowledge and skills required to effectively leverage them, potentially contributing to wider socioeconomic gaps among world citizens. Therefore, beyond the impetus for a data literate global population is the necessity to foster critically conscious ethical dispositions both within the data science field and the general public in order to safeguard against the negative effects of BDA.

The Spirit of This Dissertation

The spirit of this dissertation is driven by the recognition of the critical need for integrating ethical reasoning into mathematics education in order to empower students to become critically conscious ethical decision makers who can contribute positively to the well-being of current and future global citizens in the Digital Age. In particular, its goals are to provide empirical contributions to the mathematics education community for designing instructional materials and theory that promote students' *ethical mathematics consciousness* (EMC) in data science contexts. Here, EMC refers to the awareness *that human beings do mathematics; thus, there are potential ethical dilemmas and implications of mathematical work which may affect entities at the individual, group, societal, and/or environmental level.* It includes awareness of the *sociopolitical* and *ecological* implications of mathematics as well as an awareness of how mathematics can be *communicated* in ways that influence the beliefs and behaviors of its stakeholders. Finally, it includes a sense of empowerment and personal *agency* to dismantle the oppressive systems that are enforced and/or perpetuated through mathematical products and processes. Importantly, EMC emulates normative ethical perspectives (ethics of decision-making) concerned with identity, power, context, and justice, which are not typical of more traditional normative ethical theories (i.e., consequentialist, deontic, virtue). Therefore, an important element of this work entails characterizing the ways in which diverse high school students reason ethically in order to make design conjectures for instruction that would encourage them to reason more critically about the impact of their work on oppressed communities, the environment, and beyond.

The development of ethical dispositions in any context, however, does not occur in a vacuum. Instead, encouraging discussions that draw on students' ethical belief systems naturally include reference to their personal values, perspectives, experiences, and emotions, whether good or bad, which are tied to their individual, collective, and intersecting identities. Thus, it is crucial to recognize that in heterogeneous classrooms, students enter with different ethical perspectives that reflect their community ways of knowing and being and may be more or less empathetic towards the oppressive influences of BDA. As a result, learning environments like the Ethical Data Science course (the designed intervention for this dissertation), that foreground discussions around ethics, oppression, and privilege have the potential to cause discomfort for students, impacting the ways in which they participate in all elements of the course. Thus, a primary goal of this dissertation is to provide guidance on how mathematics educators may honor students' diverse ethical and mathematical identities while designing instruction that promotes a sense of ethical and social responsibility to the masses in their mathematics and data science learning.

Research Approach

Design-Based Research

This dissertation employed a Design-Based Research approach (DBR) to the development of an Ethical Data Science course and instruction theory. Its purpose is to develop novel forms of learning that, like an ethical data science education, either do not exist or are in need of reform (Bakker et al., 2014). Importantly, the nature of design research is one based on constructivist and sociocultural notions of learning in which students are active learners (Bakker et al., 2014; Cobb et al., 2003). A design experiment is developed and implemented in order to create educational theories about both the process and means of supporting learning in dynamic and diverse classrooms. It includes engineering particular forms of learning, systematically researching those forms of learning within specific contexts, then testing and revising developed theories in cycles (Cobb et al., 2003).

Current Efforts in K-12 Data Science Education

The decision to employ a DBR approach to this work is rooted in the lack of established instruction theory and curricula available for ethical data science teaching and learning. The importance of data science education is reflected in international trends to develop a more data-centered mathematics curriculum as well as in the updated PISA standards which promote data-based reasoning and mathematical modeling (PISA, 2020). While some U.S. postsecondary institutions have established data science programs at the undergraduate and graduate levels, a standardized data science program for K-12 students has yet to be established.

Globally, initiatives to develop a standardized K-12 data science curriculum include efforts to transform the current mathematics curriculum, or provide resources (like K-12 data sciences courses) for the eventual shift to more relevant, modern schooling (Boaler et al., 2019; Gould et al., 2016; Koh, 2020; Tong et al., 2015). However, given the interdisciplinary nature of data science and the dynamic technological landscape associated with globalization, such initiatives have taken diverse approaches to course development. Major themes across course models include attention to broad data science concepts within a specific discipline (i.e., computer science or statistics) (Ben-Zvi et al., 2001; Mike et al., 2020), an interdisciplinary approach (Heinemann et al., 2018), or a peer-learning approach to teaching data science concepts and skills (Tong et al., 2015). Unfortunately, K-12 data science programs have yet to fully integrate ethics and social justice into their coursework. They typically focus on developing students' foundational understanding of the data life cycle and the basic statistical and/or computer science concepts necessary for navigating it (Ben-Zvi et al., 2001; Gould et al., 2016; Heinemann et al., 2018; Mike et al., 2020; Tong et al., 2015). While much of the developed coursework focuses on situating data science in real world contexts, their syllabi are not explicit about the development of ethical reasoning and critical consciousness of how their decisions influence society as being a key outcome.

To combat the aforementioned detrimental effects of BDA, scholars argue for the adoption of a sociopolitical perspective within the Data Science industry. Regarding data science education, Rubel and colleagues (2021) stressed the relevance of power in relation to data, arguing that power and responsibility may be hidden when people interact with technology if they lack an awareness of how mathematics operates within the software and/or how the outcomes influence society. Thus, Register, Stephan, and colleagues argued that ethics should be an explicit design focus of any data science educational materials (Andersson et al., 2022; Register et al., 2021; Stephan et al., 2020). Analogous to this stance, third wave-feminist Nel

Noddings (1988) argued for a revival of ethics as a primary aim for modern schooling. In contrast to notions of institutionalized education as a means for the development of academic skills only, Noddings (1988) urged that schooling in the United States has always been concerned with the development of righteous citizens. However, mid-century notions of righteousness stemmed from dominant Christian, Aristotelian, and Kantian ideals concerned with rights, needs, and individualism, values that were also essential for encouraging Christian charity, American entrepreneurship, and ultimately capitalism (Noddings, 1988). Given that the U.S. population consists of individuals and social groups whose ethical perspectives differ from these ideals, our ethical goals for public education must be adapted to accommodate the needs, values, and belief systems of those beyond the dominant group. Thus, a desired outcome of this work is to develop instruction theory for the promotion of ethical reasoning in data science which honors diverse (and especially non-dominant) ideologies, since such individuals are disproportionately impacted by the decisions made using data science methods (Benjamin, 2019; D'Ignazio et al., 2020; Eubanks, 2019; O'Neil, 2016).

The Design Experiment

Design experiments are constituted by three major phases: (1) Developing the initial design, (2) carrying out the experiment with *ongoing analysis* and revision, and (3) conducting a *retrospective analysis* at the culmination of the teaching experiment (Cobb et al., 2003). The following sections describe an overview of how this approach was used to develop, implement, and analyze the designed intervention: an Ethical Data Science (EDS) course for high school students.

Phase 1: Developing the Initial Design

In the initial design phase, a team of stakeholders and educators with relevant expertise were assembled (i.e., the design team). The design team for this study was assembled in August of 2021 and consisted of eight individuals whose roles and credentials are listed in Table 1.1. The design team met approximately once a month until July of 2022 when the EDS course was taught.

Table 1.1

Design Team Members and Credentials

Occupation/Level of Schooling	Research Interests/Experience Related Credentials	Role
PhD Student, Math Education	• Ethics • Data Science • Secondary Mathematics	• Lead designer, • Lead developer, • Lead analyst, • Lead author
Full Professor of Middle/Secondary Mathematics Education	• Inquiry-Learning • Design Research	• Design Research Methodologist • Co-analyst, • Co-author
Full Professor of Ethics	• Ethics of Big Data	• Consultant • Co-analyst • Co-author
Assistant Professor of Statistics Education	• Critical Statistics	• Consultant
PhD Candidate, Math Education, Statistics Instructor	• Critical Statistical Literacy Habits of Mind	• Consultant
Associate Professor of Mathematics and Statistics	• Teaching Mathematics with Technology	• Consultant
Assistant Professor of Systems and Informatics	• Computer Science Methods • Computational Thinking • Critical Computer Science Education	• Consultant
Professional Data Scientist	• Data Science	• Consultant

During the design phase, the design team developed a high-level conjecture to identify and explain the relevance of the designed intervention (the EDS course) based on existing theory and potential pilot studies (diSessa et al., 2004; Sandoval 2004, 2014). Drawing from socio-constructivist and Freirean notions of learning that position knowledge acquisition as both an individual and social act, heavily dependent on discourse, and necessarily grounded in critical contexts (Freire, 1970/2018), the high level conjecture for developing the EDS course was that *by immersing students in an introductory data science course grounded in ethical and critical contexts, students may develop critical mathematics consciousness and ethical reasoning in data science.* Note that this conjecture was based on the review of literature, three conducted pilot studies, and existing design heuristics from Realistic Mathematics Education (Freudenthal, 1973; Gravemeijer, 1994).

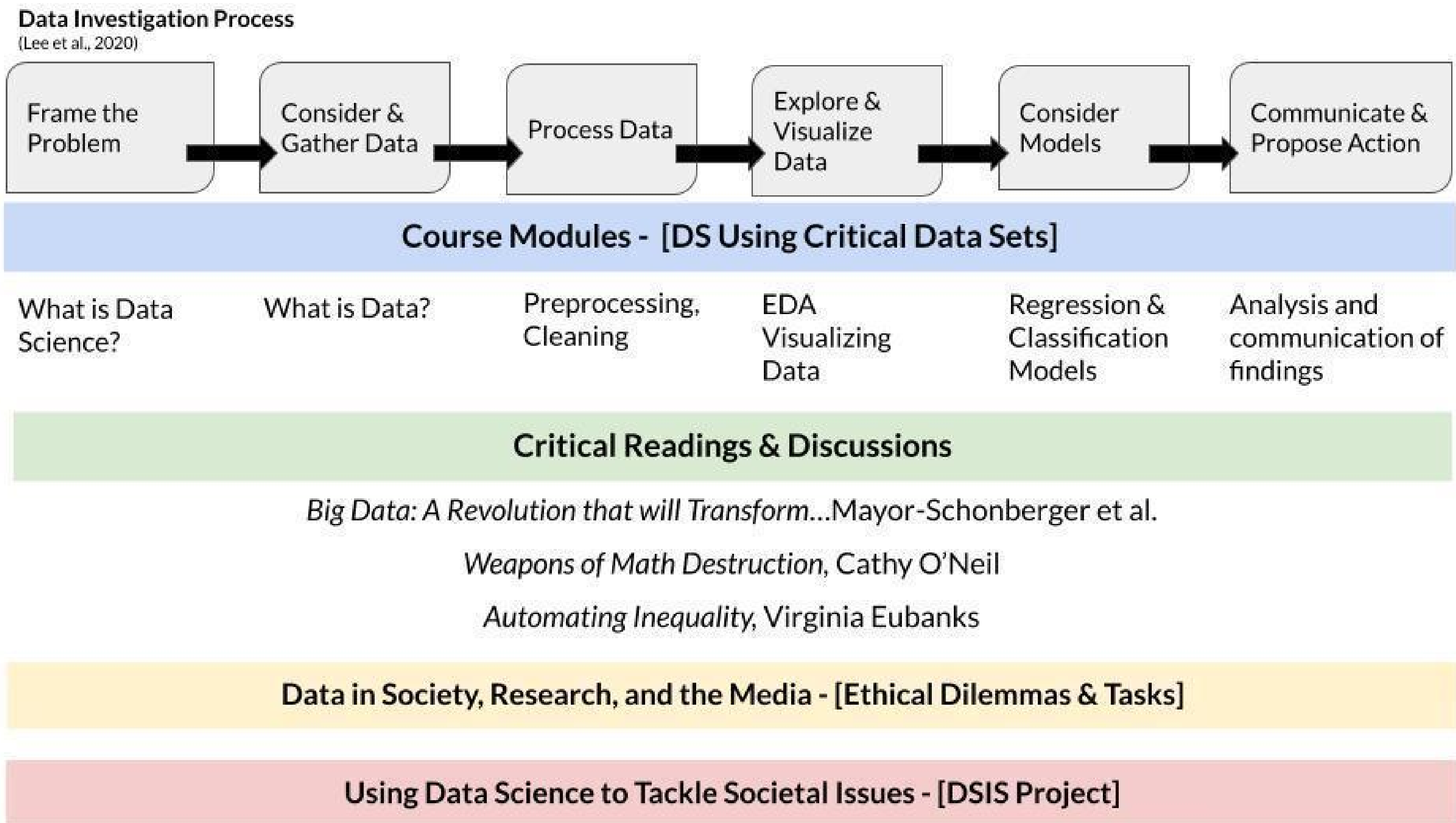
Following the high-level conjecture, design heuristics (*underlying assumptions* about teaching and learning) were identified and/or developed to guide the creation of a *conjectured* instruction theory to be refined as a product of the research (i.e., the local instruction theory). A local instruction theory describes the goals, learning trajectories, instructional activities and plans of action based on those design heuristics *within a given classroom context* (Cobb et al., 2003; Confrey et al., 2000). L*earning trajectories* consist of conjectures that are developed by the design team to hypothesize the conceptual *route* the students might take in their reasoning to reach the desired learning goal. For the EDS course, we first developed a hypothetical *course* trajectory to outline course-level learning goals for students and supporting course components. The course structure (a simplified version of the course trajectory, for readability) can be viewed in Figure 1.1, while the full course trajectory can be viewed in Appendix A.1. Individual learning trajectories for each of the course components (i.e. individual lessons or learning sequences and related materials) were subsequently developed to guide the design of individual lessons. These learning trajectories were developed by this dissertation author, then shared with the design team for feedback and modification. Once a trajectory was agreed upon, the author then developed instructional materials for the facilitation of those learning experiences. The materials were subsequently reviewed by select members of the design team, modified, and added to the EDS course curriculum. While the individual learning trajectories are outside of the scope of this paper, an overview of EDS Course Activities are included in Table 1.2. Note that this table includes only broad learning goals and some links to student materials and does not speak to the pedagogical considerations or facilitation of these specific activities.

The design heuristics used for the EDS course were primarily drawn from the core tenets of Realistic Mathematics Education (Freudenthal, 1968; Gravemeijer et al., 2000) and Critical Mathematics Education (e.g. Frankenstein, 1983; Skovsmose, 1994). However, we also recognized that students would likely enter the course with diverse ethical perspectives grounded in their respective cultures and experiences. Thus, it was necessary to consider how the instruction design may serve to build on students' existing ethical systems to develop interpersonal and systemic empathy for others. That is, a concern for the well-being of individuals and social groups outside of their communities or experiences. As such, we conjectured that the designed curricula must draw on, and aim to expand the ethical perspectives that students bring to the classroom.

For instance, if a student prescribes to deontological, consequentialist, or virtue ethics, we need to ask: what design principles must be enacted to expand students' ethical perspectives in ways that prioritize *social response-ability* and *care* for the self and others?

Figure 1.1

EDS Conjectured Course Structure



To guide our design process, an EMC Analytic and Design Framework was developed to identify students' probable ethical perspectives and critical consciousness in a given context, based on the ethical considerations they make. This tool was used in both the design and analysis phases of the DBR cycle and is offered in Chapter 2/Article 1. A description of the development of this tool is beyond the scope of this dissertation but will be published at a later date.

Course Overview. Broadly speaking, the learning goals for the EDS course are for students to develop 1) data literacy and 2) ethical reasoning and decision-making in data science characterized by pluralistic reasoning (the consideration of diverse and often contrasting perspectives and experiences), and systemic and interpersonal empathy (i.e. social responsibility and an ethic of care). The course structure included 20 instructional days which occurred over four weeks in July. It was facilitated both virtually (5 days) and in-person (15 days), where students accessed materials through the EDS Google Site.

The tools and materials used by students throughout the learning process were designed to reflect processes used and ethical considerations made in the data science industry, and to leverage students' rationale for making ethical decisions in data science contexts. For instance, students developed their Python programming skills outside of class through DataCamp.com and completed collaborative in-class labs through Google Sheets, Jupyter Notebooks, and Google Colab. The purpose of these labs was for students to gain experience following complex data science procedures and making complex decisions that have an effect on a multitude of entities in society, and to guide their methods for the Data Science in Society Project.

Table 1.2

Overview of Activities

	Broad Learning Goal	**Week 1.1** (2 days)	**Week 1.2** (3 days)	**Week 2** (5 days)	**Week 3** (5 days)	**Week 4** (5 days)
Theme	Be able to explain and execute the Data Investigation Process	Introduction to Data Science and Big Data Analytics	Frame the Problem Consider and Gather Data	Process Data Explore & Visualize Data Consider Models	Explore & Visualize Data Consider Models Communicate and Propose Action	The Data Investigation Process from Start to Finish
DS Topics Covered	Be able to define data science, BDA, its foundational components, processes, and function in society. Develop a conceptual understanding of the mathematics and statistical elements of data science.	Intro to DS, BDA, and DA Data Types Understanding Data Matrices Variables, and Attributes in Data Matrices	Descriptive Analytics & Data Collection Methods Identity in Data Data Fallacies to Avoid The Data Investigation Process	Fundamentals of Statistics for Data Science Introduction to Machine Learning (ML) Data Distributions and Regression by Hand	Correlation v Causation ML: Classification v. Clustering KMeans Clustering by Hand	
Python Programming Modules	Develop basic Python programming skills for data science.	Intro to Python Intermediate Python	Cleaning Data in Python Data Manipulation in Pandas	Exploratory Data Analysis in Python Statistical Thinking in Python (Part 1)	Supervised Learning with scikit-learn Cluster Analysis in Python	
Labs	Apply learned data science methods and programming knowledge to a real-world data set and societal issue with ethical consequences.			Lab 2 _ Salaries Lab 3_Coal Ash	Lab 4_Civilian Guns by Country Regression Lab 5_Civilian Guns by Country Classification and Clustering	

	Broad Learning Goal	**Week 1.1** (2 days)	**Week 1.2** (3 days)	**Week 2** (5 days)	**Week 3** (5 days)	**Week 4** (5 days)
Readings with Weekly Reflection	Develop a pluralistic understanding (pros and cons) of the impact of BDA in society.	Big Data: ● Ch. 1: Now ● Ch. 2: More WMD: ● Intro ● Ch1. Bomb Parts, What is a Model	Big Data: ● Ch 3: Messy Automating Inequality: ● Intro: Red Flags ● Ch. 1: From Poorhouse to Database	Big Data ● Ch. 4: Correlation ● Ch. 5: Datafication ● Automating Inequality: ● Ch. 2: Automating Eligibility in the Heartland	WMD ● Ch 4: Propaganda Machine: Online Advertising ● Ch. 5: Civilian Casualties: Justice in the Age of Big Data ● Ch. 10: The Targeted Citizen: Civic Life	Big Data: ● Ch 10: Next WMD ● Conclu sion Automating Inequality ● Conclu sion
Ethical Considerations and Dilemmas	Understand the diversity in ethical dilemmas and considerations that are made in the data science industry. Develop ethical reasoning and decision-making skills.	What do you think about the value and use of Big Data and Machine Learning in society? Miscommunication through data visualization Its Black and White	How does our identity impact how we create and interpret data-based representations? Make arguments for and against automating eligibility for social programs and government assistance (e.g. FSSA) Ethical considerations in the data investigation process	Considering the differences between traditional research and data science methods, correlation and causation, and the impact of making decisions based on correlations for society.	Ethical Decision-making in data science Corona Crisis Great Groceries Twitter Trends Face Finder	What are some key ethical considerations that should be made before deploying BDA projects in society? Data Science - Oath of Professional Ethical Standards
DSIS Project	Engage in an ethical data investigation process from start to finish to explore and develop solutions to a real world injustice.		Pick an issue that you want to change in the world that can be explored through data science	Choose project topic and real dataset	Preliminary analysis and research questions	Full analysis and report (conference style poster, presentation, research article)

Thus, they enacted the *data investigation process*, that included: (1) framing the problem, (2) considering and gathering data, (3) processing data, (4) exploring and visualizing data, (5) considering models, and (6) communicating and proposing solutions (Lee et al., 2020) in the context of real world, sociopolitical datasets, engaging in critical and ethical inquiry along the way.

The task structures for the course that defined what we wanted students to do in the activities included:

- *Decision-making task structures* that position students as decision makers who must decide and justify their choices based on both their understanding of the topic and their personal experiences;

- *Pluralistic task structures* where students explore and justify their decisions by arguing pluralistically. By pluralism we mean that students are able to adopt and understand different subject and theoretical positions regarding the ethical issue, and consider both the pros and cons of their potential action for a multitude of different stakeholders;

- *Qualitative task structures* where students consider the quality or consequences of specific mathematical actions or processes in society or based upon their personal experiences.

Some core activities that leveraged the above task structures included:

- In-class labs, where students enacted the *data investigation process* (Lee et al., 2020) in the context of real world, sociopolitical datasets, engaging in critical and ethical inquiry along the way;

- Ethical Dilemmas activities, where students explored real media related to ethical dilemmas in the data science industry and worked in groups to identify the ethical issue and make ethical considerations from the perspective of a data scientist and citizen; and

- Book Discussions, where students drew on their weekly readings and written reflections on select chapters from *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (Mayer-Schonberger et al., 2013), *Weapons of Math Destruction* (O'Neil, 2016), and *Automating Inequality* (Eubanks, 2019), that together discuss the data science methodology and its impact from both a positive and negative perspective.

- The Data Science in Society project, where students chose a societal or environmental injustice to explore and develop solutions using complex data science methods and procedures (e.g., machine learning).

Together, these designs placed the onus of responsibility on students to understand the technical aspects of the data science methodology, while considering the potential effects of their mathematical products in society. In addition, we conjectured that when working with students of privilege, positioning them as the recipient of the data science decision may help them to affirm the experiences of marginalized populations in sociopolitical contexts. Therefore, rather than jumping directly into problem types that discuss social justice issues with regard to oppressed groups in the United States, we began the course with activities that positioned the students themselves as the target population of the dataset (and potentially an oppressed group) in hopes to develop empathy and an open-mindedness to the impact of BDA on people situated differently in society. The following section describes how we implemented the EDS course in our specific classroom setting in order to test and refine our design.

Phase 2: Implementation Phase

The second phase of a design experiment consists of both enacting the intervention and conducting ongoing data analysis, reflection, and adaptation (Cobb et al., 2003). In contrast to traditional research methodologies where researchers wait until the intervention has ended to analyze data, design research is an iterative and ongoing process of refinement both during and after data collection (Prediger et al., 2015). While learning trajectories are conjectured at the onset, lessons are developed and adapted on a daily basis in response to the outcomes of the previous learning segment (Prediger et al., 2015). This ongoing analysis could be considered more formative while the retrospective analysis (phase 3) is a summative assessment of the overall design process (diSessa et al., 2004). The author of this dissertation served as the lead designer, instructor, data collector, and analyst during this phase.

Context and Participants. The participants consisted of 15 rising high school juniors and seniors selected for a competitive, state-funded, summer residential program held at a major university in the Southeastern United States (U.S.). The goals of the program are to provide hands-on, student-driven learning experiences with authentic research opportunities in Science, Technology, Engineering and Mathematics (STEM). We chose the upper high school age group due to their position in the U.S. mathematics curriculum and their familiarity with social media, technology, basic data sources, and basic data manipulation. In addition, we hypothesized that the nature of a STEM program being held over the summer at a major university typically could attract more privileged types of students in terms of parent and student education, parental involvement, race, ethnicity, and socioeconomic status, and thus, may reflect the demographic makeup of the data science industry today. The general make-up of the program from 2016 to 2021 has been predominantly White and Asian/Indian students who do not require financial assistance with a parity in gender expression. The demographic makeup of the students enrolled in the EDS course reflected these aforementioned trends, including one Black girl, one Indian-American girl, five White girls, four White boys, two Indian-American boys, and two Asian-American boys (all self-reported without the "-American" label). With that being said, students' identities are not singular. Rather, they intersect with a multitude of identities along the lines of race, ethnicity, gender expression, socioeconomic status, etc. that further influence their experiences of privilege and marginalization (Kokka, 2020). Thus, if their acceptance into the program is considered an educational privilege (as it was here) then the composition of the EDS class was homogenous in the sense that all of the students held at least one privileged identity (White, male, high SES, academic privilege, etc.), but heterogeneous in that the cultural and gendered experiences that the students brought to the class, including their ways of participating in tasks and discussions, were diverse.

Data Collection Methods. Table 1.3 outlines the data types, scope, and modes of collection that were used.

Table 1.3

Data Corpus

Data source	Scope	Modality
Student feedback forms	Individual and collective	Google Forms, class discussions, individual check-ins
Weekly written reflections and final course reflection	Individuals (all students)	Word processor
Post Ethics Interviews with 6 focus students	Individual (volunteer)	Zoom Video
Video recordings of class sessions that	Whole class, small groups	Zoom and Face to Face

demonstrate students' ethical reasoning.		Video
Community based project ● Report ● Poster ● Presentation	Individual/Small Groups	Collection of student work & video recording of presentation
Researcher field notes - ongoing	Whole class	Field notes
Regular design team meetings	Course design	Video and/or field notes

Note that video recordings were limited to situations where students demonstrated their ethical reasoning and thus did not include lesson segments devoted to programming or other solely technical aspects of data science. Furthermore, while I intended to conduct both pre- and post-ethics interviews to gauge shifts in students' ethical dispositions as a result of the course experience, we decided to forgo the pre-interview due to the controversial nature of the questions. Without having the time to build relationships with the students they might not have been comfortable responding openly and honestly to such questions, calling into consideration the validity and reliability of our resultant findings. As such, we chose to conduct only the post-interviews which demonstrated their ethical reasoning at the end of the course, but not as a product of it.

Phase 3: Retrospective Analysis

The purpose of the retrospective analysis phase was to see how the course trajectory was realized in the classroom with those students. In other words, seeing what learning happened and what revisions need to be made for future iterations. The retrospective analysis for this study served to answer the following research question through qualitative analysis of the above data corpus:

1. What are the characteristics of high school students' ethical decisions after participating in the EDS course and what EDS course activities and structures supported high school students' critically conscious ethical decision-making? (Chapter 2/Article 1)
2. How did the designed/modified task and participation structures support equitable participation from students with diverse and intersecting identities in the activities and social norms of an ethical data science course? (Chapter 3/Article 2)
3. What discursive moves support equitable participation from students with diverse and intersecting identities in sociopolitically and ethically grounded data science discussions? (Chapter 4/Article 3)

The three articles presented in this dissertation are an attempt to answer these questions.

How to Read this Dissertation

The three main chapters of this dissertation (Chapters 2, 3, and 4) serve as stand-alone articles, but also work together to provide a comprehensive overview of the larger Design-Based Research project (Cobb et al., 2003). Thus, they can be read individually or sequentially, depending on the readers' purpose. While Chapter 2/Article 1 speaks to the characteristics of students' ethical decision-making in data science contexts, Chapters 3 and 4 (Articles 2 and 3) speak to the designed course elements that encouraged equitable participation and student empowerment in the designed intervention:the EDS course. All three articles provide pedagogical recommendations for supporting the development of students' EMC in data science contexts, Chapter 2/Article 1 from a cognitive perspective, and Chapters 3 and 4 (from an identity-centric and cultural participation perspective (Hodge & Cobb, 2019). The remaining sections provide a brief overview of the contents of each chapter.

Introduction to Each Article/Chapter

This dissertation is composed of the following three articles/chapters:

Chapter 2/Article 1: Supporting High School Students' Critically Conscious Ethical Decision-Making in Data Science

As the foundational goal of this dissertation, this article describes an initial attempt to foster *ethical mathematics consciousness* (EMC) in data science contexts among 15 relatively privileged high school students enrolled in the designed Ethical Data Science (EDS) course. In this chapter/article, we report on our retrospective qualitative analysis of six students' ethical decision-making in task-based interviews at the end of the course where students were positioned as decision makers, using *the Component Model for Moral Case-Based Reasoning in Data Science*. From our findings, we offer recommendations for the mathematics education community for promoting critically conscious ethical decision-making for the future, including protocol for making critically conscious ethical decisions in data science contexts to be used and modified by the mathematics and data science education communities and beyond.

This chapter is a first authored paper with Dr. Michelle Stephan and Dr. Gordon Hull, which has been submitted to the *Journal for Research in Mathematics Education*.

Chapter 3/Article 2: Design Considerations for Facilitating Equitable Participation in an Ethical Data Science Course for High School Students

Within the first few days of the EDS course, my co-author, Dr. Michelle Stephan and I noticed that the students seemed to participate inequitably in classroom discussions. Specifically, that primarily White males dominated most class discussions, that Asian and Indian students (male or female) were often more comfortable in technical rather than sociopolitical discussions, and that the females' (of all ethnicities) participation was heavily influenced by their feelings of competence in relation to their peers (Author et al., submitted; Ridgeway, 2001; Riegle-Crumb et al., 2020). As a result, we set out to determine what aspects of the design seemed to support or constrain equitable participation among students with diverse and intersecting identities in the EDS course. Here, *equitable participation* refers to variability in the students who contribute to class discussions, but more so that these students participate in ways that affirm their identity and sense of belonging. As such, this chapter reports on the task structures, participation structures, and key discursive moves that seemed to encourage equitable participation in EDS classroom activities among students with diverse and intersecting identities.

This chapter is a first authored paper with Dr. Michelle Stephan and has been accepted to *The Journal of Urban Mathematics Education*.

Chapter 4/Article 3: Encouraging Equitable Participation in Ethical Data Science Discussions

Building on the findings from Chapter 3, this article further discusses my experiences in teaching the EDS course where I attempted to encourage equitable participation in classroom discussions among students with different racial, cultural, and gendered identities. In contrast to Chapter 3, it is practitioner-focused and offers guidance for teachers related to facilitating discussions in ethical and sociopolitical contexts while affirming students' identities. Specifically, the article focuses on the key discursive moves (moves that promote desired ways of talking and participating) that I made throughout this process which seemed to result in my students' belief in the importance of equitable participation and their commitment to encouraging it in our classroom discussions. These moves include: (1) co-establishing the desired social norms for discourse, (2) collaboratively defining equitable participation and why it is important, and (3) making explicit that there are no present experts on ethical data science in the EDS classroom environment. It then describes a timed writing activity that was used to collaboratively develop social norms for discourse, focused on the promotion of equitable participation in sociopolitically and ethically grounded whole class discussions.

This chapter is an individually-authored paper which has been submitted to the *Statistics Teacher* practitioner journal.

Author Roles and Statement of Subjectivity

My role in the overarching study is defined as the lead designer, instructor, data analyst, and author of this work. At the time of this writing, I identify as a White, female, mother, spouse, first generation University Graduate and critical educator in my 30s. I am a former high school mathematics teacher and current Faculty Development Specialist and Instructional Designer in the Center for Teaching and Learning at a major urban research university in the Southeast United States. I grew up in a middle-class family in the Northeast United States and moved to the south for my postsecondary education where I established a family and career in Mathematics Education.

While teaching secondary mathematics in a southeastern high school, I recognized many barriers for my students who did not fit the dominant demographic of the STEM industry more generally (i.e., White, Asian, male). This led me to reflect on the barriers that I encountered as a female navigating the STEM field, as well as the forms of resistance that I developed along the way, whether due to my relative privilege and ability to successfully navigate certain contexts, or as a means to overcome the oppressive forces that I encountered in others. This encouraged me to pursue the Curriculum and Instruction PhD program in Mathematics Education at my local, urban-focused research university. Throughout this program I began to recognize the impact of my own identity on my ability to navigate (or not) certain social, educational, and occupational spaces. In addition, I developed a concern for the effects of these barriers in the Digital Age, which transcend issues of gatekeeping, and translate into direct effects on the well-being of individuals, groups, and the environment. Recognizing that the data science pipeline begins in Mathematics Education, and that the dominant demographic of data scientists today reflect, at least partially, my relatively privileged identity (i.e., White, middle-class), I sought to explore how I may be able to develop instructional materials and theory to encourage critically conscious ethical reasoning in data science among relatively privileged students like myself. This further influenced my decision to earn a Data Science Master's Certificate in order to better understand the nuances of the Data Science industry and methods.

As a final note, my choice to work with students of privilege does not stem from a lack of concern for marginalized individuals or communities. Rather it is an attempt to 1) avoid the White savior mentality, 2) affect change among those who share similar privileges, demographics, values, and/or belief systems as myself, and 3) to encourage ways of thinking, communicating, and learning that consider and validate diverse and often conflicting viewpoints for the promotion of a just and equitable future.

CHAPTER 2: SUPPORTING HIGH SCHOOL STUDENTS' CRITICALLY CONSCIOUS ETHICAL DECISION-MAKING IN DATA SCIENCE

Jordan Register
University of North Carolina at Charlotte

Michelle Stephan
University of North Carolina at Charlotte

Gordon Hull
University of North Carolina at Charlotte

Submitted to the *Journal for Research in Mathematics Education*

Abstract

The emergence of data science and Big Data Analytics (BDA) for aiding human decision-making processes has catalyzed a need for critically conscious ethical decision-making in the mathematical disciplines. This article describes an initial attempt to foster *ethical mathematics consciousness* (EMC) in data science contexts among 15 relatively privileged high school students enrolled in a designed Ethical Data Science (EDS) course. We then report on our qualitative analysis of students' ethical decision-making in six task-based interviews at the end of the course using *the Component Model for Moral Case-Based Reasoning in Data Science*. From our findings, we offer recommendations for the mathematics education community for promoting critically conscious ethical decision-making for the future.

Introduction

The emergence of data science and Big Data Analytics (BDA) for aiding human decision-making processes in society has catalyzed a need for critically conscious ethical decision-making in the mathematical disciplines. Scholars argue that the costs of BDA disproportionately affect individuals from historically oppressed groups, often placing them in a recurring cycle of misclassification and socioeconomic subordination (Benjamin, 2019; D'Ignazio et al., 2020; Noble, 2018; O'Neil, 2016). One possible factor in this subordination is demographic. Data scientists have become a valuable commodity in most industries, and are typically recruited based on their mathematical, statistical, and computer science skills. As a result, the majority demographic of the data science industry today reflects the STEM industry more generally in that its members often hold one or more privileged identities (White, Asian, male, upper income, etc.) creating a *privilege hazard* whereby the mathematical products that guide our social and economic policies often do not reflect the experiences, values, or needs of those situated outside the experiences of their privileged creators (D'Ignazio et al., 2020).

The impact of BDA on marginalized communities creates a new imperative for mathematics and data science education. On one hand, there have been calls to diversify the data science pipeline to ensure that the needs of nondominant communities are met. However, as Noble (2018) argued, hiring more people of color, female, and non-binary gendered people does not ensure that they will hold leadership positions, especially when situated in the existing culture of Silicon Valley. Rather, the culture of the data science industry must shift in order to respond to the perspectives and needs of underrepresented communities (Benjamin, 2019; D'Ignazio et al., 2020; Noble, 2018; Zarsky, 2016). That is, data scientists must be equipped to make critically conscious ethical decisions that safeguard against the potential negative effects of their mathematical products in society, prior to entering the workforce.

The described study illustrates one cycle of a larger Design-Based Research project (Cobb et al., 2003) focused on developing a local instruction theory and corresponding instructional materials for an introductory Ethical Data Science (EDS) course. Here we report on our findings related to the characteristics of high school students' ethical decision-making at the end of the EDS course, with the following research questions as our guide:

1. What are the characteristics of high school students' ethical decisions after participating in the EDS course?
2. What EDS course activities and structures supported high school students' *critically conscious* ethical decision-making?

The following section will outline relevant research related to the consequences of BDA in society and the corresponding need for an ethical data science education.

Review of Literature

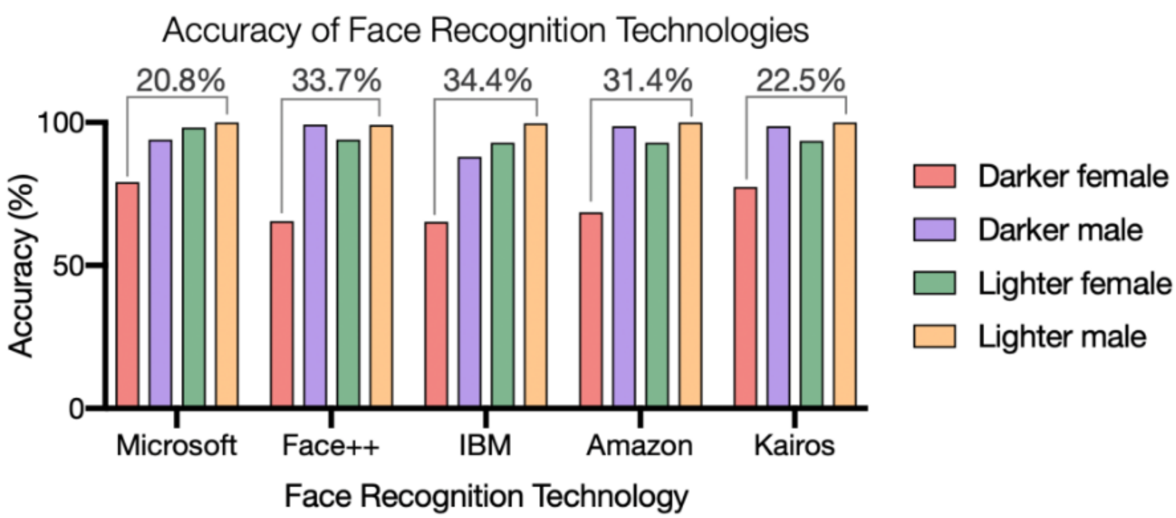
There is a significant and long-running literature base on the potential harmful effects of BDA (boyd and Crawford, 2012; Hagendorff 2020; Martin, 2015; Mittelstadt et al, 2016). Areas of particular concern include privacy, algorithmic fairness, accountability, and the opacity of decision-making. To illustrate these issues, we focus on the example of fairness in policing.

Discrimination in BDA

Training algorithms on historically biased data often reinforces social stereotypes and/or places individuals and groups in a recurring cycle of (mis)classification (O'Neil, 2016). For example, longitudinal crime data is laden with historical contexts and biases that often direct police to over-patrol underserved communities while effectively ignoring predominantly White and/or upper income areas (e.g., the War on Drugs). As a result, people of color are more likely to be arrested and convicted of a crime, contributing to their overrepresentation in the U.S. prison system and to the criminalization of communities of color (Mayson 2019; Noble, 2018; O'Neil, 2016). Beyond this, biased crime data has been known to influence predictions of recidivism that have been used to guide judicial decision-making for granting or refusing parole (Angwin et al., 2016; Washington, 2018). Analysis of *The Correctional Offender Management Profiling for Alternative Sanctions* (COMPAS) algorithm found that even when controlling for prior crimes, future recidivism, age, and gender, Black individuals are significantly more likely to have run-ins with the police and become confined to the judicial system (Anguin et al., 2016). The debate following this analysis showed the difficulty in understanding fairness as a narrow technical question, since fairness is unavoidably ethical (Fleisher, 2021; Green, 2022; Mulligan et al 2019). But compounding this issue is the use of facial recognition software to identify suspects of a crime through facial images, which have been known to identify females and people of color less accurately than their White and/or male counterparts (Buolamwini et al., 2018). Figure 2.1, published by Najibi (2020), illustrates the accuracy scores for published facial recognition software across race/gender groups. Given that predictive algorithms are developed on a training dataset (a subset of the original dataset) and tested for accuracy on a test set (the remaining observations of the original data set), the differences in accuracy may be attributed to a lack of training on darker female faces. Still, the ethical implications of allowing the police to use this software as is, are clearly more detrimental to darker skinned females who are duly disadvantaged by predictive policing algorithms as described above.

Figure 2.1

Differences in Accuracy of Facial Recognition Technologies (Najibi, 2020)



The Need for Ethics in Data Science Education

The “black box” nature of data science poses a real threat to the stakeholders of data science decisions. For starters, the contents of predictive algorithms, and identities of accountable parties in cases of harm, are neither freely available nor understandable to the average citizen (O’Neil, 2016). As a result, Rubel and colleagues (2021) argued that power and responsibility are often hidden in BDA designs, while D’Ignazio and Klein (2020) argued that one of the greatest threats to society in the Digital Age is the hard coding of discrimination in the processes that are increasingly used by world governing entities. To clarify, privileged data scientists often have limited (or no) experience with social, financial, or community struggle, so they are often ill-equipped to identify oppressive situations in the world (D’Ignazio et al., 2020). As a result, data science designs more often reflect the dominant perspectives, experiences, and values of the privileged creators, at the expense of nondominant identities and viewpoints (D’Ignazio et al., 2020; Noble, 2018).

Our societal trust in numbers further compounds the transparency issue and propels issues of accountability (Reider et al., 2016). Despite the fact that both data, and notions of trust, are historically and contextually situated, we tend as a society to view data as “raw, objective, and neutral--the stuff of truth itself” (Reider et al., 2016, p. 3). This widespread belief enables policymakers to exploit our trust to avoid making difficult and critically informed decisions, while further allowing them to rationalize unpopular or discriminatory decisions, by using “the numbers” as a scapegoat (Reider et al., 2016). While a proposed solution is to diversify the data science pipeline, Noble (2018) argued that doing this without ensuring that non-dominant identities hold positions of power will do little to dismantle the status quo. Rather, a culture shift in the data science industry—one which centers critically conscious ethical decision-making—is needed to ensure that data science designs consider their potential impact on diverse communities.

Given the dearth of empirical literature on designing for ethical data science instruction, we drew on a combination of theoretical literature in ethical mathematics education and empirical studies in critical mathematics education to guide our work. We briefly describe our relevant findings in the following section.

Defining an Ethical Data Science Education

Boylan (2016) suggested that there is a lack of discourse related to consideration of the *other* as an ethical imperative for mathematics. Critical Mathematics pedagogies typically focus on liberation of the self or that person's social group from past or current injustices, through the development of critical praxis (Freire, 1970/2018). Such studies are more often done in the context of racially and/or ethnically homogenous and historically marginalized populations of students who explore social justice issues relevant to their community through mathematics (Berry, 2004; Gutstein, 2005; Rubel et al., 2016; Rubel, 2017). Few studies concerned with teaching for social justice have done so in the context of heterogeneous and/or privileged groups of students, with notable exceptions by Kokka (2020) and Esmonde (2014), while none (that we could find) center ethical designs for the future.

In response to these gaps, we argue that an Ethical Mathematics Education must not only consider *past* and *current* discrimination and social injustices (while providing students opportunities to learn from them) but also encourage informed and ethical decision-making in the *future* (Register et al., 2023). From this perspective, ethics serves as a precursor to social justice in that it establishes relations between the self and others as the primary unit of analysis in decision-making processes (Atweh et al., 2009; Puka, 2005). That is, ethics naturally includes considerations of social justice, but also transcends them. Finally, it is our view that teaching for ethics and social justice should also attend to privileged or heterogeneous populations of students in order to promote diverse students' ethical consideration of the *other* and cooperation for justice in society (Brelias, 2016; Skovsmose, 2016). Although students of relative privilege may not be subject to certain types of social oppression (and may actually benefit from the social and economic inequalities that are studied in CME) their engagement in "reading and writing the world with mathematics" may help them to develop "radical new perspectives" that support their participation in developing a just world" (Skovsmose, 2016, p. 3). As such, the aim of this article is to contribute to the empirical research on developing privileged high school students' ethical reasoning in data science. In particular, we describe our initial attempt to develop an Ethical Data Science (EDS) course for relatively privileged high school students' using the Design-Based Research approach, and characterize students' ability to make critically conscious, ethical data science decisions at the end of the course.

Theoretical Orientation

Since the onset of globalization and its impact in society, there have been conversations related to the "need for ethics" in mathematics education. But what *kind* of ethics? The literature on ethical reasoning in mathematics education is fragmented in the sense that ethics and social justice are often discussed separately. However, as Atweh et al. (2009) suggested, the foremost concern in ethics is our relationship with and for others, therefore *ethics actually serves as the foundation for concerns of social justice* (Atweh et al., 2009). While this may be true from the perspective of relational ethics, other major *normative* theories that characterize the ethics of decision-making neither show a concern for relations nor justice. For instance, the foremost concern of:

- *consequentialists* is the outcome of the decision,
- *deontologists* is the moral intent of decision or actor, and
- *virtue ethicists* are patterns in behavior over time.

As a result, scholars argue that traditional normative ethical frameworks are insufficient for protecting against the repercussions of the data science industry due to their lack of attention to its sociopolitical elements (D'Ignazio et al., 2020). We cannot simply argue that students need to learn to be ethical in a general sense since our ethics are a product of our culture, communities, experiences, etc., which are naturally diverse and often competing (Brown University, 2013). Rather, we must champion ethical perspectives that lend themselves to empathy, justice, and sociopolitical thought.

Ethical Mathematics Consciousness (EMC) Conceptual Framework

Developing an ethical disposition in data science requires a *critical consciousness* of the ways in which mathematics and mathematical processes serve to disenfranchise some while privileging others (Stephan et al., 2020). While there is much to draw from the literature about teaching for critical consciousness in classrooms composed primarily of underrepresented or oppressed groups (e.g., Berry 2004; Gutstein, 2006; Rubel et al., 2016), it is essentially undefined when working with students with greater privilege. Therefore, in our attempts to foster critical consciousness in more privileged students, the following notions drove us to explore how individuals make ethical decisions in data science contexts.

1. Students' decision-making is driven by their normative ethical perspective, mid-level ethical principles (social norms), and role specific obligations (Diekmann, 2011; Keefer & Ashley, 2011).

2. Students hold a diversity of ethical perspectives based on their background and experiences that may or may not include concern for positive relations or justice (Stanford, n.d.; Brown University, 2013).

3. Certain ethical perspectives lend themselves better to concerns for equity, positive relations, and social justice (Noddings, 1988; Norlock, 2019).

4. Students of privilege may not have experience considering issues of social justice (Skovsmose, 2016).

The EMC conceptual framework (illustrated in Table 2.1) is a product of our research into existing normative ethical theories and their relationship with critical consciousness. It was designed to understand how students' ethical perspectives may align with their demonstrated critical consciousness in mathematical contexts that require ethical decisions (Table 2.2).

The EMC framework was derived from Freire's conception of *critical consciousness* and shares similarities with Kokka's (2020) *critical mathematics consciousness* (CMC), defined as the development of sociopolitical understanding, critical civic empathy, and action taking through mathematics. Beyond this, EMC refers to the *awareness that human beings do mathematics; thus, there are potential ethical dilemmas and implications of mathematical work which may affect entities at the individual, group, societal, and/or environmental level* that should be considered at every stage of the decision-making process. EMC therefore exists on a continuum of *both* ethical and critical thought which guide and inform one another. The *critical elements* (right side of Table 2.1) emulate Freire's work and include

1. evidence of critical thought related to the oppression of individuals, entities, or ecologies,
2. the cause of the oppressive situation,
3. and their sense of empowerment and personal agency to dismantle the given oppressive system (Register et al., 2023).

Within a given context, individuals may demonstrate one of the following six levels of consciousness: *critically transitive, systemic semi-transitive, isolated semi-transitive, disempowered, dysconscious*, or *intransitive* (see Table 2.2). Drawing from Freire, Shor (1993) defined *critical transitivity* as the actualization of full critical consciousness where the individual engages in critical reflection, recognizes the systemic influence on oppression, and is *empowered to act* by attacking the causes of oppression *at the systems level*. Freirean theory maintains this as the goal of a liberatory education.

When framing the *ethical elements* of EMC (left side of Table 2.1), we drew on the *normative* ethical perspectives that middle, high school, and college students of privilege demonstrated in our pilot studies. The *ethical elements* of EMC include:

1. The actor's demonstrated normative ethical perspectives (the systems that guide their decision-making processes),
2. their unit of analysis when the agent makes the decision,
3. the stakeholders of the decision,
4. and goals of their ethical decision.

These considerations typically correspond with the *critical components*, in that a person's ethical perspective frames their sociopolitical thought, dictating their level of concern for oppressed entities and the promotion of justice. For instance, individuals who demonstrate a solely *consequentialist* ethical perspective (e.g., utilitarians and egoists), respectively prioritize the greatest benefit for the greatest number, or self-preservation for the actor. Such individuals are typically moral absolutists (utilitarians, egoists) who rarely consider issues of power, context, interpersonal relations, or access in their ethical reasoning. Rather, their main concern is the consequence of the act in terms of the *greatest* good (supporting dominant ideologies). As such, they are less likely to demonstrate the *critical components* of EMC.

Table 2.1

Ethical Mathematics Consciousness (EMC) Framework (Register et al., 2023)

Characteristics of Actor's Ethical Reasoning					**Characteristics of Actor's Critical Reasoning**			
Ethical Perspective	**Moral Disposition**	Unit of Analysis	Ethical Stake-holders	Ethical Goals	Critical Thought	Perceived Causes	Agency + Empowerment	***Critical Mathematical* Consciousness**
Feminist Ethics *(Ethic of Care & Social Response-ability)*	Pluralistic, transnational, non-ideal	Relations, Context	Self + Others	Dismantle oppressive systems + preserve relations	Yes	Systems/ dominant group	Empowered to act by focusing on *system*	Critical transitivity ***Actualized EMC***
Contractarianism *(Social Contract, Rawl's Theory)* Edumonaism *(Virtue Ethics)*	Pluralist, Relativist,	Consequences, Agent, and/or Act/Intent	Self, Others	Equity,	Yes	Systems/ dominant group	Put faith in others to act	Systemic Semi-Transitive
						Isolated incidents	Empowered to act on isolated injustices	Isolated Semi-transitive
						Dominant group or individual	Disempowered to act	Disempowered
Utilitarianism *(Greatest Good)* Deontology *(Duty Ethics)* Edumonaism *(Virtue Ethics)* Egoism *(Self-Preservation)*	Relativist, Absolutist	Consequences, Agent, Act/Intent	Others, Self	Equality, Duty, Virtue, Self-Preservation	No	Fault of oppressed, *Technology/ media influence*	Onus on oppressed to act	Dysconscious
						God/Luck	Disempowered to act	Intransitive

Table 2.2

EMC Levels of Consciousness

Level of Consciousness	**Characteristics of Individual's Ethical Reasoning**
Critical transitivity	● Exhibits critical thought and concern for justice ● Recognizes systemic influences on the injustice ● Seeks to dismantle oppressive systems.
Semi-transitivity (isolated) (systemic)	● Exhibits critical thought ● May see the systemic cause of the oppression but does not attack it at its root. ● May perceive and attack the cause as isolated or local incidents (*isolated semi-transitive*) or put their faith in other, more powerful individuals or groups to change oppressive situations (*systemic semi-transitive*).
Disempowered	● Exhibits some critical thought ● Disempowered to act because they do not feel that they have the ability to overcome those in power.
Dysconscious	● Minimal (or no) critical thought, due to a “distorted vision of oppression” (King, 1991, p. 3). ● May “justify inequity as the natural order of the world,” think that the oppressed are at fault for their current situation and place the onus of responsibility to overcome the injustice in their hands (King, 1991, p.3). ● May be taught through familial and educational influences, or by media effects (i.e., massified consciousness) (King 1991, p. 3).
Intransitive	● Does not exhibit critical thought, perceiving their oppressive situation as a consequence of God’s will or bad luck.

	• Disempowered to act (i.e., agency is irrelevant as only a shift of luck or divine intervention are the only means to dismantle the injustice).

In contrast, a feminist ethic of care (Nodding, 1983) and a feminist ethic of social response-ability (Puka, 2005) map to higher levels of critical consciousness (Table 2.2) within the EMC Framework (Table 2.1) because *together*, they explicitly promote critical consciousness. In particular, a feminist *ethic of care* speaks to the students' interpersonal empathy and is characterized by a desire to care for others based on positive experiences of being cared for when making ethical decisions (Noddings, 1988). In contrast, *social response-ability* refers to a higher level of empathy tied to the system. It is the ability to respond to the demands of our own ethical well-being while responding to the demands of others through the promotion of justice and critique of power structures (Atweh, 2009; Puka, 2005). Together, an ethic of care and social response-ability prioritize both interpersonal and systemic empathy and sociopolitical thought, driving their explicit consideration of context, identity, experience, and power (Noddings, 1988; Puka, 2005). While this is not to say that other normative ethical perspectives are less valuable, but that for our context (public U.S. education) and goals (ethical decision-making for justice in society), a feminist ethic of care and social responsibility are most appropriate. Furthermore, these perspectives offer an extension to programs that explore past or current oppressions by examining one's current data science activities ethically in order to prevent *future* injustices.

Pluralism

As a final argument for prioritizing feminist ethics, we no longer live in bounded communities (if we ever did), where we can afford to make decisions that have an impact only on like-minded people. Instead, globalization and the increased use of BDA allow policymakers to make decisions that scale to many diverse populations with multiple, often conflicting, perspectives and needs. Unlike other normative perspectives, individuals who hold a feminist ethic of care and social response-ability typically hold a *pluralist* moral disposition characterized by their open-mindedness and ability to recognize that there are often multiple contrasting perspectives, which are all legitimate, in a given context (Norlock, 2019; Pateman, 1988). Even in situations where ethical acts are determined by a social contract between citizens, feminists reject the notion that ethical actors have equal access to the contract itself, especially for those who sit on the margins of society (Mills, 1997; Pateman, 1988). As such, we see moral pluralism as *necessary* for critically conscious ethical decision-making in data science, since the decisions made through data science impact individuals from different cultural backgrounds, with diverse needs, experiences, desires, and epistemologies.

Research Approach

Design-Based Research

This study employed a Design-Based Research approach to the development of the EDS course (Cobb et al., 2003). The pilot phase began in Fall of 2019 and included three task-based interview series intended to characterize students' ethical reasoning in data-based contexts (Andersson et al., 2022; Reinke et al., 2022; Register et al., 2021; Stephan et al., 2020). From our findings, we developed the EMC conceptual framework to use as an aid in the design phase that began in August of 2021. A design team of eight academic and industry experts were assembled to develop design conjectures and corresponding materials for the course. We drew on the findings of our pilot interviews, relevant literature, design heuristics from Realistic Mathematics Education (Van den Heuvel-Panhuizen et al., 2014), and the EMC conceptual framework to develop design conjectures and course materials.

Positionality

At the time of this writing, the first author and lead instructor is a PhD candidate in Mathematics Education and master's student in Data Science. The second author and co-analyst is a full professor of Mathematics Education and expert in Design-Based Research. Both identify as White females from middle class backgrounds who have collaborated over the past four years to develop frameworks for students' ethical reasoning in mathematics and data science. The third author served on the design team for the EDS course and was brought in as a co-analyst for the retrospective phase as a resident expert on normative ethics. He identifies as a White male from a middle-class background. At the time of this writing, he serves as a full professor of Philosophy and affiliate of the School of Data Science at their home university, with research expertise in the social implications of data science.

Context

The EDS course was offered through a competitive, state-funded, summer residential program held at a major urban university in the Southeast United States. The participants of the course consisted of 15 rising high school juniors and seniors, including one Black girl, one Indian-American girl, five White girls, four White boys, two Indian-American boys, and two Asian-American boys (all self-reported). We hypothesized that the nature of this program could attract more privileged students in terms of parent and student education, parental involvement, race, ethnicity, and socioeconomic status, and thus, may reflect the demographic makeup of the data science industry today. Students' identities, however, intersect with a multitude of identities along the lines of race, ethnicity, gender expression, socioeconomic status, etc. that further influence their experiences of privilege and marginalization (Kokka, 2020). Thus, if their acceptance into the program is considered an educational privilege (as it was here) then the composition of the EDS class was homogenous in the sense that all the students held at least one privileged identity, but heterogeneous in that the cultural and gendered experiences that the students brought to the class were diverse.

Designed Intervention: The Ethical Data Science Course

The EDS course structure included 20 eight-hour instructional days which occurred over four weeks in July of 2022. The tools, materials, and task structures were designed to reflect processes used, and ethical considerations made, in the data science industry. Therefore, a majority of the investigations were designed to leverage student discourse in the service of surfacing multiple rationales for making ethical data-based decisions. The task structures for the course included:

- *Decision-making task structures:* position students as decision makers who must decide and justify their choices based on both their understanding of the topic and their personal experiences;
- *Pluralistic task structures:* students explore and justify their decisions by arguing pluralistically. By pluralism we mean that students are able to adopt and understand different subject and theoretical positions regarding the ethical issue, and consider both the pros and cons of their potential action for a multitude of different stakeholders;
- *Qualitative task structures:* students consider the quality or consequences of specific mathematical actions or processes in society or based upon their personal experiences.

Some core activities that leveraged the above task structures included:

- In-class labs, where students enacted the *data investigation process* (Lee et al., 2020) in the context of real world, sociopolitical datasets, engaging in critical and ethical inquiry along the way;
- The Data Science in Society project, where students chose a societal or environmental injustice to explore and develop solutions using complex data science methods and procedures (e.g. machine learning);
- Ethical Dilemmas activities, where students explored real media related to ethical dilemmas in the data science industry and worked in groups to identify the ethical issue and make ethical considerations from the perspective of a data scientist and citizen; and
- Book Discussions, where students drew on their weekly readings and written reflections on select chapters from *Big Data: A Revolution That Will Transform How We Live, Work,*

> *and Think* (Mayer-Schonberger et al, 2013), *Weapons of Math Destruction* (O'Neil, 2016), and *Automating Inequality* (Eubanks, 2019), that together discuss the data science methodology and its impact from both a positive and negative perspective.

Together, these designs place the onus of responsibility on students to understand the technical aspects of the data science methodology, while considering the potential effects of their mathematical products in society. In addition, we conjectured that when working with students of privilege, positioning them as the recipient of the data science decision may help them to affirm the experiences of marginalized populations in sociopolitical contexts. Therefore, rather than jumping directly into problem types that discuss social justice issues with regard to oppressed groups in the United States, we began the course with activities that positioned the students themselves as the target population of the dataset (and potentially an oppressed group) in hopes to develop empathy and an open-mindedness to the impact of BDA on people situated differently in society.

Method

Data Collection

The data used to analyze students' ethical decision-making included video-recordings of task-based, post interviews with six student volunteers including Monica (Black female), Faye (White female), Moksh (Indian male), James (White male), Richard (White Male), and Sam (White Male). The approximately 1-hour interviews occurred on students' own time, in the week following the EDS course. Three of the original six interview tasks, called FacRec (Figure 2.2), Mapping Crime (Figures 2.3.1, 2.3.2, 2.3.3), and Target Practice (Figure 2.4), were selected because they explicitly position the student as a decision maker in the given context and our EMC Framework accounts for actor agency.

Interview Tasks

The interview tasks were developed in the pilot phase to elicit students' ethical reasoning related to the impact of facial recognition software for people of color (FaceRec), the effects of crime mapping software on discriminatory policing and historically criminalized populations (Mapping Crime), and the implications of targeted marketing practices for marginalized groups (Target practice) (Andersson et al., 2022). Black populations have been historically criminalized by society in the United States (Lainpelto, 2019), posing an issue when facial recognition technologies are less accurate for people of color, and when crime mapping software yields increased police targeting in their neighborhoods, while women and people of color are often considered less financially capable than their White, male counterparts (Harness, 2016), resulting in inequitable financial targeting. Thus, a salient goal was for students to recognize how representations of data may influence both the perceptions and behaviors of individuals within a system, and their sociopolitical awareness of the potential for negative consequences on marginalized populations and society. We therefore drew on our knowledge of local stereotypes related to the perceived criminality and economic ability of social groups that we felt might trigger students' considerations of reinforced stereotypes, social immobility, discrimination, and ecological impact due to targeted policing and advertising. Here, we hoped that the participants may speak to the cyclical nature of BDA in which what the user observes in the data will influence their behavior, which then influences the data in an ongoing feedback loop (O'Neil, 2016). Note that our purpose here is not to reinforce common stereotypes, but to draw attention to them so that students may apply reasoning to critique and dismantle such misleading discourses using data-based representations (e.g., by drawing on their knowledge of the systemic contributions to crime rates including aggressive policing, police targeting and surveillance and/or the impact of external elements on financial capability). Findings from this and the pilot studies indicated that participants reacted to the questions in the intended way, by questioning rather than upholding the illustrated stereotypes.

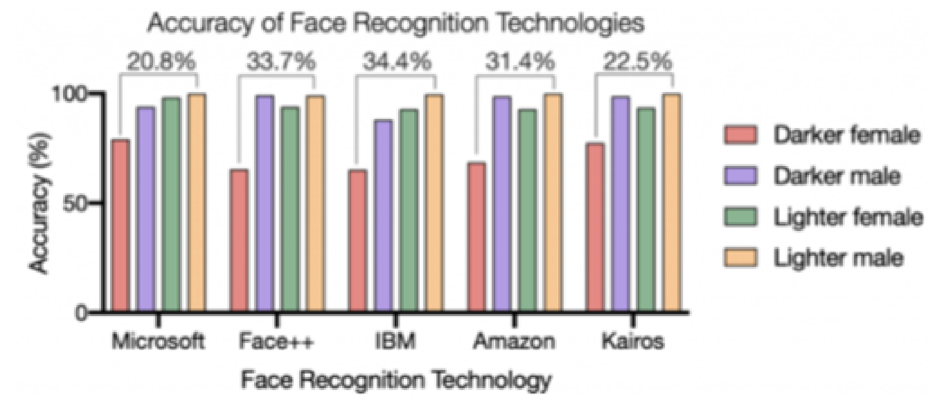
Figure 2.2

Interview Task: FaceRec

FaceRec

You work as a data science engineer for the Police Department. The chief of police would like for you to develop and/or purchase facial recognition software to help identify and locate criminals faster.
The facial recognition software is used when a crime is caught on camera (video or photo). The algorithm takes the captured image, then compares it against photos/video across social media platforms such as Facebook, Twitter, Instagram, and TikTok to identify the assailant and their address. Arrests are made based on these identifications.

The accuracy of facial recognition software, that is, its ability to correctly determine an assailants' identity based on the image comparisons, varies among race/gender groups. It also varies across software available for purchase. Comparisons in the accuracy of the software between race/gender groups for each software company are shown below:



Source: https://sitn.hms.harvard.edu/flash/2020/racial-discrimination-in-face-recognition-technology/

1. Which software company would you purchase the software from? Why?
2. Do you recommend that the police department use this software, *as is*?
3. What do you think can explain the overall pattern in accuracy between race/gender groups?
4. What risks are there in using this technology in its current state?
5. What can you do, or tell the Police, to mitigate the risks?

Figure 2.3.1

Interview Task: Mapping Crime Part 1

Mapping Crime

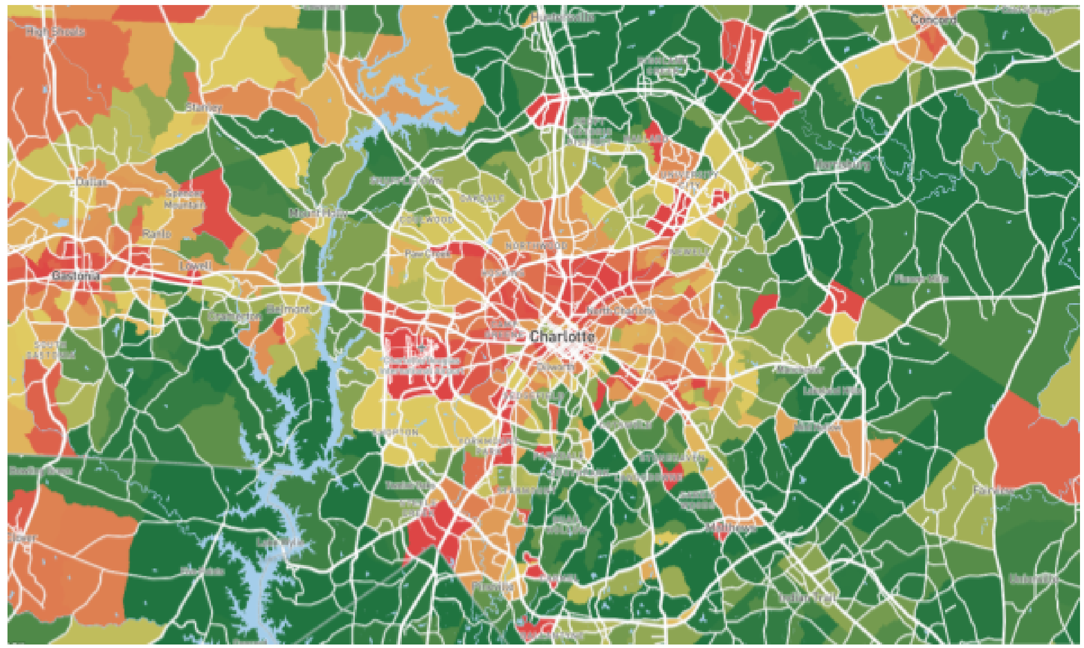
You work for a software company that specializes in geographic information. The police use an app that is based on your work. The app is called *Police Map* and it contains a heatmap that locates where known crimes based on police data, are committed. The map is used to decide where the police personnel should patrol and where they should focus if they have time left over.

The heat map to the right shows crime per 1,000 [X] County *residents* (note that some crimes may be committed by persons visiting the area). Crime rates are weighted by the type and severity of the crime. Crimes considered include violent crimes (assault, robbery, rape, murder), property crimes (theft, vehicle theft, burlary, arson) and other crimes (kidnapping, drug crimes, vandalism, identity theft, animal cruelty). The safest places in the [Y] metro area are in green, the most dangerous areas in the [Y] metro area are in red, and moderately safe areas are in yellow.

Interviewer: What does this map tell you about crime in [X] County?

Crime per Capita in [X] County

The map below shows crime per 1,000 [X] County Residents



Crime Grades

A+	C	F

A+ (dark green) areas are safest

Figure 2.3.2

Interview Task: Mapping Crime Part 2

Part 2

You have also added a feature to your app that shows a heatmap with a simple crime count that does not consider the resident population of the area. See the map to the right:

What does this map tell you about crime in [X] County?

How do the two mapping features influence your view on crime in [X] County (both separately and put together)?

How do you think the police will use the app's two mapping features (both separately and together)?

Do you think anyone else would be interested in purchasing or having access to this software? Who?

You and your company have chosen to make the app available to the public. How do you think the map will change over time given the police and public use of the software?

[X] County Total Crime Map

The map below shows a simple count for crime in [X] County

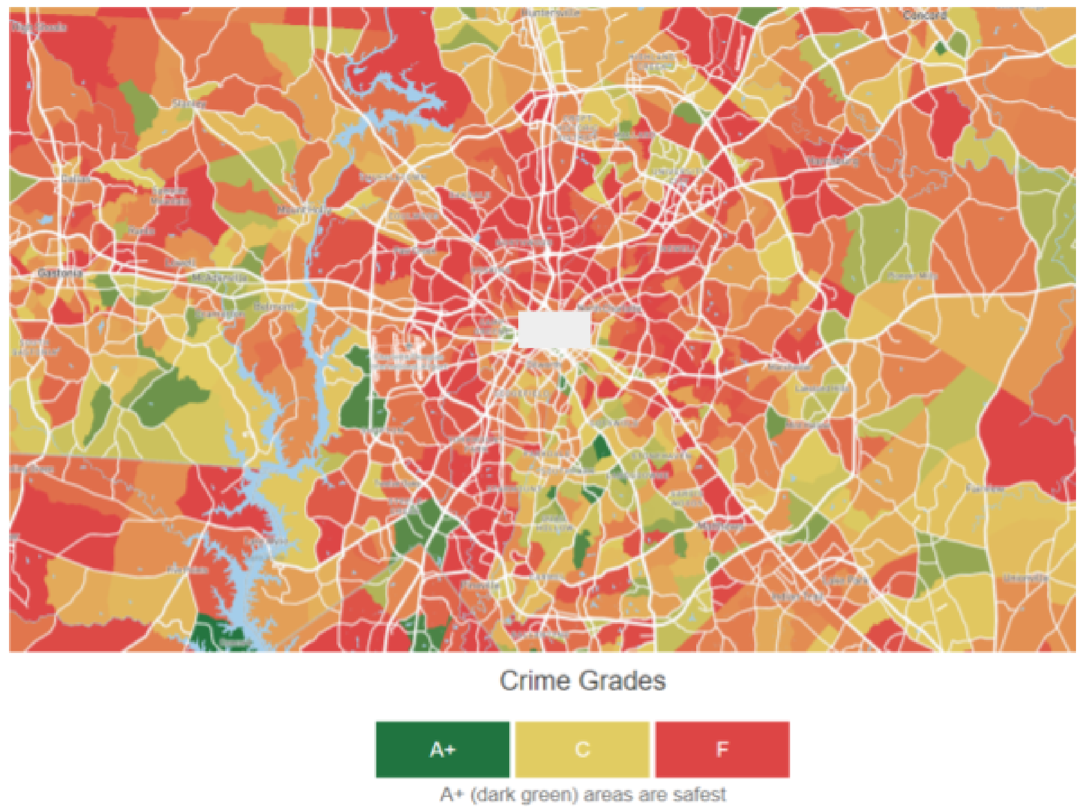


Figure 2.3.3

Interview Task: Mapping Crime Part 3

Part 3

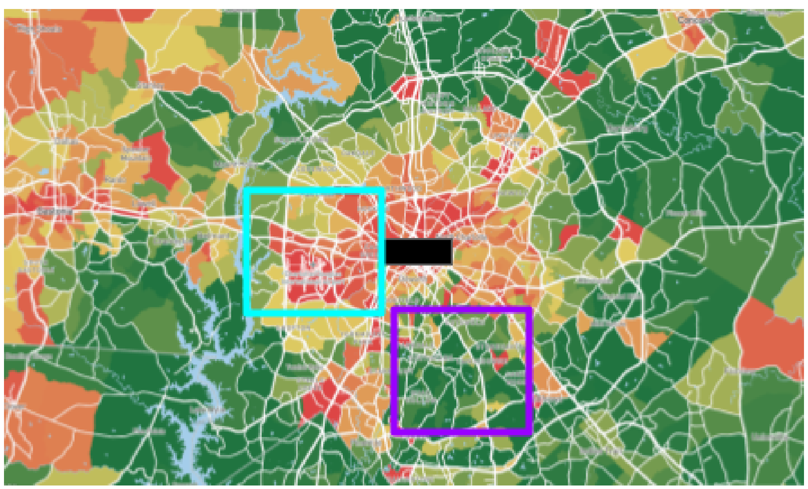
You have a friend in his 20s (an African American male) who just signed a lease on an apartment in West [Y] after graduating college. He chose the apartment due its affordability and location: He works at the airport (also in West [Y]), has high student loan payments and a low beginning salary.

Another friend (an Asian American female), also in her 20's, just bought a home in Southeast [Y] after graduating and securing a Job at Bank of America (uptown) as an investment banker. Neither of your friends has a criminal record, but each has a troubled background with some shoplifting, marijuana use and the like. Both want to put their past indiscretions behind them and invest in their education and careers.

How do you think your work on further developing the app affects your two friends' everyday lives and their living areas?

Crime per Capita in [X] County

The map below shows crime per 1,000 [X] County Residents



[X] County Total Crime Map

The map below shows a simple count for crime in [X] County

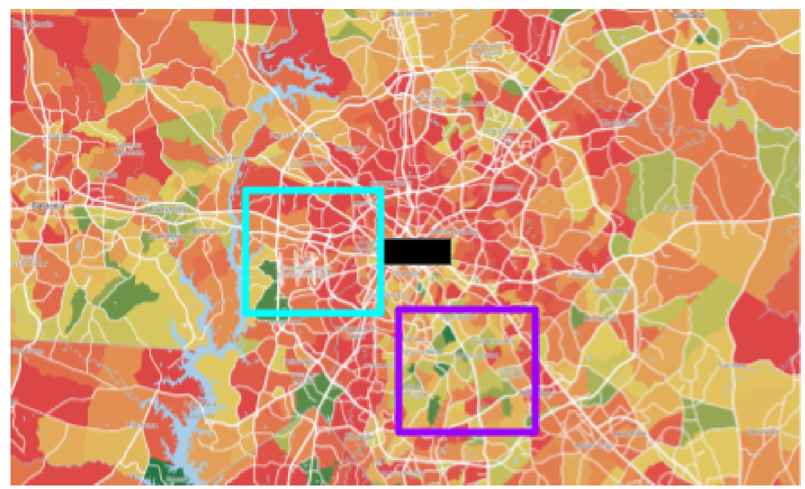


Figure 2.4

Interview Task: Target Practice

Target Practice

You work for a company that offers short-term loans with no credit check. However, your company charges high interest rates in order to compensate for the risk that they take when lending money to people who are unable to get a loan elsewhere.

Your company wants to advertise their services online, but showing the same advertisement to millions of people is expensive. Instead of advertising to as many people as possible, a large and prevalent social media company convinces you to advertise directly to specific groups through their platform for a much smaller fee.

In order to target the right customers and reject others, the social media company accesses their users' digital traces. The digital traces show the history of what the user has done on the platform and elsewhere online, as well as the history of their phone's location. If your company chooses to work with the social media company, they will use the digital trace data to analyze their customers' online behavior and develop plausible characteristics of the person, related to their risk of default (not paying the loan back). The characteristics are listed to the right with their corresponding risk factor.

Interviewer: Do you recommend that your company works with the social media company?

Characteristic	*Risk* Factor
Gender {male, female, non-binary}	{low, high, high}
Race/Ethnicity {White, Black, Latinx, Asian, Indigenous, Other}	{low, high, medium, low, high, high}
Age {18-29, 30-49, 50-69, 70+}	{high, medium, low, high}
Income level {high, medium, low}	{low, medium, high}
Employed {>2 years, <2 years, unemployed}	{low, medium, high}
Home Ownership {owns, rents, experiencing homelessness}	{low, medium, high}
Frequently purchases luxury items	low
Gambles {frequently, moderately, never}	{high, medium, low}
Impulsive	high
Been incarcerated	high

If yes: ***Interviewer:*** *Which characteristic(s) would you target and why?*

Interviewer: *Which characteristic(s) would you avoid? Elaborate.*

If no: ***Interviewer:*** *Elaborate.*

Interviewer: Are there any characteristics that you think the Social media company should add to the list?

Interviewer: In which ways can you, your family or community become targets in this or similar advertisement campaigns? What would they need to know to think critically on the advertisement they receive?

Analysis Methods

The post-interview video data was analyzed as follows: We first transcribed the six video-recordings and read through them to get an overview of students' reasoning for each task. We then used the *Component Model of Moral Case-Based Reasoning in Data Science* (Table 2.3) to characterize these students' ethical decision-making process for the FaceRec task only. We met to rectify coding differences, and then modified our codes to analyze the remaining decision-making tasks. Finally, we compared student reasoning across each task with observed agency as our reference because it speaks to their potential critical consciousness. We then identified themes in student reasoning that correspond with higher levels of agency.

The Component Model of Moral Case-Based Reasoning in Data Science

The *Component Model of Moral Case-Based Reasoning in Data Science* (Table 2.3) was developed from a similar model used by Keefer and Ashley (2011) to compare the ethical argumentation of engineering students' and ethicists. The model differentiates between eight major components (C1-C8) of moral case-based reasoning, where *moral* and *ethical* can be used interchangeably. These are the components that might be brought to bear as a person attempts to make an ethical decision. For instance, a person typically identifies a moral issue as they see it in the given context (C1). To explain why this is a moral issue, they might draw from a variety of sources of relevant knowledge (C2). When proposing an initial solution to the dilemma (C3) they may justify it (C4) by drawing on one or more of mid-level ethical principles (PRINC), their role specific obligations in that context (RSO), or by drawing on existing moral theories (MT). While we anticipate that most individuals are able to demonstrate Components 1 through 4 as they characterize a basic ethical argument, Components 5 through 7 characterize reasoning that goes beyond a simplistic or universalist solution.

Table 2.3

Component Model of Moral Case-Based Reasoning in Data Science

Component	Criteria
Component 1 *Moral Issue*	*Description of the moral issue as the student sees it.*
Component 2 *Relevant Knowledge*	● **CK:** Common/Accepted Knowledge ● **SPK:** Sociopolitical Knowledge ● **MK:** Mathematical Knowledge ● **SK:** Statistical Knowledge ● **CSK:** Computer Science Knowledge ● **GPK:** General Professional Knowledge ● **DSK:** Data Science Industry
Component 3 *Proposed solution*	*Description of the students' proposed solution(s)* [multiple solutions denoted as 3.1, 3.2, ….]

Component 4
Justification for proposed solution
	● **PRINC**: Mid-Level Principles
	● **RSO:** Role Specific Obligations
	● **MT**: Appeal to Moral Theory
	  ● ***Consequentialist*** (consequences)
	  ● ***Deontic*** (intent)
	  ● ***Virtue*** (virtuous behavior over time)
	  ● ***Ethic of Care*** (interpersonal relations)
	  ● ***Social Responsibility*** (justice)

Component 5 *Alternative scenarios*	*Description of the different contexts or scenarios that would change what the student wants to do*
Component 6 *Solution consequences*	*Description of the potential consequences of the proposed solutions that would change what the student wants to do*
Component 7 *Alternative solutions*	*Description of alternative solution(s) offered by the student that consider components 5 and 6* [multiple alternative solutions denoted as 7.1, 7.2, ….]
Component 8 *Agency/Empowerment in context*	CMC AGENCY Scale ● Empowered to act by focusing on system ● Empowered to act on isolated injustices/contexts ● Put faith in others to act ● Onus on oppressed to act ● Disempowered to act

Note. Components of an ethical argument may not occur in the above order.

For instance, some individuals may further consider alternative contexts (C5), and potential alternative consequences of their proposed solution (C6) that require modifications or additional piecewise solutions (C7) to reduce harm. In other words, the individual demonstrates that they may be thinking *pluralistically* with regard to the consequences of their original proposed solution and demonstrates an attempt to rectify any injustices that may be experienced as a result of that solution. Throughout this process, individuals demonstrate different levels of agency (C8) based on their perceived empowerment to address the issue and make change.

Coding Each Component

Components 1 (moral issue), 3 (proposed solution), and 5-7 (alternative contexts, consequences, and solutions), are descriptive in nature, and so were summarized and coded as their respective components. Components 2 (relevant knowledge), 4 (moral justification), and 8 (agency) correspond with constructs from the EMC conceptual framework, and thus include categories of reasoning that students' may reflect in their ethical decision-making. For these components, student reasoning was coded both for their respective component and the types of reasoning that they demonstrated.

Component 2 refers to the forms of knowledge that students draw on as they frame the ethical issue and develop a solution. In data science contexts, students may draw on any combination of common or widely accepted knowledge (CK), sociopolitical knowledge (SPK), mathematical knowledge (MK), statistical knowledge (SK), computer science knowledge (CSK) general professional knowledge (GPK), and data science industry knowledge (DSK).

Component 4 identifies the ethical principles and theories that the student uses to justify their proposed solution. Students may draw on any number of *Mid-level Principles*, *Role-Specific Obligations* and/or *Appeals to Moral Theory. Mid-level Principles* are those that individuals believe that one should abide by generally in society, or within a given context. They are typically not as robust as major moral theories but attend to general concerns in society or industry. For our context these may include considerations of privacy, fairness, accuracy and reliability, accountability, property, loyalty, accessibility, algorithm and data bias, transparency, ecological impact, employment, and discrimination (Register et al., 2021; Stephan et al., 2020). In contrast, *Role-Specific Obligations* are ethical principles that are tied directly to the role of the ethical actor. That is, a student may reason differently if they are positioned as a CEO of the company versus an employed data science engineer. To be coded in this category, the actor must make an explicit statement indicating how their role influenced their proposed solution or their decision to act on that solution (e.g., "*As the data science engineer, an 80% accuracy level is unacceptable.*"). Finally, *Appeal to Moral Theory* indicates that the ethical actor is drawing on one or more major moral theories to make their decision. Given the goals of our study we have delineated between a *feminist ethic of care*, and a *feminist ethic of social response-ability* as separate moral theories, where the former is concerned with interpersonal relationships and the latter is concerned with issues of power and justice. Our method does not require that students be explicit about their use of a major moral theory (e.g., "*as a consequentialist, I believe…*"). Rather, they are coded as appealing to a moral theory if they allude to a core tenet of those theories in their reasoning (e.g., *"a consequence of using this facial recognition software as is, is that people may be wrongfully arrested"* → consequentialist).

To classify student agency, we drew from our current conceptualization as it applies to the different levels of critical consciousness (Table 2.2). While different forms of agency may exist at different points of the argument, we attempted to classify their agency according to their overarching argument. Table 2.4 illustrates an example summary of the components evidenced by Moksh in the FaceRec task.

Table 2.4

Example Case-based Analysis for Moksh on FaceRec Task

Component	Evidence
C1 *Moral Issue*	• Misclassification • Wrongful arrest • Specific to people of color (who are oppressed in US society). • Incarceration cycle.
C2 *Relevant Knowledge*	• SPK • MK • DSK
C3 *Proposed Solution*	3.1: Purchase from Kairos since it is more accurate for darker males (who are criminalized in society) 3.2 But modify before PD use
C4 *Moral Justification*	PRINC: • Fairness • Accuracy • Accountability • Transparency • Discrimination • Ecological impact MT: • Conseq. • Deontic. • Social Res.
C5 *Alternative Contexts*	Use without modification
C6 *Alternative Consequences*	People of color (wrongly) incarcerated at a higher rate

C7 *Alternative Solutions*	7.1: Have more than one data engineer 7.2: Feed more data into this software to improve its accuracy 7.3: Let police know that it's not 100% accurate 7.4: Use other evidence to make sure its the right person
C8 *Agency*	Empowered to act by focusing on system

Findings

Our analysis of students' ethical decision-making resulted in three main findings:

1. Students who demonstrated higher levels of agency (i.e., critical transitivity, semi-transitivity) typically
    - demonstrated a concern for social responsibility,
    - justified their proposed solutions by drawing on a multitude of ethical principles and moral theories (i.e., moral pluralism),
    - and drew on sociopolitical knowledge (SPK) and data science knowledge (DSK) as a basis for their ethical decisions;
2. Only one student drew on an ethic of care; and
3. Students' perceived empowerment seemed to influence the characteristics and robustness of the solutions they developed.

Our rationale for these findings with examples of student reasoning across the three tasks are described in the following sections.

Component 4: Social Responsibility

We conjectured at the onset that students concerned with an ethic of care and social responsibility would likely yield higher levels of critical thought and agency, and therefore, critical consciousness. This conjecture was partially confirmed in that when social responsibility was an explicit concern of students, most of them demonstrated agency at the systemic level (critical transitivity):

- In the FaceRec task, only Moksh drew on social responsibility in his reasoning, and was classified as critically transitive. The remaining students reached isolated (James, Monica, Faye) and systemic semi-transitive (Richard) agency but did not demonstrate a concern for social responsibility.

- In Mapping Crime, Faye, James, and Monica were classified as critically transitive, with all three demonstrating a concern for social responsibility and Monica demonstrating an ethic of care. The remaining students did not demonstrate social responsibility and were classified as systemic semi-transitive (Sam) and dysconscious (Moksh and Richard).

- In Target Practice, Faye, Monica, and James were classified as critically transitive, while Sam and Richard were classified as isolated semi-transitive, with all five students demonstrating a concern for social responsibility. The remaining students were classified as systemic semi-transitive (Sam and Richard) and dysconscious (Moksh).

Regarding our initial conjecture, the evidence is less clear regarding an ethic of care, with only Monica drawing on this perspective during the Mapping Crime task. However, Monica's reasoning in this task was indicative of her critical consciousness and systemic agency, indicating that our original hypothesis may be valid.

Continuing with our discussion of the role that social responsibility played in students' ethical reasoning, we offer an example case of Moksh from the FaceRec task. Table 2.5 provides a chronological excerpt of Moksh's reasoning with corresponding codes. Here, Moksh does not show concern for interpersonal relationships (ethic of care) but demonstrates a clear sense of responsibility to protect those marginalized in society from the potential effects of facial recognition software (social responsibility).

Table 2.5

Moksh, FaceRec

Component Code	Characteristic Code or Description	Evidence
C3	● Purchase from Kairos	I would purchase my software from Kairos. [...]
C2 C4	● MK ● PRINC: accuracy	because although I see that the least difference [in the accuracies of race/gender groups] is from Microsoft, when you compare that to Kairos, the light male percentage is the same [and] the darker female percentage [...] seems to be almost the same, like a 2% difference.
C2 C4	● MK, SPK ● MT: Deontic	But the main thing is: would you rather have a lower darker male percentage and a higher lighter female percentage, or have a higher darker male percentage and a little bit less lighter female percentage?
C1 C2 C4	● Feedback loop (incarceration cycle) for men of color ● SPK, DSK ● PRINC: Discrimination, accuracy, ecological impact ● MT: Consequentialism	Considering today's society, I would rather have my police department recognize darker males with more accuracy. [...] because, and this is kind of what we also read in the books, that if you incorrectly recognize a darker male and they get incarcerated, it creates a loop where they will never get out of the socioeconomic conditions.
C4	● PRINC: Fairness ● MT: Social Responsibility	And if I'm pushing for equality, I would say that's a bad thing.

As Table 2.5 shows, Moksh began his moral decision-making process by first stating his solution to purchase from Kairos (C3). He justified this solution by drawing on the mid-level ethical principle of accuracy, recognizing the differences in each software company's ability to correctly identify facial images among race and gender groups (C4). In his justification (C4), he drew on his SPK (C2) from the course reading, *Weapons of Math Destruction*, where O'Neil (2016) describes the role of predictive algorithms in the ongoing and mass incarceration of men of color in the United States. Moksh used this as the basis for his decision, stating that although the Kairos software has a lower accuracy for lighter females, darker males have a history of wrongful incarceration and so it is more important to recognize darker males with higher accuracy. In sum, Moksh drew on his SPK that men of color are an oppressed group in society with respect to the legal system (C2) and used his perceived power to protect those individuals (C8), indicating his attention to social responsibility. When asked if he would recommend that the software be used by the police without modifications (C5), he briefly pondered his ability to develop alternative or piecewise solutions (C8).

Table 2.6

Moksh, FaceRec

Component Code	Characteristic Code or Description	Evidence
C2 C4 C7	● DSK ● Discrimination ● 7.1	I would recommend the police department to have more than just one data engineer and a team
C2 C4 C7	● DSK ● PRINC: Accuracy ● 7.2	to feed more data into this software to improve its accuracy and make sure that the software can detect to its best potential.
C4 C7	● PRINC: Transparency, accuracy, accountability ● 7.3	[And] let [the police] know that it is not 100% accurate and to make sure that they ID them properly,
C4 C7	● PRINC: Accountability, accuracy ● 7.4	and double make sure that these are the correct people that you may be looking for.

However, after being reminded of his role as the data science engineer for the department, he quickly responded with the alternative solutions (C7) outlined in Table 2.6. Note that his alternative solutions are disaggregated as specific actions and are denoted as 7.1-7.4 in the table.

Moksh's final solution was seen to attack the issue at the systems level because its potential positive impact goes beyond an isolated incident or local context. That is, by starting with an algorithm that better identifies individuals from criminalized groups (darker males) then establishing a data science team to quickly train the data to improve the accuracy for other populations, he tackles the technical side of the issue. Then by engaging in dialogue with the police department about current detection capabilities, Moksh adds safeguards to ensure that individuals at risk of wrongful detection are not convicted based on the algorithm alone. In sum, his sense of social responsibility, SPK and DSK related to the context, seemed to drive a need to protect those at risk of further marginalization thereby influencing the multidimensional nature of his solution.

Component 4: Moral Pluralism

Our findings also indicated that students who did not explicitly draw on an ethic of care or social responsibility could still reach higher levels of agency when their reasoning drew on a combination of ethical perspectives and moral theories in that context (i.e., moral pluralism). For instance, Table 2.7 illustrates the type and quantity of ethical principles/theories that the students drew on in each task in relation to their demonstrated level of agency. Note that many students did not express concern for social responsibility or an ethic of care, but still were able to demonstrate high levels of agency when they drew on 3 or more ethical principles or theories.

Table 2.7

Demonstrated Ethical Perspectives/Theories

Task	**Level of Agency**	**# of Students**	**# of Principles/Theories used in each task**			**# of Students who demonstrated:**	
			Mid-Level	*RSO*	*MT*	*SR*	*Care*
FaceRec	CT	1	2-4	0	2	1	0
	Semi	5	2-4	0-1	1-3	0	0
Mapping Crime	CT	3	3	0	2-3	3	1
	Semi	1	1-3	0	0	0	0
	Dys	2	1-3	0	0	0	0
Target Practice	CT	3	1-4	1	2-3	3	0
	Semi	2	1-4	0	2	2	0
	Dys	1	1	0	2	0	0

To illustrate this finding, we offer an example from James in the FaceRec task (Table 2.8) Here, James' reasoning does not explicitly demonstrate a sense of social responsibility, but instead, draws on his role specific obligations as the data engineer, citing a lack of alignment to professional standards for accuracy.

Table 2.8

James, FaceRec

Component Code	**Characteristic Code or Description**	**Evidence**
C3	● Do not use facial recognition software	**James:** Okay, so which software company would you choose to purchase the software from? Why?--- Is none an option? **Instructor:** Yeah, it is. **James:** Okay, then none.

C8	from these companies ● Empowered to act	**Instructor:** How come?
C4	● PRINC: Accuracy ● RSO: Data scientists have a responsibility to ensure high levels of accuracy	**James:** Considering an industry standard for a lot of professional software is either a 10th or a hundredth of a percent in terms of inaccuracy. I think a 22.5% to 33% inaccuracy is unacceptable for any sort of paid software. **Instructor:** All right. Now let's say that you have to choose
C2 C3 C8	● MK, DSK ● PRINC: accuracy ● RSO: contractual agreement to meet accuracy requirement ● Empowered to act on an isolated injustice	**James:** I'd say Microsoft because it has the smallest difference. And then include in the contract that they meet a certain accuracy requirement by X date. Period. **Instructor:** Okay, what risks are there in using this technology in its current state?
C2 C4	● SPK ● MT: Consequentialism	**James:** The same risks that we have in current police departments where we're alienating part of our population and destroying communities and losing trust in government companies or government funded groups because they use inferior technology. **Instructor:** Ok, what do you think can explain the overall accuracy pattern between these race and gender groups?
C2	● DSK	**James:** The amount of training data they gave it. If the training data is biased towards males, then you're gonna see a higher accuracy rating on males. If it's biased towards females, which it's obviously not, you're gonna see this, those accuracy ratings increase. **Instructor:** So, what can you do as this data engineer, or tell the police to do, to mitigate those risks?
C2 C8	● DSK ● Empowered to act on an	**James:** I don't think a warning would be strong enough but finding a way to enforce

	isolated injustice	this as a secondary identification method [and] having a human intervention as primary means of identification and whatnot.

As Table 2.8 shows, James draws on his role specific obligations as a member of the data science industry, and then takes a consequentialist approach to analyzing the ethical issue. Despite his lack of explicit attention to social responsibility or an ethic of care, James is still able to develop a reasonable solution to the issue, first demanding a contractual agreement to improve the accuracy before it is used. While he does not explicitly state how they should improve the accuracy, he is able to speak to how the differences are due to bias in the model itself, indicating that he is leaning towards increased model training. Finally, James demonstrates his attention to alternative contexts and consequences by explaining that despite the safeguards of the contract, warning the police about potential inaccuracies may not be enough to mitigate the risks of the technology. Rather, it must be enforced as a secondary identification method and include some form of human intervention to ensure that people are not wrongfully incriminated.

Reasoning like James's hints at the potential adoption of a pluralistic moral disposition in that he drew on a combination of different ethical perspectives and principles indicating that he either upheld them as a part of his own ethical disposition, or that he saw them as valuable for developing solutions that have an effect on others. Significantly, drawing on a diversity of ethical perspectives in their reasoning allowed them to develop solutions that attend to more than one affected entity, and enabled them to demonstrate higher levels of agency. With that being said, their solutions were not a result of their ethical perspective alone. Rather, they also had to draw on relevant knowledge to understand the issue and its potential implications.

Component 2: Relevant Knowledge

While we conjectured several forms of relevant knowledge that students might use to identify an ethical dilemma in the problems, the findings show that students most often drew on their mathematical knowledge (MK) (e.g., comparing accuracies in FaceRec, graphical analysis and proportional reasoning in Mapping Crime, and interest rates in Target Practice), sociopolitical knowledge (SPK) (e.g., historically criminalized populations in U.S. society, social stereotypes related to financial capability, cycles of socioeconomic subordination), and their data science knowledge (DSK) (e.g., model training, targeted marketing practices, digital traces, feedback loops) to develop solutions. Significantly, the students who demonstrated higher levels of agency, consistently drew on *both* SPK and DSK together, while those who demonstrated lower levels of agency, did not. Table 2.9 illustrates the relevant knowledge used by each student across the three tasks with their demonstrated level of agency.

Table 2.9.

Relevant Knowledge Used in Each Task

Task	Level of Agency	# of Students	# of Students who demonstrated knowledge types in each task			
			MK	*SPK*	*DSK*	*Other*
FaceRec	CT	1	1	1	1	
	Semi	5	5	2	5	
Mapping Crime	CT	3	3	3	3	
	Semi	1	1	1	1	
	Dys	2	2	0	1	
Target Practice	CT	3	1	3	3	
	Semi	2	2	0	2	1-GPK
	Dys	1	0	1	1	

Knowledge for Low Agency

Students with low agency typically placed the responsibility to avoid harm on other seemingly more powerful entities or on the oppressed group themselves. While these students may have drawn on SPK or DSK when trying to frame the moral issue (C1), they typically failed to incorporate both knowledge bases into the justification for their solution. As a result, their solutions were fairly superficial in that they 1) did not offer discipline-specific actions that they could take to reduce harm, and 2) did not include technical modifications to the model itself. For example, in the FaceRec task, Richard discussed the potential misclassification and wrongful arrest that could result from police use of the software (Table 2.10). While he framed this issue as unfair, he did not position himself as the agent of change in his solution. Rather, he placed the onus of responsibility on others to ensure that people were not incorrectly classified by the software.

Table 2.10.

Richard, FaceRec

Component Code	Characteristic Code or Description	Evidence
C2 C3 C4	● MK ● Purchase from Facebook ● PRINC: Accuracy	**Richard**: I think I would purchase this software from Facebook because out of all of them, it has almost the highest accuracy [...] **Instructor**: Okay. Um, do you recommend that the police department use this software as is?
C2 C3 C4	● MK ● Use only on lighter females, lighter males, darker males ● PRINC: Accuracy	**Richard**: You can use the three columns that are already good, but you can't use the darker female one yet because it only looks like 60% accuracy. That's, that's almost a coin flip and the three other columns are like 90, 95.

		Instructor: …why is it that the darker females and the lighter males have such a big difference in accuracy?
C2	● CK	**Richard**: Because there are more lighter men than darker females in America. **Instructor**: And why would that affect the accuracy?
C2	● DSK (incorrect)	**Richard**: Oh. Because there's more data to train on. For the machine learning, it would have more data to train on the lighter males than the darker females. **Instructor**: What risks are there in using the technology in its current state?
C2	● MK	**Richard**: Well, it's still not a hundred percent accuracy. It still has that, like 5 to 10% miscalculation in here... And you can't use it on darker or females yet **Instructor**: So, let's say that the police go out and use the software as is—with darker females being 60% accurate and the rest being higher accuracies. What risks would there be in using this?
C2 C4	● MK ● PRINC: Accuracy, fairness	**Richard**: It wouldn't be always right. And they can get a lot of innocent people in trouble because this facial recognition technology got it wrong.
		Instructor: So, remember that you are the data science engineer for the police department, right? **Richard**: Mm-hmm. **Instructor**: So, what could you do or tell the police to do to mitigate those risks?
C8	● Place onus on others	**Richard**: If you use this technology as is, you have to do the extra research on the darker females because it doesn't get them right as much. And also with the Facebook software, the

	lighter females have the second worst, so you would also have to watch out for that.

As evidenced in Table 10, despite his recognition of the potential for harm, Richard ignored his role as the individual with the power to make changes to the algorithm. Furthermore, he demonstrated a lack of SPK and as well as misguided DSK in that he suggests that algorithms are trained on entire populations as opposed to being fed facial images by a data science team. As such, we conjecture that his lack of SPK and misguided DSK may have constrained him from developing a feasible and industry specific solution that protects marginalized groups in this context, thereby limiting his agency.

Knowledge for High Agency

In contrast, students who attempted to tackle the issue at the systems level (high agency) consistently drew on their SPK and DSK together in their reasoning and used them to develop creative piecewise solutions that included technical modifications to the model under examination. In the Target Practice task, students who demonstrated high levels of agency drew on their DSK and SPK to develop creative solutions like targeting only those able to pay the high interest loan back (low-medium risk as opposed to specific characteristics), and targeting only financial characteristics while attending to the fact that many could serve as proxy variables for sensitive attributes like race or gender. A prominent example of the use of SPK, DSK, and MK for high agency however, occurred in Monica's reasoning during the Mapping Crime task.

In Mapping Crime, Monica first drew on her graphical and proportional reasoning (MK) to understand the maps, arguing that while crime seems to occur everywhere, the crime grades seem to correlate more with the resident population of the area than its demographic characteristics (i.e., areas with high crime grades have high resident populations). She then reasoned that because of their limited personnel and resources, police would likely patrol the red areas from the first map (crime per capita) because patrolling all red areas in the simple crime map would not be feasible (SPK). She then decided that she would not release the application to the public and argued that the police should not have access given "their history of not using their resources ethically or properly" (SPK). When pressed to elaborate on the potential effects of the mapping application if it were accessed by both the public and the police (C5, C6), Monica drew on her understanding of feedback loops to suggest that the maps would change as they are used by both entities (DSK). That is, as police used the maps to target their patrols, and as citizens used the maps to determine where to travel and live, the resident population in high crime areas would likely decrease due to a higher number of arrests and move outs. When asked how their use of the application would affect the everyday lives of her friends in their respective locations (C5, C6), she further drew on her SPK and demonstrated an *ethic of care*—an ethical perspective that few participants expressed in the interviews—focusing on the interpersonal relations and the effects on the well-being of those impacted by the application. See below:

> **Monica:** I think the first effect is definitely their perception of where they live and how well they think their life is going. For example, my friend who's an African American male, he'll look at the map and see that he's in a high crime area and probably not think that he's come very far [...] Whereas my friend who's an Asian American female will probably think that she's living better because her area is green on the "Crime per capita" map and she'll measure herself in terms of her successes and not her past failures. So mentally, I think it'll affect them both --negatively in the case of the African American male and positively in the case of the Asian American female. [And] in the area where the Asian American female lives [...] there will be a lot less police around. [...] [But] for the African American male, since there will be a lot more police, he's more likely to be stopped, questioned, arrested, interrogated, et cetera, by the police, which will definitely make him more likely to go to jail, have to restart his life, [and lose] progress from that point when he decided to change.

In sum, Monica's SPK seemed to drive her decision to not allow public and police use of the application, that is, her understanding of the historical misuse of police resources, the ongoing cycle of incarceration and overrepresentation of African American people in U.S. prisons, and the effects on African American peoples' perceived and actual well-being. In addition, her DSK allowed her to understand how the mapping application might contribute to these issues, as well as its potential impact on public perceptions of criminality.

Importantly, those (including Monica) who demonstrated higher levels of agency, consistently drew on *both* SPK and DSK together, or at the very least, one of the two. While this finding might seem obvious, it is significant because the rectification of ethical data science dilemmas requires that decision makers understand the nuances of the Data Science industry, the specifics of the methodology, and the potential impact for different individuals and groups in society. Thus, in addition to MK, it is essential to promote the development of SPK and DSK in order for students to develop feasible, creative, and industry specific solutions to dismantle current and future injustices.

Component 8: Agency and Perceived Empowerment

The findings further indicated that students' perceived empowerment seemed to have an effect on their ability to offer robust, feasible, and creative solutions. Recall in a previous FaceRec example how Moksh's solution to the issue became more robust only after reminding him of his role as the data science engineer. Similarly, across the three tasks, students seemed to ponder how their designated role could impact the types of solutions they are able to offer. For instance, consider James's reasoning in the Target Practice task:

> **Instructor:** Let’s say that you decide that you're going to work with a social media company. If that's the case, which of these characteristics would you target or not target, and why?
>
> **James:** Are we being ethical or are we being effective?
>
> **Instructor:** You tell me—you are working for this company, so you have to make that decision.
>
> **James:** I've been pretty idealistic this whole time—continuing with that trend.
>
> **Instructor:** Are you saying that if you actually worked with them that you wouldn't have the ability to be as idealistic as you have been?
>
> **James:** Yes. Efficiency is king. If I say, no, I don't think we should do this, I think we should follow more general advertising that targets a less specified, but larger audience—that costs more, and results go down, and if they run a trial that uses gender, race, age, income level [etc.] and they see a 30% increase in revenue, it's not gonna look good. And they're not gonna listen to me anymore.

James recognizes that there are consequences to making ethical decisions that conflict with the values of the company. For instance, if his goal to protect individuals from financial exploitation conflicts with his company’s goal to increase profits, how can he make the ethical decision without losing clout in the company? When asked how he would answer differently if he were to make an ethical versus a practical decision, he struggled with the former, stating, “It's frustrating. Everything else is just either extremely intrusive or targets small populations that are gonna end up being exploited.” Reasoning like James’s suggests that ethical decisions are highly impacted by the actors’ role in that context. This is significant since the overwhelming expectation in global and U.S. industry is to increase profits, implying that students may struggle to make decisions that deviate from a profit-based orientation.

Discussion

The results of this study suggest that students of privilege are quite capable of making ethical data science decisions in that all students in our study regularly made arguments composed of elements C1-C4 and C8, and many addressed C5-7. However, not all students demonstrated a concern for social responsibility or an ethic of care, and some did not demonstrate high levels of agency to dismantle the injustice, speaking to their potential lack of critical consciousness in the given context.

Based on our findings, we argue that differences in the characteristics of students' ethical decisions may be explained by their ability to consider diverse perspectives in their reasoning, the forms of relevant knowledge they hold, and the role that they hold in the context. With regard to relevant knowledge, the students in our study typically drew on their MK to recognize the differential impact of the phenomenon across populations, their SPK to identify forms of oppression, and their DSK to identify unethical practices. DSK then played a larger role in their ability to develop industry specific and feasible solutions to the issue. That is, high DSK enabled students in our study to create solutions that used or dismantled data science industry practices, while also tackling the forms of oppression that they identified when characterizing the issue (e.g., Moksh and James in FaceRec, and Monica in Mapping Crime).

Regarding the ethical perspectives that students draw on to make decisions, we argue that high levels of agency may be supported by pluralistic ethical reasoning. In our experience, students who are able to consider more perspectives typically developed solutions that would have wider positive impact because they attempted to understand and resolve the issue by tackling it from multiple angles. Importantly, this does not imply that these students held these ethical perspectives (i.e., concern for consequences or intent does not mean that students prescribe to a solely consequentialist or deontic ethical perspective), but rather indicates that they considered those perspectives as valid in their reasoning.

Finally, the role of the student in the given context seems to impact the solution that they will choose to enact. For instance, in Target Practice, James contemplated the impact of making an idealistic (ethical) decision versus a practical (profit-based) solution on his continued role in the company, potentially losing clout as a decision maker if he chose a solution that reduced profit, while in other cases, students pondered their ability to enact the solution itself. These findings are consistent with our pilot study findings where preservice mathematics teachers, middle, and high school students consistently questioned their ability to enact their solution and keep their job. Significantly, the students in our study who demonstrated their SPK and DSK when framing the issue, sometimes chose to enact a solution that did not address the sociopolitical impact, either because they feared for their job or did not feel that they had to power, or responsibility to enforce it.

In response to these findings, we developed the *Ethical Decision-Making in Data Science Protocol* modeled after the *Component Model of Moral Case-Based Reasoning in Data Science* analytic framework. This model includes guiding questions intended to promote SPK, DSK, as well as other forms of knowledge, and a pluralistic moral disposition including concern for social responsibility and an ethic of care. In addition, it prompts a systematic analysis of alternative contexts and alternative consequences at the forefront of their decision-making process to promote the development of piecewise alternative solutions that protect against the potentially harmful effects of their solution. Finally, given the impact that students' perceived empowerment seems to have on both their devised solution and their role in enacting them, the protocol further prompts students to engage in a meta-analysis of their perceived empowerment. We hope that use of this protocol to guide future course designs and reasoning processes may allow students to make sociopolitical considerations in their ethical decision-making, and to center themselves as an agent of change at the systems level. In sum, our ultimate goal is for our students to internalize the components as necessary elements of an ethical argument and continue to draw on them in their future decision-making processes, whether in data science or beyond.

Limitations

The findings of this analysis are contextualized around six students of relative privilege, and therefore may not translate to other student populations. Furthermore, we initially planned to conduct pre-interviews to gauge shifts in their ethical arguments, but we questioned whether students would feel comfortable speaking openly about controversial issues at the beginning of the course. Thus, our findings only provide evidence of the characteristics of their ethical decisions after participating in the course, but not to the full effect of the course itself on those decisions. In other words, their reasoning may reflect proficiencies they had prior to our collaboration.

Conclusion

We conclude this article with a call to action for the mathematics and data science communities to begin thinking about and designing for students' critically conscious ethical decision-making. Given the rapid expansion of data-based decision-making processes in society, the predominantly privileged demographic of current data scientists, and the role of mathematics and data science education in the development of future data science teams, it is imperative that we center ethics in our mathematics and data science instruction. That is, students must be regularly exposed to both the benefits and drawbacks of the methodologies associated with BDA and must be given opportunities to practice making ethical decisions that would protect those at risk of harm.

As a contribution to the literature, this article describes some potential first steps for developing a data science industry concerned with social responsibility and the deconstruction of systemic injustices caused or reproduced through data science. It offers guidance regarding course activities and structures that seem to promote ethical decision-making in data science contexts among students of privilege, and by describing a general structure, tools, and activities for a course intended to promote students' critically conscious ethical decision-making in Data science. Furthermore, it offers an *Ethical Decision-Making in Data Science Protocol* to be used and modified by the mathematics and data science education communities in order to promote such decision-making in data science contexts using a structured approach to ethical argumentation. We see these contributions as significant, given that neither an ethical decision-making protocol nor curricula seem to exist at this time in the literature, despite the need for tested, refined, and ethically grounded course materials in data science.

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CHAPTER 3: DESIGN CONSIDERATIONS FOR FACILITATING EQUITABLE PARTICIPATION IN AN ETHICAL DATA SCIENCE COURSE FOR HIGH SCHOOL STUDENTS

Jordan T. Register

University of North Carolina at Charlotte

Michelle Stephan

University of North Carolina at Charlotte

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Abstract

The purpose of this article is to understand how educators may support students from different backgrounds (both relatively privileged and marginalized) to participate equitably and meaningfully in ethical data science discussions. To do this, we draw on the literature regarding STEM identity formation, use Cobb and Yackel's (1996) framework for analyzing social norms for discourse in inquiry-based classrooms, and draw on Hodge and Cobb's Cultural Participation Orientation towards developing an inclusive classroom environment. Finally, we describe the course elements (task structures, participation structures, and discursive moves) from a designed Ethical Data Science course that supported students' equitable participation in ethical data science discussions (Sandoval, 2004).

Keywords: Data Science, ethics, cultural participation, privilege hazard, social norms for discourse

Introduction

With the onset of globalization and increased neoliberal attitudes in society, world governing entities have increasingly relied on the use of data science and Big Data Analytics (BDA) to process such data in order to make impactful decisions in society (Mayer-Shonberger et al., 2014). Yet, despite the social and economic benefits afforded by the data science industry, there are concerns about its marginalizing effects on non-dominant individuals, namely, that training algorithms on historical data often reinforce social stereotypes and place individuals in a recurring cycle of misclassification (i.e., feedback loop) (O'Neil, 2016).

Exacerbating these marginalizing effects is the dominant demographic of data scientists and professional mathematicians in the field (i.e., White or Asian, male, and upper income). This phenomenon, called the *privilege hazard* by D'Ignazio and Klein (2020), occurs when teams of data scientists are composed of people primarily in privileged positions. Although often unintentional, designs created in these contexts reflect the dominant perspectives and experiences of the privileged creators at the expense of non-dominant identities and viewpoints (D'Ignazio et al., 2020; Noble, 2018). Note that when we refer to "privilege" we use Kokka's (2020) conceptualization as a "set of advantages one group has over others, granted because of membership or perceived membership in social categories (e.g., race, class, gender identity, sexual orientation, etc.)" (Kokka, 2020, p. 3). Consequently, one of the biggest threats to society that has come from globalization is the hard coding of discrimination in the processes that are increasingly used by world governing entities (D'Ignazio et al., 2020). Thus, it is imperative that mathematics and data science education be both grounded in ethics and rich with opportunities for students to think critically about the ways in which their mathematical products influence those who may be situated differently in society (Atweh, 2013; Ernest, 2018; Authors, 2021b; Skovsmose, 1994).

Purpose

The context of this study is situated in a Design Research Project whose purpose is to characterize students' ethical reasoning in mathematics and data science in order to develop instructional resources. The Ethical Data Science course was developed through this project and was implemented over a four-week period in summer of 2022 at a major Urban Research University in the Southeastern United States that serves urban intensive, urban emergent, and urban characteristic schools in both its city of residency and surrounding counties (Milner, 2012). The high school students who participated in the course came from a range of urban intensive/emergent/characteristic communities across the state and held a variety of cultural and gendered backgrounds, although predominantly economically and academically privileged. Some of these students attended their home schools while others attended the state school of Mathematics and Science.

Importantly, a course that foregrounds discussions around ethics and privilege has the potential to cause discomfort for students, impacting the ways in which they participate in all elements of the course. For instance, we noticed in the first few days of the course that the females were less likely to participate in discussions that were heavily grounded in the technical and mathematical components of data science. At the same time, White males and Asian students were more likely to participate in the technical discussions and less so in the sociopolitical or ethical grounded discussions. Given that the current demographic of professional mathematicians and data scientists are vastly overrepresented by White and Asian males, while underrepresented by females and people of color, we viewed our students' cultural and gendered ways of participating in the EDS course as indicative of the current trends in these fields (D'Ignazio et al., 2020). Thus, we argue that in order to reduce the privilege hazard and its negative impact on non-dominant communities, we must prioritize the diversification of the data science industry, beginning by understanding how students with diverse backgrounds participate in these disciplines prior to entering the workforce. As such, the purpose of this study was to understand how designed course structures may support equitable participation among students with diverse and intersecting identities in ethical and sociopolitical data science discussions, where *equitable participation* refers to variability in the students who contribute to class discussions, but more so that these students participate in ways that affirm their identity and sense of belonging. As such, this article contributes to the urban mathematics education literature in that it explicitly addresses issues of power, race, and identity in diverse classrooms (Larnell, 2013) for the purposes of promoting nondominant representation in the data science industry to promote justice in the global economy.

In the sections that follow, we will briefly discuss literature regarding factors that influence identity in the STEM disciplines. Following a description of the Cultural Participation Orientation and methods that ground our study, we will then present evidence of the social norms that became stable in EDS course, accompanied by our conjectures for students' participation in the social norm to explain one's reasoning. Finally, we introduce a new social norm to the literature, called *making space*, and propose several recommendations for promoting meaningful and equitable discourse in high school ethical data science learning contexts.

Factors in STEM Identity Formation

Fragile, Designated, and Relational Identity

According to Solomon et al., (2011), many learners, despite being successful in mathematics, see themselves as “existing only on the margins of the practice, or as lacking stability in it” (p. 565); such *fragile* mathematics and science identities, though not restricted to females, have been shown to appear in girls and women more often (Solomon et al., 2011). Scholars suggest that difficulties for females are closely related to cultural beliefs about gender, wherein common perceptions of what counts as mathematical/scientific knowledge and processes are inimical to women’s’ traditional roles, and their ways of knowing, thinking, and learning (Ridgeway, 2001).

Women are often cast through dominant social discourses as best suited for caretaking roles in society, which may be tied to Gilligan’s (1982, 1993) argument that the moral dispositions of women are more readily concerned with selflessness and care for others. At the same time, Gilligan (1993) argued that men tend to be *separate thinkers* (e.g., those who prefer methodologies associated with logic, rigor, rationality, and absolute truth) while women are more often *connected thinkers* who rely on intuition, creativity, personal processes, and experience. With regard to their preferred ways of learning, Becker (1995) claimed that while males more often prefer competitive and pressurized environments, females prefer more cooperative and supportive working environments that often conflict with notions of the traditional mathematics classroom setting. Such designated identities thus contrast with the ideal ways of thinking and behaving in the STEM disciplines and contribute to the widespread assumption that women are less intellectually capable in these fields than their male peers (Sfard et al., 2005). Importantly, individuals often subscribe to their designated identities unconsciously and without realizing that there are alternatives (Sfard et al., 2005).

An effect of these stereotypes on STEM classrooms is an inhospitable learning environment for females in which teachers, peers, and/or the students themselves do not see females as possessing the necessarily skills, knowledge, or dispositions to become successful scientists and mathematicians (i.e., stereotype threat) (Carli et al., 2016). As a result, students' relational identities are a salient factor in females' participation in STEM environments. That is, despite having similar agentic goals for learning (those which promote self-interest, self-satisfaction, competence, and ability), scholars argue that gender shapes differences in STEM goal achievement as evidenced by women's underrepresentation in the STEM disciplines (Moss-Racusin et al., 2012). On the one hand, this gender gap is due to teachers' subordination of feminine ways of thinking and participating, but it is also greatly affected by peer and self-expectations for what counts as acceptable behavior in STEM spaces (Riegle-Crumb et al., 2020). Furthermore, because mathematics and the sciences are often cast as an elite male domain (Castro et al., 2019), women pursuing STEM fields necessarily transgress traditional gender roles and norms, whereas their male counterparts have only to be concerned with demonstrating their knowledge in ways that are tailored to them (Grunspan et al. 2016; Ridgeway et al., 2004). Unsurprisingly, this phenomenon can be seen in postsecondary STEM classrooms which, due to the gendered expectation of faculty and peers, have been described as negative, exclusionary, and "chilly" towards female students (Riegle-Crumb et al., 2020).

Intersectional Identity

There are also differences in motivation within gender classifications that can be ascribed to culture, race, and ethnicity. For instance, despite having similar agentic goals across genders, certain cultures place a greater emphasis on communal goals resulting in “different patterns between goal affordances and commitment to STEM occupations” (Riegle-Crumb et al., 2020, p. 106). As an example, scholars have argued that, generally speaking, the social orientation of Asian cultures promotes a stronger emphasis on community, interdependence, and connections with others (i.e. communal social orientation) (Varnum et al. 2010) while the overrepresentation of Asians in U.S. STEM fields is, at least partially, due to a greater cultural emphasis on the value of STEM fields (Lee and Zhou, 2015). In the United States, this overrepresentation is generally accepted by dominant groups in society as a result of the so-called “model minority myth” that positions Asian students generally as academically and occupationally successful while also “passive, compliant, and apolitical” (Riegle-Crumb et al., 2020, p. 106; Shah, 2019; Shrake, 2006). At the same time, the ideals of the model minority and the “good at math” stereotype are often pitted against other racial/ethnic minorities (e.g., Black, Latinx, indigenous) resulting in the devaluation of those cultures in STEM spaces (McGee, 2018). However, because Asians are often perceived as foreign and un-assimilating, they are positioned in U.S. society as superior to Black and Brown individuals in STEM, but subordinate to the ideal White American (McGee, 2018). As a result, students of color in the United States experience educational environments as both racialized *and* gendered spaces that differ according to their cultures (Riegle-Crumb et al., 2020) while students of relative privilege (e.g., White or male) may experience racialized or gendered marginalization despite holding one or more privileged identities (e.g., males of color, White females, non-binary gender identifying students). For instance, although Asian and White students are often considered talented in STEM disciplines, White and Asian females and non-binary students are simultaneously subordinated according to their gendered identities, while Black, Latinx, and indigenous females and non-binary students may be subordinated according to both their racial and gendered identity. Similarly, Black, Latinx, and indigenous males, despite being viewed as more logical or rational than females, may experience racialized marginalization in STEM classrooms. Furthermore, these students may also encounter forms of marginalization within their own communities where cultural values and traditions related to gender roles may conflict with their educational aspirations (Lee, 2006; Riegle-Crumb et al., 2020).

Impetus for Equitable Participation

The effects of the classroom environment as a racialized and gendered space include different forms of participation among diverse students. Given that students participate in classroom activities according to their identities and culture, Cobb and Hodge (2019) suggested that the classroom may serve as a space to promote cultural participation among students from different backgrounds. Furthermore, there is sufficient evidence that diversity in educational and professional spaces may promote collective understanding (e.g., Wilson, 1992). Therefore, if the learning goals tied to classroom discussions in a data science course grounded in sociopolitical and ethical contexts are to develop a holistic and collective understanding of the effects of data science on the wellbeing of individuals and groups in society, then it is imperative that a diversity of voices and perspectives are authentically considered. Put differently, a well-rounded understanding of who these methodologies affect, and how they are affected, is needed to safeguard against the privilege hazard in both learning and industry settings to ensure that the needs of marginalized groups are reflected in potential solutions.

Taken together, these research findings helped shape the design of the EDS course. As Sandoval (2004) argued, “the embodiment of the high-level conjecture articulates its reification in features of the learning environment design” (p. 23) that may include tools and materials, task structures, participation structures, and discursive practices. Therefore, these course elements were explicitly designed to encourage equitable participation and positive data science identity formation from students with diverse and intersectional identities. We elaborate on each of these designed elements next, beginning with a description of the course structure, tools, and materials.

Designing for Equitable Participation

While there have been initiatives in K-12 data science education (e.g., Gould et al., 2016; Heineman et al., 2018; YouCubed, 2020), none to date have consistently incorporated ethics into their coursework. Furthermore, we could find no data-based analyses that document the learning that occurs as students engage in an ethical data science course. To this end, the co-authors initiated a multi-year program of Design-Based Research (Bakker et al., 2014) to develop an introductory ethical data science (EDS) course for high school students.

The EDS course was developed based on the high-level conjecture that students would be more likely to develop their ethical mathematics consciousness if they were immersed in an introductory data science course grounded in ethical and critical contexts. Here, ethical mathematics consciousness (EMC) refers to *the awareness that human beings do mathematics; thus, there are potential ethical dilemmas and implications of mathematical work which may affect entities at the individual, group, societal, and/or environmental level.* Core tenets include sociopolitical, ecological and communicative mathematics awareness, and a willingness and commitment to act on past injustices, share data-based knowledge, and/or create ethical mathematical designs for the future (i.e., ethical mathematics agency) (Andersson et al., 2022; Register et al., 2021; Stephan et al., 2021).

In developing these design conjectures, the design team for the larger study conducted three separate task-based, pilot interview sessions: one with middle school students (Reinke et al., 2022), one with high school students (Register et al., 2021; Stephan et al., 2021), and one with preservice teachers in the United States and Sweden (Andersson et al., 2022), for the purposes of characterizing how students and preservice teachers think ethically in data science contexts. Based on their responses and literature related to ethical dilemmas in the data science discipline, course activities were designed to elicit ethical and critical conversations related to the pros and cons of data science decisions for different groups in society.

With respect to course activities, Sandoval (2004) suggested that learning outcomes are influenced by the learning environment itself and the "changing social infrastructure of the settings" in which these designed environments function (p. 23). As such, we recognized that grounding a data science course in critical and ethical contexts has the potential to cause discomfort in students as well as influence their ways of participating in class discussions. Thus, we explicitly designed the task and participation structures to foster equitable participation and student belonging in the EDS classroom.

Task Structures for Equitable Participation in EDS

Task structures refers to the goals, criteria, and standards of the tasks that learners are expected to do (Sandoval, 2014). A majority of the investigations in the EDS course were designed to leverage student discourse in the service of surfacing multiple rationales for making ethical data-based decisions. Thus, the task structures for the course included: (1) *decision-making*, (2) *pluralistic*, and (3) *qualitative* designs. *Decision-making task structures* position students as decision makers who must decide and justify their choices based on both their understanding of the topic and their personal experiences. They must also demonstrate support for and/or challenge the decisions made by their peers. Related to this are *pluralistic task structures* which require that students explore and justify their decisions by arguing pluralistically, considering both the pros and cons of their potential action. Finally, *qualitative task structures* are those in which students are expected to consider the quality or consequences of specific mathematical actions or processes in society or based upon their personal experiences. Together, these task structures place the onus of responsibility on students to understand the technical aspects of the data science methodology as well as reflect on and anticipate the potential effects of their mathematical products and analyses in society by drawing on their personal, cultural, and gendered experiences.

Participation Structures for EDS

Participation structures refers to how students and teachers are expected to participate in tasks including the roles and responsibilities that they take on (Sandoval, 2014). To support the discursive and reflective nature of the data science process, the task structures were implemented with the following *participation structures*: 1) individual reflections, and 2) structured, problem-based, and open-ended inquiry in individual, small group, and whole group contexts. Here, structured inquiry refers to a sequential process where students conceptualize how to ask questions and investigate real-world issues according to the data investigation process. Problem-based inquiry refers to inquiry-based learning centered around the act of solving a real-word problem, and open-ended inquiry allows students the freedom to explore and develop data-based solutions to an issue of their personal interest. Together, these participation structures serve as a means to scaffold students' inquiry processes in data science contexts by first learning to engage in the data investigation process, apply that process to real-world issues, then investigate an issue of their choosing according to those learned processes.

Discursive Practices and Attention to Identity

Finally, designs must also include the intended *discursive practices*, or ways of talking in the intended learning environment. To this end, the teacher attempted to facilitate discussions that drew upon social norms that are productive for inquiry-mathematics environments (Cobb & Yackel, 1996). These norms include the expectation that students 1) explain and justify their thinking, 2) indicate agreement and/or disagreement, 3) attempt to understand the reasoning of others, and 4) ask clarifying questions when the need arises. Due to the controversial nature of the discussions that surface when examining sociopolitical datasets and engaging in ethical discussions, as well as the diversity of identities present in these discussions, we expected that the negotiation of these norms would look different than in our previous work and that new social norms may emerge. Thus, we conjectured that the teacher would need to make a conscious effort to support students' development of a positive data science identity while also affirming their gendered and cultural identities in the classroom environment. The moves that the teacher intended to foster positive identities included being explicit about, co-establishing, and modeling norms for discourse, and promoting rough draft thinking by encouraging students to share their unfinished and developing ideas while being open to revising those ideas (Jansen, 2020). Given the scope of this paper, we report only on the task structures, participation structures, and select discursive moves made by the teacher that were found to support students' enactment of, and individual beliefs in the importance of equitable participation.

Theoretical Orientation

Generally speaking, scholars concerned with equity work often adopt a Cultural Alignment Orientation towards learning wherein culture is defined as a way of life within a bounded community that is passed down from generation to generation (Hodge et al., 2019). Instructional designs from this perspective attempt to align classroom practices to those from students' home communities (Hodge & Cobb, 2019). This has caused some resistance, given that the composition of U.S. classrooms often does not reflect separate bounded communities, but rather a collection of intersectional ones. In addition, the realities of globalization, rapid technological advancements and increased global immigration imply that bounded communities no longer exist in society and thus do not translate into the culturally homogeneous classrooms that are more conducive to the methods associated with the Cultural Alignment Orientation (Hodge et al., 2019).

In contrast, we adopted the Classroom Participation Orientation elaborated by Hodge and Cobb (2019), which views culture as "a network of local hybrid practices that people jointly constitute as they negotiate their places in specific settings" (p. 863). Through this lens, students develop ways of participating in or resisting classroom practices based on a range of resources, practices, and identities that they bring to the classroom from their home, community, societal discourses, popular culture, and the media (Hodge et al., 2019, p. 863). In other words, the Cultural Participation Orientation views classroom culture as something to be negotiated by students with different experiences and intersecting identities. Rather than starting by aligning classroom practices with those from students' home communities, the Classroom Participation Orientation begins with classroom practices that promote rigorous disciplinary (e.g., data science) learning. From there, the central question seeks to understand how that instruction can be modified, either by adjusting specific classroom practices, modifying activities, or providing additional evidence-based supports that may enable students who draw on diverse resources and identities to participate equitably and substantially (Hodge & Cobb, 2019). Importantly, equitable participation does not mean that all students participate in the same way or to the same extent since their identity influenced ways of participating are different.

Due to our commitment to the Cultural Participation Orientation, our analysis serves as an attempt to understand the role that each of the instructional design elements played in supporting social norms and equitable participation in ethical data science discussions, with particular attention to the ways the teacher adjusted those elements in-situ. As a consequence, the following research questions were formulated to guide our analysis:

1. Which social norms became stable over time, and in what ways did students participate in and contribute to their constitution?

2. How did the designed/modified task and participation structures support/constrain equitable participation in the activities and social norms of an ethical data science course?

In the sections that follow, our methodology and relevant findings will be discussed.

Methodology

Course Structure

The course structure included 20 instructional days which occurred over four weeks in July, 2022. The tools and materials used by students throughout the learning process were designed to reflect processes used and ethical considerations made in the data science industry, and to leverage students' rationale for making ethical decisions in data science contexts. Some core activities include in-class data processing and machine learning labs, the Data Science in Society project, Ethical Dilemmas activities and discussion, and Book Discussions.

Students developed their Python programming skills outside of class through DataCamp.com and completed collaborative in-class labs through Google Sheets, Jupyter Notebooks, and Google Colab. The purpose of these labs was for students to gain experience following complex data science procedures and making complex decisions that have an effect on a multitude of entities in society, and to guide their methods for the Data Science in Society Project. Thus, they enacted the *data investigation process*, that included: (1) framing the problem, (2) considering and gathering data, (3) processing data, (4) exploring and visualizing data, (5) considering models, and (6) communicating and proposing solutions (Lee et al., 2020) in the context of real world, sociopolitical datasets, engaging in critical and ethical inquiry along the way. For instance, we used Jupyter Notebooks and Google Colabs to enact the data investigation process through machine learning labs in the contexts of coal ash contamination in the United States, and civilian gun ownership across the globe. At this time, coal ash contamination was a major issue in the participant's home state, while gun rights were a looming public policy issue due to increased mass and school shootings in the United States. Students explored, cleaned, and processed the data, then attempted to build regression, classification, and clustering models to predict outcomes based on their generated research questions. Students then applied their learning to their Data Science in Society Project, where they chose a personally meaningful sociopolitical injustice to explore, develop solutions, and communicate their findings through a conference style poster, presentation, and research report. The program culminated with a gallery walk of student projects.

Simultaneously, students explored the ethical implications of their potential work by exploring real media related to ethical dilemmas in the data science industry. They selected articles from a repository created by the instructor and worked in groups to identify the ethical issue and make ethical considerations from the perspective of a data scientist and citizen. Furthermore, they explored the potential impact of such dilemmas by reading select chapters of *Weapons of Math Destruction* (O'Neil, 2016), *Automating Inequality* (Eubanks, 2019) and *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (Mayer-Schonberger et al, 2013). The purpose for reading *Big Data: A Revolution That Will Transform How We Live, Work, and Think* was to give students an overarching understanding of the data science methodology and the uses of Big Data Analytics in society. This text explores BDA from a generally positive perspective, speaking to its benefits for global society and explores the differences between the BDA methodology and traditional research. At the same time, they read *Weapons of Math Destruction*, a text that describes the negative implications of the BDA methodology for marginalized populations and individuals in society that result from accepting messiness and making causal inferences from correlations in data that hold historical biases. For instance, O'Neil discussed the impact of the feedback loop on the mass incarceration of people of color in the United States and the poverty cycle that results from commercial targeting of services like for-profit colleges towards single mothers and women of color. Finally, their third assigned reading, *Automating Inequality*, describes the impact of using BDA to automate eligibility systems for social programs like the Family and Social Services Administration (FSSA). This reading provides anecdotal evidence of the failures related to fully transitioning the FSSA program to an automated system, resulting in a lack of access and loss of benefits for people in need, having short term and long term detrimental effects on the well-being of individuals and their families.

Participants

The participants consisted of 15 rising high school juniors and seniors selected for a competitive, state-funded, summer residential program held at a major university in the Southeastern United States (U.S.). The goals of the program are to provide hands-on, student-driven learning experiences with authentic research opportunities in STEM. We chose the upper high school age group due to their position in the U.S. mathematics curriculum and their familiarity with social media, technology, basic data sources, and basic data manipulation. In addition, we hypothesized that the nature of a STEM program being held over the summer at a major university typically could attract more privileged types of students in terms of parent and student education, parental involvement, race, ethnicity, and socioeconomic status, and thus, may reflect the demographic makeup of the data science industry today. The general makeup of the program from 2016 to 2021 has been predominantly White and Asian/Indian students who do not require financial assistance with a parity in gender expression. The demographic makeup of the students enrolled in the EDS course reflected these aforementioned trends, including one Black girl, one Indian-American girl, five White girls, four White boys, two Indian-American boys, and two Asian-American boys (all self-reported without the "-American" label). With that being said, students' identities are not singular. Rather, they intersect with a multitude of identities along the lines of race, ethnicity, gender expression, socioeconomic status, etc. that further influence their experiences of privilege and marginalization (Kokka, 2020). Thus, if their acceptance into the program is considered an educational privilege (as it was here) then the composition of the EDS class was homogenous in the sense that all of the students held at least one privileged identity (White, male, high SES, academic privilege, etc.), but heterogeneous in that the cultural and gendered experiences that the students brought to the class, including their ways of participating in tasks and discussions, were diverse.

Researcher Roles and Positionality

The first author served as the sole instructor for the EDS course while the second author was positioned as an observer, data collector, and co-analyst. Both authors identify as White females from middle class backgrounds who taught inquiry and discourse-based mathematics at the middle and high school levels and currently work with preservice mathematics teachers. At the time of this writing, the first author/instructor is a doctoral candidate in a Curriculum Instruction in Mathematics Education program with a bachelor's degree in pure mathematics and a master's certification in both secondary mathematics teaching and data science. The second author is a full professor of mathematics education and an expert in Design-Based Research and inquiry mathematics teaching. Both authors have worked over the past four years to develop potential profiles for students' ethical reasoning in mathematics and data science contexts from the perspective of promoting critical mathematics consciousness in students with relative privilege (like themselves). The goals of this work have centered around the promotion of ethical reasoning among students who may not have experience working with marginalized populations, while also promoting intercultural participation and communication for the future.

Data Collection and Analysis Methods

The data used to analyze the emergence of social norms, equitable participation, and students' feelings of belonging in EDS whole class discussions included video recordings of class sessions that demonstrate students' ethical reasoning, individual and collective student feedback from Google Forms, class discussions, individual check-ins, and focus groups, research field notes, and design team meeting notes. The video data was analyzed according to Glaser and Strauss's constant comparative method for analyzing longitudinal data sets in discursive settings (Glaser, 1965; Cobb & Whitenack, 1996). Generally, this method follows a multi-phase approach to analyzing video recorded student discourse in which students' social relationships and mathematical learning are first characterized in an episode-by-episode analysis, followed by a macro-level analysis-to shed light on sociological and psychological patterns in their interactions over time. Our process of analysis is documented in Table 3.1 below, where *student contributions* refer to verbal statements that students make in whole class discussions that fall under one of the social norm categories, occurring when they attempt to explain, question, critique or indicate agreement with purpose, going beyond simplistic responses such as a yes or no. Figure 1 illustrates trends in student contributions over time, where a bold vertical line indicates macro level shifts in student contributions.

Table 3.1

Process of Analysis

Phase	Actions	Purpose
Overview	Read through all of the video transcripts chronologically.	Capture an overview of the negotiation of social norms, e.g., when the teacher prompted the students to explain, did they oblige or resist?
Micro Analysis #1	2 authors independently coded video transcripts for social norm contributions in Google sheets. Met weekly to calibrate codes.	Qualitatively capture the ways in which students contributed to the negotiation of social norms as well as the quantity and nature of contributions for each student.
Macro Analysis #1	Transformed coding spreadsheet into a data frame with social norms and student identity features as attributes. Analyzed trends in student contributions using statistical visualization software (Tableau and CODAP) to identify: ● Where student contributions were high or increased ● Where the variability of contributing students was high	Select key activities that illustrate significant shifts in student participation patterns (see Figure 3.1, where macro level shifts in student contributions are designated by a bold vertical line.)
Micro Analysis #2	Independently coded selected activities for activity structures, participation structures, and discursive moves made by the teacher within these activities. Met weekly to calibrate.	Identify design elements that may have supported stability of social norms and equitable participation in discourse.

Macro Analysis #2	Chronologically documented how and when the social norms were being negotiated and/became stable (if at all), and looked at variability in student participation in these norms.	To determine when/if participation was equitable among the students.
Identity Analysis	Read through relevant student feedback and focus group notes.	To determine what elements of the design, or teacher moves likely contributed to student empowerment and equitable participation.

Limitations

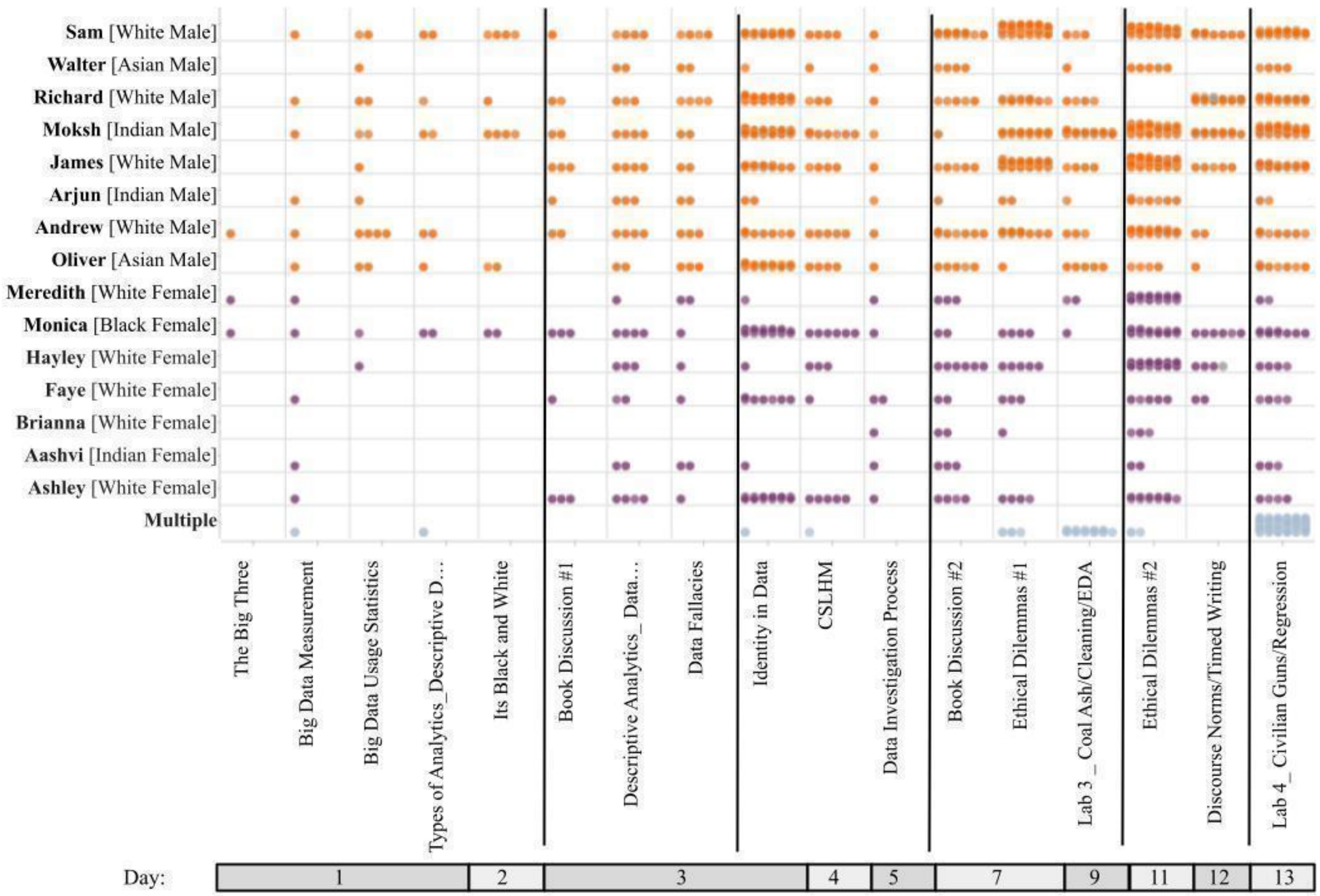
There were several limitations with regard to the course experience and the study itself, the most salient of which are related to the course being only four weeks long, the first week being virtual, and the student research requirements of the program. Although students were with the instructor for five hours per day, relationship-building, developing knowledge about students' ways of participating, and establishing social norms for discourse takes a considerable amount of time, especially in learning contexts that students may not be familiar with. In addition, the program requirement for students to individually conduct research for publication over the course of four weeks served as both an opportunity and constraint for the students and teacher in the EDS course. On the one hand, immersing students in the research process was meaningful in that it developed their understanding of the scientific method and data investigation process. On the other hand, students had little experience conducting literature reviews and writing research reports, requiring that the instruction forgo several ethical data science activities to support students in their writing and research more than she had anticipated. Finally, we were met with difficulties related to the nature of a residential program during the COVID-19 pandemic that included the temporary removal of COVID-positive student and teaching assistant. In addition, our ways of participating were sometimes negatively influenced by the need to social distance. Despite these limitations, our analysis of the first three weeks of the course yielded some unexpected but important findings. Significantly, it was found that the negotiation of a new social norm to make space, coupled with students' developing beliefs in the importance of meaningful and equitable participation, proved to be essential for students to contribute equitably in the social norm to *explain* one's thinking.

Findings

The findings of our analysis related to the first research question include that 1) the norm to explain was the first and only to become fully stable, while the remaining norms were still in the negotiation stages at the end of the course, and 2) in their enactment of equitable participation, a new norm emerged where students attempted to *make space* for others' explanations. Regarding the second research question, the task structures that supported student empowerment and equitable participation in EDS course discussions include decision-making, pluralistic, and qualitative task structures. The participation structures that supported equitable participation include requiring that all students present when reporting out as small groups and that students engage in small group talk prior to reporting out individually in whole group discussions. Furthermore, the discursive moves that supported student's equitable participation in the EDS course included: 1) co-establishing social norms by facilitating a space for students to negotiate them according to their cultural, gendered, and personal resources, 2) collaboratively defining equitable participation as necessary for collective understanding, and 3) promoting rough draft thinking by explicitizing that there are "no experts on ethical data science" in the classroom.

Figure 3.1

Count of Students Verbal Contributions by Date and Activity



To illustrate these findings, we first document the social norms that appeared to become stable within the first three weeks of the course (e.g., the norm to explain), followed by evidence of the emergence of the new social norm to make space for others' explanations. We then characterize the negotiation of this new norm to make space and provide conjectures related to the designed and/or modified course elements that seemed to promote equitable participation. Finally, by drawing on insights from the identity literature and students' feedback throughout the course, we further attempt to characterize the core design elements that promoted students' belief in the norm to *make space* for others and their observed empowerment to take up that space.

Observed Stability of Social Norms for Discourse

Our analysis indicates that the social norm that students were expected to explain their thinking became stable early on while the norms to indicate agreement/disagreement, ask clarifying questions and attempt to understand each other's thinking were still in the negotiation stages at the end of the third week (Week 4 was dedicated solely to their research projects and thus did not include whole class discussions). Initially we found it encouraging that students felt obligated to explain their thinking with or without prompting from the teacher. However, the discourse patterns further revealed that certain students explained only when called on by name by the teacher. For instance, the following discourse patterns, where some students respond to prompts from the teacher and others without, were typical in the first few days of the course.

Instructor	Gerrymandering, um, yeah. Uh, Arjun, did you wanna talk about [your experience with] that a little bit?
Arjun (Indian male)	Yeah. Back when I lived in Atlanta, we had like these districts that was like, Super long and super thin. And they were all like messed up and I was like, what's going on?

Instructor	Yeah. Are any of you familiar or not familiar with what gerrymandering is?
Instructor	All of you have heard of it?
Sam (White male)	I am, but I would also like to add on to the point, um, that Arjun made that just because there are districts, which are like long and skinny and all that, it doesn't necessarily mean they're gerrymandered. Um, if you want to see like more about gerrymandering stuff, I think you need to look a little bit more into the details than just the shape--like you gotta see the race makeup, the, you know, age, makeup, stuff like that and make sure it's even that way.

Interactions like this indicate that at the individual level, some students consistently felt obligated to explain, while others (namely most of the females and Asian students) only did so when explicitly asked. Significantly, the latter students were more often females and/or Black and Asian students, indicating that their disproportionate contributions may be attributed to their identities and cultural or gendered ways of participating.

A New and Essential Social Norm: Making Space

Over the first three full weeks of the course, the students seemed to notice that the same few students contributed to class discussions, stating in their feedback that “our discussions were typically dominated by the same students” or that they noticed that “not a lot of [the girls] spoke up.” Significantly, many of these students seemed to handle this by either making an effort to contribute when others seemed to dominate the conversation (step up), or by providing *space* for their quieter peers to speak (step back). Thus, a new social norm emerged that involved students feeling obliged to *make space* for others' voices to be heard in classroom discussions.

Importantly, the designed task and participation structures seemed to encourage the students themselves to negotiate behaviors that would allow them to share their own ideas while also providing space for others to share theirs. For instance, in the excerpt that follows, which occurred on day 3, Moksh began to negotiate how to make space for his group mates to explain their thinking by explicitly deferring to them in their group presentation:

Moksh (Indian male)	For society in general, data science can provide multiple opportunities because [...] if they teach at least some part of data science to the general population in high school, they can get to know that it is something that they could pursue, and it could like help society [...] *and I'll leave it to my group.*

By Day 7, the students began to adopt more explicit techniques for eliciting their peers' contributions, as seen in Monica's reflective feedback below:

Monica (Black female)	The teacher set [expectations for meaningful and equitable participation] in the way of giving us instructions or what to talk about, but the students mainly took hold of and regulated those things. One specific example of this I remember was during a group discussion where all the tables were in a circle. We were discussing a reading, and, while I had something to say, I was too nervous to say it. One of my friends in that class was directly across from me and noticed I didn't say anything, so he repeatedly looked at me and gestured in a way that told me to speak. I couldn't at first, but he was so persistent that I did end up saying what I had thought.

While the designed course elements seemed to foster students' participation in the social norm to explain, there was evidence that specific task and participation structures seemed to encourage both the provision of space by dominant students and empowerment in those with seemingly fragile data science identities in EDS classroom discussions. In the following sections we respond to research question 2 by presenting each of these supports and plausible identity connections to validate our conjectures.

Task Structures that Supported Making Space

The task structures that supported equitable participation and the provision of space included *decision-making*, *pluralistic*, and *qualitative* task structures. That is, in sociopolitical contexts, students were given the opportunity to decide for themselves, argue, and challenge diverse ideas related to the ethical decisions that they would make as a data scientist or as a citizen. These decisions were drawn from their personal experiences and research into the positive and negative aspects of the Big Data industry. Notably, positioning students as decision makers seemed to be one of the most important structures for inviting diverse students to participate more equitably in class discussions. This not only placed the onus on the students to argue what they believe is right, but the requirement to argue *pluralistically* (make arguments both for and against automated eligibility systems, facial recognition software, predictive policing, etc.) further pushed them to contribute in a manner that went beyond simplistic responses or those intended to demonstrate competence. Rather, this task structure enabled students to consider perspectives that they may not have otherwise considered, giving value to their peers' diverse perspectives and experiences. As an example, consider the following excerpt from the second Reading Discussion where students discussed data messiness and its implications for automated eligibility systems like the Family and Social Services Administration (FSSA) and Food Assistance Programs (SNAP). Here the students not only demonstrated that the social norm to explain one's thinking had become taken-as-shared, but the variability in contributors indicated that some of the more hesitant students may have felt empowered to have their voices heard:

Ashley (White female)	So, with these systems [FSSA/SNAP]—I don't think that we should automate it. Cause just because you're eligible, sometimes what you're given is not what you need. Cause these systems, they might give you money, but you might like, you might need food instead or a job. You're just giving them what they need, like supplies, but you're not giving them a way to survive. [...] And if you're automatically eligible and you're

	getting services, you might not have the incentive to go out [...] and find a job?
Sam (White male)	Going off of that um, I think it's important to think about how like—I think most people today, even if they're getting money, [...] like all of us, we wanna be productive members of society, right? Even if we get a million bucks, I think some of us would still try to do something with that money instead of sit around. So, I don't think that giving money through welfare lowers people's willingness to work. And in addition to that, I don't think that giving welfare money is really a good place to stop. I mean like creating new jobs by public works is a great way to go and the government's done that a lot before to get us out of recessions and what not [...]
Instructor	[Students look for teacher's response] Don't look at me, this is y'all's conversation!
Monica (Black female)	I agree with that point and I was gonna say um the idea that um giving money to those in need will stop them from wanting to get a job is a good argument against keeping the automated systems like they are because they don't actually help people in the program, [...] So if we work more on trying to help the population that's receiving these [benefits], or even people who are denied eligibility—even giving them resources [...] Something that'll help them cultivate skills instead of just trying to push them away with what little things we give them.

As this excerpt shows, the book readings served as a starting point for students with fragile data science identities to enter the discussion and make relevant connections to their communities and personal experiences. For example, Monica's reasoning related to insufficient resources for eligible citizens was based on her personal experiences and community knowledge of public assistance programs. That is, she drew on her observations that people receiving benefits are often given minimal support while being denied the opportunity to cultivate life skills. Therefore, we conjecture that these task structures may have empowered the girls who were uncomfortable speaking out in technical settings the opportunity to contribute in a meaningful way, according to their experiences and identities.

Consequently, discussions of this nature served two purposes: 1) to open the floor for non-dominant students to speak to their experiences; and 2) to promote collective understanding of the social positioning of marginalized groups in society as it relates to the data science methodology. Yet, an additional point to make regarding these task structures is that unlike Critical Mathematics Pedagogies that forefront social injustices of the past or present, the act of making decisions for the future enabled the students in the EDS course to look beyond who is the oppressor/oppressed and toward making informed decisions that are not harmful to others. Rather than create a polarizing environment for heterogeneous students, positioning students as decision makers in sociopolitical and ethical contexts both created a space for students with fragile data science identities to contribute in a meaningful way and served to develop a unified sense of community and caring in the classroom (collective social orientation). Importantly, this required that the students consider alternative viewpoints and experiences and use them to develop reasonable solutions to the issue at hand. That is, they were required to measure the quality, feasibility, and consequences of their actions based on both their personal experiences and their collective understanding of the potential implications of data science for different groups in society, constituting what we refer to as *qualitative* task structures. With regard to space, the qualitative task structures deterred students from contributing to show competence and forced them to provide and consider alternative viewpoints in order to promote collective understanding.

Participation Structures that Supported Making Space

We further noticed that students' active participation in the social norm to explain was heavily dependent upon the participation structures that the teacher enacted, in particular, whether students were required to participate in groups or individually, and whether each student was required to speak out. On Day 1, there was a noticeable lack of structure to whole class discussions. As a result, the students attempted to negotiate the social norm to explain one's reasoning, recognizing that at least one student should respond to the teacher's prompts, but they did not show concern for diverse perspectives. In the early lessons, this was evidenced by a select few students, primarily boys, continuously responding first to prompts. As a result, the instructor implemented small group presentations within the whole class discussion to provide structure and encourage non-dominant voices.

Small Group Presentations

While this participation structure did not necessarily promote equitable participation, it did catalyze a peer negotiation of space within those presentations. For instance, in the context of the excerpt that follows which occurred on Day 1, students were required to work in small groups to conceptualize the scale of Big Data measurement, then report on their findings as a group to the rest of the class. While the teacher still had to prompt certain group members to jump in, students demonstrated the negotiation of space by deferring their explanations to their group members.

Instructor	So, group one, please jump in.
Moksh (Indian male)	So, uh, we, we just felt like we should go with like the base bases of life, I guess. And we chose bases of matter. We chose atom. Then we moved on to the molecule and then we thought

Instructor	So, group one, please jump in.
	that we're gonna do a human next. So, we slowly went to the cells[...] and *I'll let the other guys take over.*
Monica (Black female)	Um, from there we went to tissue and then blood vessels and then the organ as a whole, and *I'll save the last one for our last member.*
Arjun (Indian male)	Then we did the organ system, the human body, and then groups of people.
Instructor	And every individual bite or unit is an atom is that correct? Awesome. I love that. [...] group two?
Ashley (White female)	So, we set it up, um, with the byte being the smallest of the yellow ones [starting with a single grain of sand]
Instructor	I love how you showed your scale through the sizes of the blocks. That's interesting
Instructor	Somebody else from group 2?

As seen in this excerpt, some of the students began to make space for their peers' contributions by explicitly deferring to them in their presentations. Yet, these norms were still being negotiated as evidenced by the teacher prompting students to jump in and explain (e.g., “Somebody else from group 2”). Furthermore, this structure alone did not result in equitable participation as evidenced by males taking the lead in presentations or by presenting for their entire groups in surrounding activities. Consequently, the teacher again modified the group presentation participation structure on Day 3, explicitly requiring that all students in the group present.

All Students Present

Enactment of the required participation structure, that all students present, resulted in a student-to-student negotiation that focused not only on the provision of space, but on who was afforded that space. That is, dominant students began to step back for others to have their voices heard, while quieter students began to step forward. By Day 7, in their group presentations to the whole class, the students required no prompting to step in from the teacher or their peers and demonstrated variability in presenters, indicating that the students were negotiating the social norm to *make space* from the perspective of equitable participation, while the social norm to explain one's reasoning had become taken-as-shared.

Support for Individual Participation

Outside of small group presentations, we noticed that females were more apt to participate early on if participation was an explicit requirement made by the teacher (like in the group presentations). However, this requirement is more difficult to make in a whole group setting where students are expected to report out individually. This was a point of contention for the instructor as she did not want to force students to report out on topics in which they do not feel empowered to speak to, but still wanted to resolve issues of inequitable participation in whole group discussions. Significantly though, the teacher noticed that after imposing the group participation structure in course activities, girls began to participate more readily in whole group discussions where a group presentation structure was not enacted. Thus, it is conjectured that the group participation structure in surrounding activities may have served as a motivator for those students who typically sit on the margins of class discussions to speak up in discussions without that enacted structure. In addition, a final participation structure that was sought by the female students in their feedback, was to integrate small group talk into whole class discussions, e.g., affording time for students to confer with their group mates before responding publicly to a prompt. According to the female participants, this allowed them to consider and discuss the prompt prior to speaking out in the whole group context, and thus removing some of their feelings of vulnerability.

Establishing the Need for Meaningful and Equitable Participation

The process of establishing social norms for meaningful and equitable participation requires ongoing attention. For instance, after a breakdown of the social norms on Day 11, the instructor modified her lesson plan to facilitate a Timed Writing activity on Day 12 for the purposes of reestablishing the social norms for meaningful discourse and to promote students' belief in the need for equitable participation. The discussion that ensued was significant because it not only gave us evidence of how students framed the idea of equitable participation, but also had a significant impact on their ways of participation moving forward.

In this activity, students were to open a Google Doc, and write continuously for two minutes each in response to eight prompts. The teacher then asked the students to respond to the first six prompts verbally as a class. The final two prompts were intended as reflective questions that supported the first six, but students were not expected to discuss them publicly unless they were comfortable doing so. She took projected notes on their responses in order to provide a collective visual representation of the class expectations for discourse and participation. The timed writing prompts are listed in Table 3.2, followed by our analysis of student responses to Prompt 6 and identified discursive practices that seemed to support their beliefs in the importance of meaningful and equitable participation.

Table 3.2

Timed Writing Prompts

1. What is your purpose for being in this course? What are your goals? What can you do to accomplish these goals? What can your classmates do to help you accomplish these goals?
2. What does it mean to be an academic? What behaviors does this entail?
3. What does it mean to engage in academic discourse with your peers? What behaviors from you and your peers may support academic discourse?
4. What counts as a "good" question in an ethical data science course?
5. What counts as a "good" explanation in an ethical data science course?
6. What counts as meaningful and equitable participation in class discussions and tasks? Why is this important?
7. Do you feel that you meaningfully participate in every discussion/activity? Why or why not? If you hesitate to meaningfully participate in every discussion, why do you think this is the case? What changes could be made to encourage your meaningful participation?
8. Do you feel that your participation allows for other voices to be heard? Explain. What could you do differently to encourage and value the voices of your diverse peers?

Regarding Prompt 6, it was necessary to define the term equity in order to help students conceptualize and qualify equitable participation as necessary. Consider the following excerpt from the whole class discussion:

Instructor	What is the difference between the word equitable and the word equal?
Sam (White Male)	Equitable is just getting what they need, uh, equal is everyone gets the same thing.
Instructor	[...] So when we are having equitable participation, what do you think that means?

Moksh (Indian Male)	When people who speak most speak a little bit less and people who don't speak much, speak more.
Instructor	Right? And it just means giving that space. And it's not saying that people who speak up need to be quiet and, and not talk the entire time, but it's waiting, encouraging others maybe to speak up that don't necessarily speak up more often.[...] it's being aware of how your position in the classroom or in whatever room you're in, can affect how others communicate, and then being someone who can encourage those others to communicate, or vice versa. It's if you are not necessarily someone who likes to speak up, challenging yourself to get out there and, and speak up and ask those questions and share your opinion because it's a valid and valuable opinion that people should hear.
Richard (White Male)	[...] I was kind of thinking like, equitable is like, you give your participation, and you receive like output from other people.
Instructor	Knowledge from others, right? [...] Why is it important to have diverse people in different institutions or in different classrooms or in different jobs or as data scientists?
Moksh (Indian Male)	So that represents the population. So that our values and stuff are represented.
Instructor	Yeah. Why?
Monica (Black Female)	Because like, people from different backgrounds carry like, like different experiences with them. So, if you don't have one person's experience that may be representative of that person's group, then you're missing that kinda nuance and those kinds of things that could help your product or whatever you're doing, be more fair and equal for everybody else.

In the excerpt above, the students themselves conceptualize the meaning of equitable (as opposed to equal) and apply this conceptualization to the classroom learning environment by describing what this means in terms of student behaviors (e.g., Moksh explained that equitable participation translates to conversationally dominant students stepping back to let others have a voice). The teacher then uses this as an opportunity for students to make conjectures about why equitable participation is important. Significantly, this discussion served to redefine students' expectations for meaningful participation such that, rather than place the onus of participation on individual students as a means to evidence their competence, intelligence, or work ethic (typical of traditional classrooms), as negotiated in the EDS classroom, equitable participation must be positioned as essential for the promotion of authentic understanding.

Connecting Back to Student Identity

We conjectured that students' participation in the social norm to make space for others to explain their reasoning is intricately connected to their personal identities and social orientation. That is, their beliefs about who should have a voice in the classroom depends on their positioning in that space and in society, while their obligations for learning (self, peers, society, etc.) (Cobb et al., 2009), may dictate how students participate within that space. Thus, to better understand students' motivations for participating (or not) in the social norm to explain one's thinking, we drew on student feedback collected by the instructor throughout the course.

Male Participation

Findings from these data sources confirmed that despite the enacted task and participation structures, elements of students' fragile STEM identities related to gender and culture may have had an effect on their ability/willingness to participate in the norm to explain. For instance, our analysis of student participation and feedback from the EDS course suggests that, from the onset, males as a collective group seemed much more comfortable explaining in class activities, though some of the Asian males expressed discomfort in qualitative discussion. This held for most task and participation structures and was seemingly stable from the first week of classes. Consider the following male students' responses regarding their feelings toward participating at the beginning of the EDS course:

Oliver (Asian Male):	I did not feel any reservations about participating at the beginning of the course. Asian identity likely impacted this, because it's usually stereotypical to think that Asians are at the top of the class, so it influenced my ability to participate.
Sam (White Male)	I felt pretty good as in school it's pretty normal for me to be active in discussions, so it wasn't too hard for me here.

Arjun (Indian Male)	At the beginning of the course, I didn't feel much competence in my ability to meaningfully contribute to the class/group discussions. This was because I didn't know much about data science and its ethical implications. Thus, I didn't have a lot of meaningful ideas to share with the class. Hence, I put in a lot of effort to understand how data science works and its ethical implications upon the society. [Additionally] I didn't know my peers that well and didn't know how they will perceive my responses. I was very anxious about not making a fool of myself, so I refrained from participating.

We conjecture that differences in male participation and their feelings of belonging could be due to cultural differences between the males in the course. Namely, the White males were comfortable in any setting (potentially speaking to their dominant positions in U.S. society), while the Asian males and one of the Indian males seemed less comfortable speaking out in qualitative discussions than in the more technical lessons. When compared to Sam's responses, Arjun and Oliver's responses reflect findings from the literature regarding differences in the agentive and communal goals between White and Asian cultures, their positive STEM identities, and their cultural emphasis on STEM fields which are traditionally situated in technically, abstract, and/or procedural settings (Riegle-Crumb et al., 2020). Thus, it is possible that effects of the Asian minority myth or the "good at math and science" stereotype are internalized by Asian males to favor "masculine" technical educational settings. At the same time, such designated identities also convey Asian males as "passive, compliant, and apolitical" (Riegle-Crumb et al., 2020, p. 106), qualities that are societally projected as positive characteristics that align with their academic and occupational success but restrict them from being comfortable in sociopolitical settings.

In addition to males' generally high levels of participation, we also observed a noticeable lack of space given to others, namely females, in class discussions. At the beginning of the course, class discussions were largely dominated by four White males and one Indian male. Gradually, as participation and task structures were modified to allow more space for their quieter peers, some of the females began to take up that space either by their own volition (Monica) or by designed participation structures from the teacher (e.g., all group members must present). However, while navigating participation norms and structures, the dominant males continued to control, albeit subtly, by consistently presenting first or contributing most to group presentations. Importantly, this did not seem to be a conscious move on the part of these students. Rather, it seems more likely that their conditioning from performance-based classroom environments that promote quick responses, coupled with their agentive goals, may have played a role in how they participate in class discussions. That is, their comfortability with and motivation to prove their competence and ability in what they would typically consider a competitive environment was a factor (Abele et al., 2007; Ridgeway 2001).

It was further conjectured that the males in the EDS course may have consciously or unconsciously viewed their female counterparts as less competent (Grunspan et al., 2016), as evidenced by the males consistently taking the lead or presenting for their female counterparts. The males either placed themselves in a superior position according to their agentive motivation to show competence, or in what they may have considered a supportive group role from a communal standpoint. With that being said, after the Timed Writing activity in Week 3 (discussed in a subsequent section) there was evidence that dominant students were beginning to think deeply about the space that they afford to others. For instance, consider Andrew's (White male) statement:

> I am by no means the leader of every discussion and the most frequent speaker, but still speak more than a handful of other students in this class. I think this is because I don't like silence, but *that is just an excuse and more conscious awareness will make it very easy to just wait for other voices to be heard*.

Female Participation

With regard to the girls in the course, our findings were analogous with the STEM identity literature which states that the designated identities of females in STEM impact both the self-efficacy of the females themselves and the social expectations of their peers. In the context of the EDS course, this in turn seemed to affect the girls' feelings of subordination and their ways of participating in classroom activities and norms. After noticing the lack of participation from females in class discussions in the first two weeks of the course, the teacher attempted to understand the girl's hesitations by conducting a small focus group discussion between class sessions. Responses included that they (1) felt others knew more about the subject and thus preferred to listen, and (2) were fearful of being wrong in front of classmates and/or the teacher. Thus, the collective female students' perceptions of others knowing more about the content and thus having more important contributions contributed to their lack of confidence in participating in the norm to explain their reasoning during whole group discourse. However, like for the males, the females demonstrated different ways of participating in and negotiating this social norm, supporting that self-efficacy and participation in data science settings are not only gendered but cultural as well (Riegle-Crumb et al., 2020).

At the beginning of the course, the White females' lack of participation appeared to stem primarily from their feelings of incompetence regarding their data science and sociopolitical knowledge in relation to their peers and the teacher. That is, they did not want to seem less intelligent or able, by saying something wrong.

Faye (White Female)	At the beginning of the course, I did not feel very competent in my ability to meaningfully contribute to discussions in class. This was because I knew little of the subjects being discussed, since I had no previous experience in data science.

In contrast, Aashvi, the sole Indian female in the course, felt very comfortable with the data science content but felt more discomfort in the sociopolitical/ethical discussions and with public speaking in general. In addition, she cited her discomfort sitting away from her friends in cases where small groups were assigned, indicating a potential internalization of the gendered, racial, and intellectual *other* stereotype imposed upon Asian females (Shah, 2019; Shrake, 2006), that is, the model minority and "good at math" stereotypes position Asian females as superior to their female counterparts, but as subordinate to her male peers in a technical setting. At the same time, like her Asian male peers, she may be viewed as passive and apolitical, potentially speaking to her discomfort with public speaking and sociopolitical conversations (Riegle-Crumb et al., 2020, p. 106).

Aashvi (Indian Female)	At the beginning of the course, I felt very competent in my abilities in meaningful contribution to the class because I had a little prior knowledge in the field of data science. [...] In the middle of the course, I realized that the class discussions were more than just specific knowledge of the field of data science. It was also about the impact of data science to the people around the world [...] which I wasn't very well-versed in. As a result, I felt a little less confident in my abilities to meaningfully contribute in class discussions. However, towards the end, after the encouragement from the instructor and feeling more confident about myself, I felt more propelled to express my opinions.

Unlike the other females in the class, Aashvi's prior knowledge related to data science contributed to her feelings of competence at the beginning of the course. Yet, her observed lack of participation in the norm to explain her reasoning during class discussions resonated more with her expressed discomfort speaking in sociopolitical contexts. Thus, Aashvi's negotiation of the norm to explain her thinking was intimately tied to her feelings of competence both with the technical and qualitative course content and in relation to her peers.

Finally, Monica, the sole Black female in the course, again participated differently than the others, likely due to her cultural positioning. At the beginning of the course, she felt few reservations about participating in class discussion, but felt much more comfortable discussing sociopolitical topics than technical ones. Like Asian females, Black females deal with the effects of intersectional marginalization (Crenshaw, 1991) and stereotype threat (Spencer et al., 1999) in STEM classrooms. In contrast however, Black women are simultaneously subordinated based on gender *and* race to both their White and Asian counterparts (Riegle-Crumb et al., 2020). While it could be expected that this would impact her participation and performance in a negative way, Monica demonstrated resilience to such stereotypes through her agentic and communal motivation. Namely, she noticed a lack of participation from other females which catalyzed her motivation to speak up and dismantle the male dominated discourse that had taken a hold on the class.

Monica (Black Female)	I felt obligated to participate for the other girls in my class. I noticed that not a lot of them spoke up and I felt that if I talked more, they would eventually do the same.

Thus, she was determined to make herself heard if not for herself (agentic motivation and personal empowerment), then for her female peers (communal motivation). She first took up this space in the sociopolitical/ethical discussions where she felt that she had more experience/knowledge, speaking to the effect of the task structure on her sense of empowerment.

Identity Connections to Task Structures

The argument for implementing *decision-making, pluralistic*, and *qualitative* task structures in data science learning environments is related to the gendered and cultural positioning of students in those spaces and in society. Currently, women are positioned on the margins of the STEM disciplines and as subordinate to men in society (Ridgeway et al., 2004). To foster a sense of belonging, it is therefore imperative to provide opportunities for girls that support their ways of knowing and learning (like Monica above). For instance, Carol Gilligan, a pioneer on gender differences in moral development, argued that girls tend to be more *connected thinkers* with a desire for understanding, relevant experiences, and discourse while prioritizing selflessness and caring for others (Gilligan, 1982, 1993). As such, activities which promote qualitative and ethical reasoning could be argued as essential for girls' development of self-efficacy in mathematical or technical settings. For instance, consider Monica's feedback related to *qualitative* task structures:

Monica (Black Female)	In the beginning of the course, I felt very incompetent in my ability to contribute in our discussions about data science because I knew nothing about it. I knew that others knew about the topic and felt that it would be better if people who knew what they were talking about dominated the floor. When we talked about ethics, I felt more competent because that is an area I know a lot about.

Monica's comment here is indicative of the opportunities afforded to the mathematics education community by the data science methodology. Generally speaking, data science sits at the intersection of mathematics and statistics, computer science, and disciplinary knowledge. It is used daily by a myriad of entities across the globe to make impactful decisions in society. In a classroom context, the seamless integration of sociopolitical and ethical issues into the data science curriculum (i.e., the notion that data science cannot be studied separately from the target population of the dataset), allows instructors to encourage students at different levels of understanding to contribute to the discussion. That is, students who may not yet feel comfortable speaking to the technical components, can speak to the impact of data science and BDA within their own communities. This serves both as a means to increase their confidence and sense of belonging, as well as promote collective understanding of the differential impact of data science.

While activities that promote qualitative and ethical reasoning seem to benefit students with fragile identities, such activities are often uncomfortable for males and other students of relative privilege (e.g., White females) in the STEM disciplines. However, we argue that engaging students from dominant groups in qualitative tasks may support their development of a collective social orientation as well as serve to dismantle the *privilege hazard* in the STEM disciplines due to their required consideration of the effects of their technical products and newfound experience navigating diverse conversational spaces. In sum, *qualitative task structures* provide a space for the typically masculine and/or relatively privileged students to discover their affective qualities.

Walter (Asian Male)	I thought that the readings gave me an insight on data science that I haven't considered beforehand. They provided real life examples and perspectives and allowed me to understand the adverse effects of not considering ethics while investigating data.
James (White Male)	Ethical Dilemmas in Data Science, Ethical Task, and the Documentaries allowed us to analyze different points of view and discuss among people with varying life experiences.
Meredith (White Female)	In the Readings and Ethical Dilemmas assignments, I got to see real world examples of how big data is used and think about whether or not it is being used in an ethical way [...]. The readings showed examples where people are being affected [...] and how big data is pretty much screwing up so many people's lives, which I didn't even know was really an issue before starting

> this course. Just seeing these real-life examples opened up my eyes to things that I didn't know were happening in the world.

Importantly, enacting decision-making, pluralistic, and qualitative task structures is not enough to promote equitable participation. While the task structures themselves seemed to foster student empowerment by allowing a space for them to speak to their experiences, it did not guarantee that they would be afforded the space by their peers to do so. Rather, the teacher must also be intentional about the participation structures that are enacted to create space until its need becomes internalized by the students.

Identity Connections to Participation Structures

The participation structures that supported students' equitable participation in data science activities and discussions included first implementing a small group reporting structure where all students are required to present. This structure allowed non-dominant students the space to have their voices heard, while promoting the provision of space by dominant students. With regard to students' relational and fragile identities, requiring that all students present in a group reporting structure helps to establish the notion that all students' contributions are important and valid.

In the context of whole group discussions, especially those situated in technical or rigorous mathematical activities, non-dominant students further benefited from engaging in small group talk prior to reporting out. From these students' perspectives, small group talk reduced their feelings of incompetence because they were given a chance to both think and talk through the topic before being required to speak on it. This simple structure served to reduce their feelings of vulnerability and empowered them to have their voices and perspectives heard. With that being said, it was also essential to decenter the authority in the class by positioning the students and instructor as co-learners, and by consistently reminding students that "no one here is an expert." Rather, we are all there to learn and discuss the myriad of ways that data science can impact humans and ecologies, drawing on the diverse perspectives and experiences in the room, in order to develop feasible solutions that reduce harm for the future.

Furthermore, as evidenced in their timed-writing responses, many of the students began to consider their positioning in the classroom in relation to their peers (navigating their privilege, participating to encourage others, stepping back to encourage others, using their peers as a source of knowledge, etc.). This was a salient finding since, as Cobb and colleagues (2009) argued, shifts in the students' thinking about participation and learning are related to their self-identified obligations for doing so. Findings from the post-course feedback form related to participation revealed that by the end of the course, students felt obliged to learn and participate for others (collective social orientation), likely contributing to the increase in equitable participation. Significantly, the majority of students' obligations from the beginning to the end of the course shifted to include one or both of their peers and society, as evidenced in student responses that follow:

Oliver (Asian Male)	I included my peers for the end of the course because of how I realized that me participating in class would help my peers possibly gain new ideas about a certain topic and pushes them to also contribute to discussions.
Sam (White Male)	Thinking deeper about the actual content of the course led me to realize who really benefits from this.
Monica (Black Female)	I felt obligated to participate for, specifically, the other girls in my class. I noticed not a lot of them spoke up and I felt that if I talked more, they would eventually do the same.

Faye (White Female)	I developed relationships with my teacher and my peers, and so my obligation to contribute on their behalf increased. In addition, I realized that data science affects society quite a bit, and so I felt obligated to contribute so I could make a difference in society hopefully in the future, and help others understand some of the things I learned.

On a final note, the results of this study indicate that the process of taking up social norms for participation and discourse are neither the same for all genders or across cultures. Thus, it is imperative that students are not only a part of the conversation in which the norms are developed, but that they serve as both leaders and beneficiaries. For instance, in the Timed Writing activity, the act of students first reflecting on their purpose for being in the course (i.e., to learn and transform society) and what it means to meaningfully and equitably participate, enabled them to engage in a collective discussion about their own needs and the needs of their peers in an academic discussion. This discussion served to remove the impetus to individually perform and instead learn for collective understanding and the betterment of society. Finally, collaboratively framing equitable participation as a means to achieve collective understanding functioned as a key discursive move for fostering students' beliefs in its importance. For instance, in a preceding section, we discussed the teachers’ hesitation toward calling on specific students in classroom discussions. A key solution to this issue came in the form of students’ contributions being treated as diverse and legitimate knowledge that serves to amplify collective understanding of the topic at hand. As a result, the teacher was able to comfortably call on specific students because it came from a place of seeking a valuable perspective for others to consider. As time passed, the students began to internalize this framing and typically quiet students began to contribute without prompting to have their perspectives heard.

Implications and Conclusion

As demonstrated in this paper, a Cultural Participation Orientation towards analyzing and refining educational design elements can support the negotiation of social norms for equitable participation in ethical data science classrooms. Given that students participate differently and according to their fragile, relational, and designated identities in STEM spaces, it is the teachers' responsibility to develop a cultural awareness of herself and her students and select course design elements that facilitate opportunities for learning which both honor and empower those students and foster collective learning for the class. In addition to the design structures offered in this paper, we argue that by facilitating a space where students with diverse intersecting identities are able to co-create a hybridized learning environment, educators are positioned to analyze student participation structures and modify classroom practices to support participation and meaningful discourse from students with different backgrounds. Importantly, and in contrast to the Cultural Alignment Orientation, this hybridized space is not intended to reflect the practices of bounded outside communities, but is instead developed by the students, for the students, in that particular space, and may not translate outside of that environment.

On a final note, with regard to privileged student populations, the intentional discursive moves and designed structures of the EDS course enabled the dominant students to reflect on their positions both in society and in the classroom as well as to value and encourage the voices and perspectives of others. Thus, it is essential to accept that privileged students are very capable of giving space, but they need the impetus to do so along with ongoing opportunities to reflect on why it is important. However, creating such an environment entails explicitly attending to the design elements that privilege some and restrict others in the classroom, industry, and societal contexts. Continued commitment to such initiatives by educators may help to dismantle gendered notions of STEM and data science success, as well as promote a communal social orientation both within and beyond the classroom. As a culminating point, consider the following course takeaways from select students:

> *What is your biggest takeaway from this course related to you as a learner, collaborator, human-being, etc.?*

Walter (Asian Male)	That seeking help is not something I should be afraid of. I feel like [Instructor] created an environment that allowed us to comfortably ask questions and I really appreciated it.
Andrew (White Male)	This course has helped me become more confident in forming opinions and participating in academic discussions. I have been very unproblematic and un-opinionated for most of my life, but this class (content and people) have helped me be less indifferent.
Faye (White Female)	My biggest takeaway [...] is probably learning to try to share my viewpoints. It was discussed a lot in the course how important it is to share my viewpoint because different viewpoints are valuable. I hope in the future I will be more willing to speak up and communicate better.
Aashvi (Indian Female)	My biggest takeaway [...] is to showcase my opinions. I learned that it is very important to partake in discussion and talk about my opinions so that others and I can gain more insight and learn new information.

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CHAPTER 4: ENCOURAGING EQUITABLE PARTICIPATION IN ETHICAL DATA SCIENCE DISCUSSIONS

Jordan T. Register
University of North Carolina at Charlotte

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As a teacher of diverse students, I have often struggled to define and implement equitable learning and instruction. Like many educators today, I have pondered over the definition of the term “equity” and what that means for my students and I, knowing that the idea of “giving students what they need" in inquiry and discourse-based mathematics classrooms is not particularly straightforward. However, when initiatives to implement Culturally Responsive and social justice teaching reached my attention, I was awestruck at the possibilities for learning, but also by my fears as a relatively privileged, White female teacher. I wondered, how do I create equitable learning opportunities for the students in my diversely populated classroom while also exploring and discussing potentially uncomfortable and controversial issues? My classroom had never looked like the learning contexts written about by the scholars who were successful with this work (e.g., more homogenous in terms of race, socioeconomic status, etc.) (e.g., Berry, 2004; Gutstein, 2005; Rubel et al., 2016). Rather, my students identified differently according to their race, gender identification, sexual orientation, socioeconomic status, educational experiences, etc., creating a tension for me regarding how I might facilitate classroom discussions related to sociopolitical topics. Given that some of my students were considered relatively privileged, while others were marginalized by definition, my fears translated into the following actionable questions:

1. How might I provide equitable learning opportunities for students who are situated differently in both society and the classroom?
2. How might I guarantee that all students are given the same access to class discussions, knowing that they likely have different emotions and motivations related to participating in them?
3. How might I facilitate sociopolitical/ethical discussions in the mathematics classroom while not creating a polarizing environment between relatively privileged and marginalized students?

This article will discuss my experiences in teaching an introductory ethical data science (EDS) course for high school students, where I attempted to encourage *equitable participation* in classroom discussions among students from different racial, cultural, and gendered identities. Here *equitable participation* refers to variation in the students who speak up in class discussions, and that those students participate in ways that honor their gendered, cultural, and mathematics (or data science) identities, resulting in their sense of belonging in that space. Specifically, I will discuss the key *discursive moves* (moves that promote desired ways of talking and participating) that I made throughout this process which seemed to result in my students' belief in the importance of *equitable participation* and their commitment to encouraging it in our classroom discussions. Although this is discussed in the context of an EDS course, the strategies offered are applicable to other mathematics and STEM courses.

Classroom Context and Course Design

The EDS course was taught in the context of a 4-week, competitive summer program dedicated to offering authentic research opportunities and learning in STEM. Its intent was to introduce high school students to the data science methodology and its impact in society. Generally speaking, data science sits at the intersection of mathematics and statistics, computer science (programming), and domain knowledge (e.g., business or medical knowledge). Its purpose is to capitalize on computer science techniques (programming, data extraction, Machine Learning, etc.) to perform advanced statistical, mathematical, and visual analysis on massive amounts of available data (Big Data) in order to propose solutions to commercial, economic, and societal issues. However, evidence has shown that these solutions typically benefit certain groups in society while they may disadvantage other, often marginalized, groups. Therefore, a secondary goal was to prepare students as ethical decision makers concerned with equity and justice.

The students in the course were rising juniors and seniors and included one Black girl [BG], one Indian-American girl [IG], five White girls [WG], four White boys [WB], two Indian-American boys [IB], and two Asian-American boys [AB] (all self-identifying). The students were all from the same state but traveled from separate congressional districts to join the program. While all students were academically high performing, only four of these students had some experience programming, two had experience with some Machine Learning, and fewer had experience in discourse-based, ethical, and social justice-oriented learning environments.

In preparing for the EDS course, the goal to teach data science principles while considering their impact for ethical decision-making, made me question the feasibility of aligning classroom practices to my students' realities. Because the students came from different towns, it was difficult to design course activities that reflected their specific home communities. I recognized that any attempt to do so would likely be superficial (since I did not yet know my students) and/or draw on gendered, racial, or ethnic stereotypes. Instead, my colleagues and I chose to plan from the standpoint of developing rigorous data science activities using real-world and sociopolitical data sets. In choosing these contexts, we selected those that we felt would speak to sociopolitical and/or ethical issues that the majority of the students would be familiar with through their interactions with technology and the media (e.g., commercial and political targeting, facial recognition software, COVID vaccination rates, U.S. Census data, civilian gun ownership, etc.). We drew on their intersecting identities (Crenshaw, 1991), including those tied to youth culture, social media, and technology.

Course tools and materials included Python programming modules through Datacamp.com, data science content modules and labs grounded in sociopolitical contexts, sociopolitical readings and explorations related to the positive and negative effects of data science on marginalized groups in society, and an ongoing research project where students chose a social injustice to explore and develop ethical solutions. The majority of classroom activities included either small or whole group discussion and the students were expected to participate in classroom discussions either by individually contributing or by presenting in small group formats.

Motivation for this Article

Since the course was grounded in sociopolitical and ethical contexts, and the students did not know each other, I expected that many of the students would be uncomfortable engaging in class discussions. What I did not expect was that students would participate (or not) according to their designated gendered and cultural identities (Author, submitted; Riegle-Crumb et al., 2020; Sfard et al., 2005), specifically, that primarily White males would dominate class discussions, that Asian and Indian students (male or female) would be more comfortable in technical rather than sociopolitical discussions, and that the females' (of all ethnicities) participation would be heavily influenced by their feelings of competence in relation to their peers (Author et al., submitted; Ridgeway, 2001; Riegle-Crumb et al., 2020). In an attempt to resolve these inequities, I began to encourage *the students themselves* to bring their community ways of knowing, learning, and participating in academic discussions to the classroom, creating what Hodge and Cobb (2019) refer to as a *hybridized learning environment*.

The goal of *a hybridized learning environment* is to create a space where students from different cultures can come together, identify, and enact ways of participating that work for the individuals in that setting, but that may not translate outside of that space. Importantly, creating this learning environment *together* with high school students in the EDS course required that I guide students' expectations for participation and learning differently than I had in the past, to ensure that all students developed a sense of belonging in the classroom and in discussions. Therefore, I enacted several *discursive moves* to promote *equitable participation* among my students, as well as their belief in the need for equitable participation in society more generally. The following three moves were key for the students in the EDS course to begin participating meaningfully and equitably and can be adapted for any group of students in sociopolitically grounded mathematical learning contexts.

Key Move #1: Co-Develop and Model Desired Behaviors for Discourse

For the EDS course, the behaviors that I sought to encourage in classroom discussions included that the students explain their reasoning, ask questions when they did not understand, challenge others' perspectives, and indicate agreement or disagreement when applicable (Yackel & Cobb, 1996). While I modeled and encouraged students to engage in these behaviors by asking clarifying and extending questions, this did not result in equitable participation in classroom discussions because I had not yet facilitated a classroom community that valued it. By the third week of the course, I noticed that despite having discussed the desired behaviors, not all students were participating accordingly. That is, some students felt obligated to have their voices heard while others were either hesitant to speak out or were not given the space to express their thinking. As a result of these observations, I hypothesized that because the students were not a part of the process when I dictated those expected behaviors, some of their cultured and/or gendered ways of participating may not be reflected in our classroom practices. This begged the question: how do I facilitate class discussions in a meaningful way that also honors each of their diverse perspectives and ways of participating?

Timed Writing Activity

On Day 12 of the course, I developed the following Timed Writing Activity as a means to accept feedback from students related to the classroom environment, and to provide a space for the students and I to negotiate expectations for participation in classroom discussions moving forward. The students were to open a Google Doc and write continuously for two minutes for each of eight prompts. After responding to all eight prompts in writing, I then asked the students to respond to the first six prompts verbally as a class. Prompts 7 and 8 are personal in nature, so I did not require that they speak to them publicly but hoped that they would influence their response to Prompt 6. I then recorded their verbal responses to each prompt on the board in order to provide a collective visual representation of the class expectations for discourse and participation. Prompts and students' collective responses can be seen in the Table 4.1 below:

Table 4.1

Timed Writing Prompts and Collective Responses

Prompt	Collective Responses
1. What is your purpose for being in this course? What are your goals? What can you do to accomplish these goals? What can your classmates do to help you accomplish these goals?	● To learn! ● Ask questions, engage in ongoing learning, seek additional information… ● Classmates can challenge, push our thinking, etc. ● Facilitate an environment where you're free to be wrong.
2. What does it mean to be an academic? What behaviors does this entail?	● Behave professionally in an academic setting: ● Be a professional learner ● Be a lifelong learner
3. What does it mean to engage in academic discourse with your peers? What behaviors from you and your peers may support academic discourse?	● Evidence-based claims/warrants… ● Push others' understanding/reasoning, etc. ● Be productive! Engage to get something out of it: to better understand, propose a solution, critique, etc.
4. What counts as a "good" question in an ethical data science course?	● A question the speaker can answer or speak to and that serves an academic purpose ● Brings up something that others may not have thought of/or may not understand ● Respects past, present, future impact of the question or topic being discussed
5. What counts as a "good" explanation in an ethical data science course?	● Thorough ● Debatable ● Answers the whole question ● Audience appropriate ● Evidence-based
6. What counts as meaningful and equitable participation in class	● Meaningful → active engagement, focused on the topic, thinking deeply

	discussions and tasks? Why is this important?	about the topic, adding meaning by tying back to experiences, giving constructive input ● Equitable → Considering other viewpoints, participate for a reason (not just to hear yourself talk or show how smart you are, not to bring others down)
7.	Do you feel that you meaningfully participate in every discussion/activity? Why or why not? If you hesitate to meaningfully participate in every discussion, why do you think this is the case? What changes could be made to encourage your meaningful participation?	
8.	Do you feel that your participation allows for other voices to be heard? Explain. What could you do differently to encourage and value the voices of your diverse peers?	

As evidenced by the students' collective responses, this discussion served to reframe our purposes for being in the course and engaging in academic discussions. That is, the students themselves characterized our time together as a means to learn about data science and its influence on society, while identifying explicit behaviors that would promote meaningful discourse related to those topics. Namely, they focused on participating *not* to hear themselves talk or showcase their competence, but rather to develop whole-group (collective) understanding by pushing each other, asking questions, critiquing claims, making space for other perspectives, asking meaningful questions, and providing acceptable explanations. When it came to Prompt 6, I realized that in order to effectively characterize meaningful and equitable participation in our classroom setting, it was necessary to collectively and publicly define it, specifically, what does equitable participation mean in the context of our classroom environment, for society in general, and why is it important in each of these spaces?

Key Move #2: Defining Equitable Participation

For the EDS students and I, Prompts 6-8 were the meat of the discussion and thus required a bit of extra attention. When asking students to discuss their responses to Prompt 6 publicly, I asked them to first define meaningful participation and then equitable participation. The students initially defined equitable participation as “considering different viewpoints and not being biased.” Critically, the concept of bias jump-started a discussion regarding whether or not it is possible to be completely unbiased in ethical data science discussions. The following excerpt illustrates the discussion that ensued:

Instructor	What about equitable participation? What do we mean by that?
Faye [WG]	Um, taking into consideration different viewpoints and not being biased [...]
Sam [WB]	I was just gonna build on the, um, biased part—I was just gonna simply say that perfection is the enemy of good—trying to remove all biases is gonna make it impossible to remove any bias.
Instructor	[...] Good point, but what we can do is recognize our own biases and try to control for that in situations[...] Because when we say “just don't be biased” it gives us the idea that we can be, and that's false. No offense. I mean, let’s think about it: You have belief systems that make up who you are. You can't just throw those away because you're looking at something mathematically or you're having a discussion—those are a part of you—so we have to make room for other opinions or other experiences and be very transparent about what our biases are.

Beyond discussing the need to identify and control our biases, I realized that equitable participation was not yet defined in terms of student behaviors, meaning that we had not yet established guidelines for how to promote equitable participation in our learning environment. Therefore, I felt that it was necessary for the students to define the term equity in order to help them conceptualize why equitable participation may be important both in the classroom and in society. By doing this, I also anticipated that the students may be better able to reflect on how their own ways of participating may affect their peers, which I will discuss in the following section. The following excerpt, which occurred directly after the one above, shows how we collaboratively defined equity, and then equitable participation in the EDS course:

Instructor	What is the difference between the word equitable and the word equal?
Sam [WB]	Equitable is just getting what they need, uh, equal is everyone gets the same thing.
Instructor	[...] So when we are having equitable participation, what do you think that means?
Moksh [IB]	When people who speak most speak a little bit less and people who don't speak much, speak more.
Instructor	Right? And it just means giving that space. And it's not saying that people who speak up need to be quiet and not talk the entire time, but it's waiting, encouraging others maybe to speak up that don't necessarily speak up more often [...] it's being aware of how your position in the classroom or in whatever room you're in, can affect how others communicate, and then being someone who can encourage those others to communicate, or vice versa. It's if you are not necessarily someone who likes to speak up, challenging yourself to get out there and speak up and ask those questions and share your opinion because it's a valid and valuable opinion that people should hear.
Richard [WB]	[...] So I was kind of thinking like, equitable is like, you give your participation, and you receive like output from other people,
Instructor	Knowledge from others, right? [...] Why is it important to have diverse people in different institutions or in different classrooms or in different jobs or as data scientists?
Moksh [IB]	So that represents the population. So that our values and stuff are represented.
Instructor	Yeah. Why?
Monica [BG]	Because like, people from different backgrounds carry like different experiences with them. So, if you don't have one person's experience that may be representative of that person's group, then you're missing that kinda nuance and those kinds of things that could help your product or whatever you're doing, be more fair

and equal for everybody else.

Sam [WB]	So, if your company or whatever is just made up of non-diverse people who all come from the same background then you're going to much easier fall into, perhaps, like group things. And just like not thinking critically about problems and stuff.
Instructor	Absolutely. And when we're in here—I mean, this is a space where we have a diverse group of individuals where we can learn a lot about each other and each other's cultures and each other's experiences [...] We all have different strengths. We are each other's human resources. I have a niche that I know and understand. You have a niche that you know and understand. Every single person does. And so, we can capitalize on each other's knowledge to help make a better world, or make better products or whatever it is.

The excerpt above shows that, as intended, the students themselves conceptualized the meaning of equitable and applied this understanding to the classroom learning environment by describing what it means in terms of student behaviors (e.g., Moksh explains that equitable participation translates to dominant students stepping back to let others have a voice). Their definition was consistent with my thinking and helped to establish that our diverse ways of participating often position some students on the outskirts of classroom discussions, requiring that space be made for those students to have their voices heard. I then used this as an opportunity for students to make arguments about why equitable participation is important, drawing on previous statements made by Richard and Monica about the importance of diverse perspectives in professional settings. This discussion served to redefine students' expectations for meaningful participation as evidenced by shifts in the ways that they talked about participating in classroom discussions and their ways of actually participating. That is, rather than place the responsibility to engage in discussions on individual students as a means to evidence their intelligence or work ethic (typical of traditional classrooms), equitable participation can be argued as essential for the promotion of authentic and whole-group understanding from the standpoint that diverse perspectives give us a more well-rounded understanding of the topic at hand.

As anticipated, defining equitable participation also supported students in their ability to reflect on their own ways of participating and making space for others to participate in class discussions. In addition, it allowed them to identify classroom practices that they felt either supported or constrained their ability to participate equitably. While the students identified several desired supports that included keeping the conversation friendly, allowing small group talk before having to speak out publicly in whole class discussions, and giving more wait time after prompts, the most salient of these for the quieter students (namely girls) was for the teacher to be explicit that there are *no experts* on the course content in the classroom.

Key Move #3: Decentering Expertise by Explicitizing "No Experts"

In the first few days of the course, I noticed that many of the girls hesitated to participate in class discussions, especially those that were heavily technical (e.g., Machine Learning labs) or that were centered around sociopolitical topics (White and Indian girls). When asked about their hesitations, the girls expressed that they (1) felt others knew more about the subject and thus preferred to listen, and (2) were fearful of being wrong in front of classmates and/or the teacher. As a result, I began to express some version of the following statements during our daily class discussions:

- Data science is a relatively new and not yet well-defined field. Therefore no one, (including myself) is an expert on ethical data science.
- The purposes of our discussion are not to show how much we know, but to share our diversely educated opinions and experiences related to the effects of data science, so that we all can gain a more well-rounded understanding of the field and its potential impact.

From the girls' perspectives in the EDS course, this translated into a third key move: to make explicit that *no one in the class (including the teacher) is an expert about the subject of ethical data science*, which was expressed by Monica, the sole Black female student, during the Timed Writing activity:

> Sometimes I think it's important to bring up in our conversations [...] that you don't always need to know about it […] I think it would be beneficial for that reminder to be there that it's okay not to know, but also you can talk about it.

Monica's comment seemed to resonate with the majority of the students in the course, especially those who were hesitant to participate early on. Due to the observed power of this move, I continued to be explicit about the fact that no one in this class (including myself) is an expert in this field. The result of using this language seemed to have a significant impact on the quieter students' feelings of self-efficacy. That is, once I began to consistently highlight that there are no experts in the classroom, feelings of inferiority seemed to become less prominent for the girls in that they began to participate more often and more meaningfully. At the end of the course, Monica spoke to the impact of this move on her participation, stating:

> I participated a lot more in the EDS course than my typical math courses because it was a lot more open, welcoming, and fun to me because the students were part of the authority so it wasn't like a typical math class where everything that everyone did was only to seek validation from the teacher, but instead to actually learn, ask questions, and further our own understandings […] The phrase we repeated so often, "no one is an expert in this field" helped me a lot because it meant that we were going to mess up and be incorrect but that was okay because it's not something we're supposed to come in knowing. I felt that I could contribute whatever idea that came to mind, no matter how foolish it seemed.

In sum, consistent use of the language that "no one in the classroom is an expert in this field" served to dismantle notions of others as more or less knowledgeable about the content and for the girls, was essential for reducing their feelings of vulnerability and to increase their feelings of belonging (Author et al., submitted). In addition, it served to reduce pressure for students to showcase their competence in classroom discussions and instead, engage in meaningful academic discourse. As a result, we were able to treat classroom discussions as a brainstorming space as opposed to an intellectual showcase.

Effects of the Discursive Moves on Student Participation

The effects of the Timed Writing activity were observable in the days that followed. For instance, students who typically dominated classroom discussions stepped back for others to speak, and those who were often quiet began to take up that space by offering their perspectives in class discussions. A notable example occurred in a Machine Learning lab on the following day. In this activity, we explored real world data on civilian gun ownership across the globe. Students were expected to develop statistically investigative questions that could be answered using the available data, then apply descriptive and predictive Machine Learning algorithms to answer those questions. Within this lab, I noticed that there was increased diversity in the number of students who contributed to the class discussion and that the students who were typically quiet in Machine Learning contexts (girls), noticeably stepped forward to have their voices heard. This was something that I had not observed in previous Machine Learning labs and other technical activities. In addition, sociopolitical discussions were much less dominated by a subgroup of students, as they were in the beginning of the course. Instead, the students seemed to internalize the notion that our discussions were a brainstorming space as opposed to a stage to showcase knowledge.

A Note on Timing

I stated previously that the Timed Writing activity was designed and implemented on the spot in order to combat the inequitable participation patterns that I observed in class discussions, however, this was not the first time that we had discussed social norms for discourse. On Day 1, I communicated my expectations for students' participation in class discussions but because the students were not a part of this conversation, their gendered and cultural ways of participating were not reflected in those expectations. In hindsight, I would have included the students as contributors and stakeholders of this discussion. With that being said, in our context, students were engaging with new ways of participating and learning, and thus, may not have been able to identify supports and constraints for equitable participation on the first day of class. So, while I would have facilitated the discussion on Day 1 differently, the Timed Writing activity seemed to be effective on the third week because the students could speak to their needs and desired ways of participating now having experience with our specific classroom context (i.e., learning goals, teacher expectations, personalities, etc.). Therefore, it may be prudent for students to engage in this type of activity regularly throughout a course so that they can adapt their expectations according to their ever-changing needs and newfound ways of interacting with their peers.

Concluding Remarks

For many teachers, establishing an environment where students feel comfortable participating without prompting, and where they do so meaningfully and equitably, is difficult to enact in practice. For the learners in the EDS course, facilitating an environment where my students with diverse and intersecting identities were expected to participate according to their ways of knowing and learning (while also drawing on their personal experience and emotions), allowed them to develop a sense of belonging in that space. This required that we (1) co-establish the desired social norms for discourse, (2) collaboratively define equitable participation and why it is important, and (3) make explicit that there are no present experts on ethical data science in the EDS classroom environment.

Significantly, our collaborative framing of *equitable participation as a means to develop whole-group and authentic understanding* while promoting the fact that *no one in the class is an expert at ethical data science*, allowed us to develop a mutual understanding that their contributions, whether fully conceptualized or not, provide a unique perspective that can help us gain a more well-rounded understanding of the content. This helped to reduce nondominant students' feelings of vulnerability in class discussions. As an example, Aashvi [IF] expressed that our class emphasis on equitable participation and discourse, coupled with her perceptions that "*the teacher greatly valued the opinions of the students and encouraged them to express their feeling*s," made her feel that she was *"more responsible for learning things in depth and looking at different perspectives."* This motivated her to participate more than in her typical math courses and "*would help [her] a lot in [her] future endeavors.*"

In sum, by facilitating a *hybridized learning environment*, my students' commitment to meaningfully and equitably participating in class discussions improved because it became tied to the benefits of understanding diverse perspectives. Importantly, these recommendations are not restricted to ethical data science settings. Rather, the described teacher moves can be adapted for a range of classroom contexts and are fruitful for encouraging equitable participation in classroom discussions.

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CHAPTER 5: CONCLUSION

The purpose of this dissertation was to investigate how educators may design for the development of high school students' Ethical Mathematics Consciousness (EMC) in data science. In Chapter 2/Article 1, I described the use of the EMC analytic and design framework used to guide the development of course materials for the EDS course in order to promote students' pluralistic ethical reasoning, interpersonal and system empathy (ethic of care and social responsibility). I then described the characteristics of students' ethical decision-making in a series of ethical data science interview tasks after they completed the course and offered both an analytic framework for characterizing the elements of students' ethical data science decisions, and an Ethical Decision-Making in Data Science Protocol to guide students in their critically conscious ethical decision-making in data science contexts.

In Chapter 3/Article 2, I described the designed task structures, participation structures, and discursive moves that supported students' participation in established classroom norms, and their equitable participation in classroom activities. To reiterate, the designed task structures included decision-making, pluralistic, and qualitative task structure. The designed participation structures included: small group exploration and reporting, individual, small group, and whole group inquiry, and whole group discussion. I also described some of the dilemmas we encountered in the implementation phase of the design experiment. In particular, it was found that despite the designed task and participation structures that were intended to support critical discussions and inquiry in data science, students participated differently according to their designated, relational and fragile individual, cultural, and data science identities. Thus, we modified the initial participation structures to require that all students present in small group reporting scenarios and to include small group talk in whole group discussions. The result of this modification was that students began to "make space" for others in classroom discussions, constituting a new norm in our space as well as in the literature. I then described a Timed-Writing activity that was incorporated as a modification to the course, to respond to and redirect the breakdown of established classroom norms for discussion, while honoring students' diverse identities, including their ways of knowing and learning. The Timed Writing Activity was leveraged to promote students' belief in equitable participation as well as their own ethical empowerment, which is expanded upon in Chapter 4.

Chapter 4/Article 3 builds off the findings of Chapter 3, focusing primarily on the discursive moves that I made as the instructor that further supported students' belief in equitable participation. The identified moves include: co-defining classroom norms for discourse, co-defining *equitable participation* though the Timed-Writing activity as a means for developing collective understanding, and de-centering expertise by verbally reminding students that there are "no experts" in the room on ethical data science, so we all have valuable experiences and knowledge that we can communicate and learn from. The effect of these structures and discursive moves was an environment of cultural participation in which students brought their own ways of knowing, learning, and participating into our specific learning space, creating a hybridized learning environment that worked for us. Furthermore, it allowed me to step back and analyze student participation structures in order to modify classroom practices to better support equitable participation and meaningful discourse from my students with diverse backgrounds. In sum, the totality of these design structures and discursive moves allowed us to co-develop an inclusive classroom environment and learning experience, concerned with the investigation of rigorous data science processes and ethical data science decision-making. Products of this dissertation that may be leveraged to replicate the EDS course learning environment are summarized next.

Products

Products of this dissertation related to how mathematics and data science educators may encourage students' development of EMC in data science contexts include:

1. An initial 4- week curriculum and instructional materials for an ethical data science (EDS) course for high school students grounded in a relational *ethic of care* and *social response-ability* (Atweh et al., 2009; Levinas, 1969, 1997; Noddings, 1988; Puka, 2005) (referenced in Chapters 2-4);
2. identification of the design heuristics that support students' critically conscious ethical decision-making (Chapter 2);
3. an analytic framework, the *Component Model of Moral Case-Based Reasoning in Data Science*, for analyzing students' ethical decision-making in data science,
4. and an *Ethical Decision-making in Data Science Protocol* for encouraging critically conscious ethical decision-making in data science contexts (Chapter 2).

Products related to how educators may support student's ethical empowerment data science contexts among high school students with diverse and intersecting identities include:

5. Design heuristics that support equitable participation from students with diverse and intersecting identities (Chapter 3), and
6. discursive moves that support equitable participation from students with diverse and intersecting identities (Chapters 4).

These products serve as an initial design attempt to foster students' EMC in data science and STEM more generally. They are not considered final products but are intended to be shared to the wider mathematics and data science community to be modified and further developed.

Limitations

In Chapter 3, I defined several limitations related to the program structure. Because the course was only four weeks long, with the first week being virtual, it was difficult to develop the intended classroom culture prior to exploring content. For instructors in a more traditional setting, this should not be as much of a concern given the extended time they are afforded with students. In addition, the research requirements of the program were often overwhelming for the students' who had little prior experience conducting and disseminating academic research. As a result, I chose to forgo many data science activities to provide writing support. With that being said, their research experience was valuable, and rather than removing the research component, I would modify the course structure to facilitate more intentional writing support. The greatest barrier here, again, is time. Finally, I discussed difficulties related to teaching during the COVID-19 pandemic. In a discourse and inquiry-based learning environment, social distancing and extended student and instructor absences are a major barrier. Despite these difficulties, we were still able to establish a safe and inclusive classroom environment for rigorous data science learning and ethical discussions.

In Chapter 4, I described limitations related to our research methodology, the most salient of which is that, since we chose not to conduct pre-interviews, our findings only speak to students' ethical reasoning at the end of the course and not necessarily as an effect of the course. Beyond this, the interview findings are contextualized around six students of relative privilege, and therefore may not translate to other student populations. This limitation can be broadened to suggest that the findings of this dissertation as a whole may not translate to contexts significantly different from our own (15 diverse high school students of relative privilege from the Southeast United States attending a summer STEM program). With that being said, the purpose of

Design-Based Research is to develop learning theories and materials for new forms of learning that either do not yet exist or are in need of reform. They are intended to be developed within a specified environment or community for those who participate in it. Thus, the potential limitations of this study for the wider community do not limit the value of its findings for our context.

It may also be said that the findings are not generalizable because we co-created a hybridized learning environment that worked for the specific individuals in our specific learning environment. While this is certainly true to some extent, the nature of a course designed for cultural participation implies its flexibility in terms of the classroom culture, including which classroom norms and ways of participating are valued and taken up by students. When replicating this study, a key takeaway is that we can begin our designs with rigorous (data science) content, processes, and procedures. From there, we can invite the students to be a part of the conversation where we collaboratively define what classroom behaviors are valued for the promotion of equitable participation for collective understanding. Once this space is established (and continuously calibrated), the instructor's focus can shift towards moderating activities and discussions that promote students' consideration of diverse perspectives and experiences, modeled by the students themselves, but in the context of the discipline that they are exploring (i.e., data science).

Contributions to the Field

The implications of this research are vast. First, it has been argued that the mathematics curriculum is outdated and must be adapted to the 21st century needs of society (Mike et al., 2020; Tong et al, 2020; YouCubed, 2020). The products of this dissertation contribute to the literature base by offering instruction theory, materials, and design heuristics for the development of future-focused curricula, where the EDS course serves as an example of a relevant, cross-curricular, and situated mathematics course.

This research further provides evidence of rigorous data science instruction grounded in a feminist ethic of care and social responsibility for the promotion of critically conscious ethical decision-making. Critical Mathematics pedagogies like Teaching Mathematics for Social Justice have been critiqued for a heavy focus on social justice at the expense of mathematical rigor (Gutstein, 2003; Miescu et al., 2011). This dissertation offers a model for learning in which students develop 21st century and technical proficiencies while engaging in ongoing analysis of social and ecological injustices and critical reflection on the potential consequences of their mathematical products.

Finally, the focus on privileged students' reasoning will supplement the dearth of literature in critical mathematics for students in comfortable social and political positions. This has grand implications for disabling the *privilege hazard* beginning in K-12 education, and for encouraging students with different ideologies, privileges, and experiences, to work together in solidarity (D'Ignazio et al., 2020; Friere, 1970/2018). This is significant given the societal impact of BDA, the present (primarily privileged) demographic of data scientists today, and that the BDA industry is projected to continue its rapid expansion, providing a significant number of employment opportunities for our students in the future (CareerCast, 2019; Darling-Hammond, 2015). In addition, by identifying how students in comfortable positions consider issues of oppression, it may be possible to develop learning environments that will push them to question their role in perpetuating the disenfranchisement of others, and to formulate equitable solutions to issues inherent in the age of globalization. This dissertation represents one such initiative.

Future Research

The nature of Design Research is iterative in the sense that each implementation should highlight necessary modifications to the design. These modifications are often done in real time during the implementation phase of the design cycle but are not always refined. In addition, findings from the retrospective analysis often illuminate flaws in the initial design that either may not have been recognized or that were not feasible to modify in real time. Thus, the next steps for this research are to conduct further retrospective analyses for the purposes of modifying the EDS course.

In addition to continuing our analysis of the first cohort of EDS students, the design team has recruited a current data science professor who teaches undergraduates at our home university to take over the instruction of the EDS course in its upcoming iteration. This new instructor plans to work from and modify the EDS course materials according to his own experience with teaching data science to undergraduate students. At the end of the course, the design team will conduct another round of ethics interviews for comparative analysis.

With regard to materials, the rapid impact of new BDA technologies (e.g., open access generative Artificial Intelligence), warrants that we continuously update the course and interview materials to reflect relevant ethical dilemmas in the industry. Thus, we plan to develop a series of new ethical data science tasks that align with more recent technological advancements and ethical dilemmas in the field.

In sum, this dissertation serves a first iteration of a long-term project committed to the development of ethical data science learning experiences. The nature of teaching, learning, and the data science industry itself are constantly changing and adapting to the world around us and the realities of globalization. Thus, it is natural to expect that each iteration will provide evidence of new ways of teaching, learning, and engaging in discourse that serve to promote students' development of EMC in data science. Our commitment to this work is to stay up to date with both these changes and innovations to provide materials and instruction theory that support innovative and ethical learning experiences. It is our hope that others in the field will also take up this call, either by contributing new ideas, or by leveraging the findings of this work for their own context.

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Appendix: Course Structure