"Should AI Be Used At All?": Examining How Youth Decenter AI Solutionism

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Abstract

AI is increasingly framed as a solution to societal challenges, particularly educational inequities. Yet, AI systems often reproduce the very exclusionary structures they claim to address. Despite this, there is limited research on empowering minoritized youth to shape AI in ways that align with their communities' needs. This systemic issue is especially significant for Child–Computer Interaction research, which must examine how young people critically engage with AI technologies. Drawing on data science projects, surveys, and semi-structured interviews, we document how youth develop anti-AI solutionist perspectives alongside data science practices, and how they re-imagine more justice-oriented roles for AI. Our primary contribution shows how our critical AI fluency curricula enable youth to determine when AI should be adopted or refused because they understand racial inequities as sociotechnical rather than technological problems. We position this capacity for AI refusal as essential for redistributing power under algorithmic governance.

CCS Concepts

• **Computing methodologies** → **Artificial intelligence**; • **Human-centered computing** → **Empirical studies in collaborative and social computing**; • **Social and professional topics** → **Children**.



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Keywords

AI education, critical AI literacy, youth participatory action research, AI solutionism

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1 Introduction

Recent advances in AI, have intensified calls to expand AI education for youth [60]. These efforts are often framed as essential for preparing youth to participate in an AI-driven economy and society[68, 75, 98]. While teaching students how AI systems work is undeniably important, this emphasis on technical proficiency alone risks reproducing the assumption that AI is a neutral or inevitable solution to complex human problems[76]. As AI systems are increasingly positioned as responses to issues such as racial disparities, it becomes critical to teach students how to question whether AI is improving society or deepening harms (exacerbating inequality, amplifying biases, deskilling workers, etc), and whether it is necessary at all in a specific situation[7, 45].

Existing approaches to AI and computing education increasingly encourage students to adopt critical or justice-centered perspectives[34, 59]. Some studies advocate for children to take an activist stance toward computing and broader societal challenges[41, 49]. However, these related works rarely offer a thorough empirical account of what such an activist stance concretely entails, particularly in relation to AI[46]. Moreover, few studies provide empirical examples of youth AI projects that move beyond critique to produce tangible,

real-world change. As a result, students may learn how to critique or audit AI systems, but not how to refuse technosolutionist logics or reimagine alternative roles for AI in social contexts[46].

Moreover, much of the existing research and practice in AI and data science education implicitly assumes that students already understand how to conduct a historical analysis of the social problems they are asked to "solve"[26, 46, 74]. Without grounding in histories such as slavery, mass surveillance, racial classification, and state violence, students are often taught to address contemporary inequities as technical puzzles rather than as systems of power[49, 63]. This lack of training in how to be a data activist disproportionately affects Black youth[66], particularly in a field where Black AI developers and other minoritized groups remain underrepresented, and where developers' limited ability to imagine experiences beyond their own makes bias more difficult to identify and prevent[70, 91].

To examine how youth learn to recognize and challenge the matrix of domination[20], this paper draws on the Data Activism Program, a justice-oriented data science and AI informal learning space[95]. The program integrates technical instruction (including Python, Pandas, data analysis, and AI) with African American history, critical race theory, and reflexive practice. During their final data activism projects, students collaborated with social justice organizations to use data science to mitigate systemic oppression[95]. Also, students are explicitly challenged to consider whether they should incorporate AI. This structure creates opportunities to examine how they navigate recentering, constraining, or refusing AI within justice-oriented research. Two questions guided our research:

(1) **RQ1:** How do Black youth engage with or contest AI solutionism while developing technical data science skills?
(2) **RQ2:** What design principles support youth in critically examining AI solutionism and transferring those insights beyond the Data Activism Program?

Using surveys, semi-structured interviews, and analysis of final projects from 34 high school and college students, this study documents how youth move from superficial or largely positive understandings of AI toward more justice-oriented perspectives. Across projects, students transformed deeply personal experiences of harm into collective forms of action, amplifying minoritized voices and demanding accountability where it has long been denied. This paper contributes: (1) empirical evidence of how Black youth move beyond critique to enact justice-oriented refusals and reimaginings of AI through real data activism projects, (2) an empirically grounded account of the value of historical analysis in youth AI assessments, and (3) documentation of youths' critical awareness and ongoing uncertainty regarding AI's liberatory potential to mitigate systemic oppression.

2 Related Works

Situated at the intersection of critical AI literacies (CAIL) and Child–Computer Interaction (CCI), this work demonstrates the importance of preparing youth to critically engage with and contest solutionist approaches to AI. Also, our work builds on a growing tradition of critical data literacy research that documents how youth interrogate, question, and debate the implications of data collection and algorithmic systems[26, 43]. Our research contributes to this emerging research field by introducing historical analysis and critical evaluations of AI "solutions" alongside data activism as novel pedagogical strategies[49].

2.1 AI Reproduces Racial Inequalities Among Youth

While Responsible AI is most often discussed in relation to adult workplaces, it has become increasingly relevant for minoritized youth[77, 79, 83]. Clarence Okoh highlights the importance of students understanding two key concepts: school surveillance technologies and data criminalization[64]. He describes school surveillance tools as systems that collect and analyze sensitive information about students for the purposes of monitoring or exerting control over them[14]. Examples include student device monitoring software, facial recognition systems, vape and weapons detection tools, and other campus surveillance cameras. Okoh also defines youth data criminalization as the practice in which public or private actors leverage sensitive student data (e.g., such as educational records, biometric information, or mental health data) to further the aims of law enforcement or carceral institutions[64]. Operational tactics can include data-sharing agreements between schools and police departments, and the use of risk assessment tools targeting youth. Civil rights advocates have raised concerns that these tools are disproportionately deployed in schools serving predominantly minoritized students, often without public oversight, transparency, or legal accountability[22].

Rather than addressing structural causes of harm, these systems translate inequality into data points that justify increased monitoring and punishment[22, 87]. In one widely reported incident, a squad of police officers rushed toward a group of unarmed Black teenagers at a Baltimore County high school to search for a gun that did not exist[61]. The confrontation was triggered by an AI weapons detection system that misidentified a bag of Doritos as a handgun. Instead of promoting safety, the system escalated risk for students already subject to racialized suspicion[65].

Similar dynamics appear in predictive policing programs connected to schools[17, 97]. In Pasco County, Florida, the Sheriff's Office operated an At-Risk Youth program that generated a secret list of children deemed "destined to a life of crime"[50]. Developed in part through a predictive policing algorithm, the list classified children based on their perceived likelihood of future criminal activity. Neither students nor parents were notified, and at its peak the list included more than 17,000 children, some as young as kindergarten and first grade, who were flagged for additional monitoring by law enforcement[50]. The data used to construct the list (e.g., prior contact with the criminal legal system, school disciplinary records, and documentation of childhood trauma held by child welfare agencies) are deeply prone to bias against Black, Latine, and queer children.

The injustices embedded in these technologies cannot be separated from the longer history of racial inequality in education[9, 31, 33, 37, 80]. There is growing evidence that AI surveillance in schools reflects what Ruha Benjamin describes as the "New Jim Code," in which digital technologies reproduce and legitimize social and racial injustice[7]. In public education, AI surveillance

risks reinventing the school-to-prison pipeline by automating discipline. This historical logic also extends into contemporary AI education [72]. Although often marketed as objective, innovative, and future-oriented, AI education frequently reproduces exclusionary structures rooted in Eurocentric epistemologies, treats data as neutral rather than relational, and frames AI as a tool for optimizing systems rather than transforming unjust ones[84].

Black and other minoritized people remain largely underrepresented in the AI and CCI research field and practice, where they are more often positioned as data subjects or critics rather than as designers, decision-makers, or owners of technology[46]. They are rarely given the time, resources, or institutional trust needed to design AI systems grounded in their own histories, values, and community priorities. Even in classrooms that address AI ethics or algorithmic bias, student agency is typically constrained in two ways:

(1) Students are asked to audit or critique AI systems built by others, reinforcing the idea that expertise lies elsewhere and that their role is limited to evaluation rather than creation[73, 82].
(2) Students engage in rapid ideation exercises about how AI might support their communities, without access to funding, mentorship, or technical infrastructure to make those ideas real [46].

These approaches offer proximity to AI without granting sovereignty over it: students are invited to analyze systems but not to build, own, or transform them. This reflects what Givens describes as the enduring "grammar of education" in the United States: expanding access to knowledge while withholding power over its production and use[38]. In contrast, Design Justice argues that those most impacted by sociotechnical systems should lead their design rather than audit or consume what others build[21], and within CCI, the computational empowerment tradition positions children as reflexive, critically engaged participants capable of constructing and deconstructing digital systems rather than as users alone[28, 44, 88]. Critical youth research traditions such as Youth Participatory Action Research (YPAR) similarly position young people as knowledge producers with the authority to define problems and pursue change[2, 57]. Our incorporation of YPAR and liberatory computing, alongside these adjacent commitments in Design Justice and computational empowerment, shows how justice-centered AI learning can cultivate critical agency that enables young people to envision more accountable technological futures or to reject technological intervention when it reproduces harm[3].

The Data Activism Program's curriculum design is grounded in liberatory computing, a pedagogical framework built around five pillars that support minoritized students in using computing to serve their communities[91]. Liberatory computing draws on liberation tools originally developed by Aaliyah El-Amin[30]. These principles extend naturally to what we describe as "liberatory AI": engaging with AI systems not as neutral tools but as socially and historically shaped technologies that can be critically examined, contested, and reimagined in service of community liberation. The first pillar, critical consciousness, prompts students to examine how AI systems reproduce or challenge existing power structures. The second, liberation-centered academic identity, encourages students to see their own skills as instruments of transformation, asking how their knowledge can be used to address systemic issues affecting their communities. The third pillar, sound racial identity, centers lived experience, inviting students to reflect on how their own identities shape the way they trust, question, and interpret AI systems. The fourth, collective obligation, moves students beyond individual gain toward communal responsibility, asking what obligations they have to ensure AI serves and protects their communities. The fifth pillar, activism skills, translates reflection and analysis into action, challenging students to identify concrete ways to challenge or transform unjust AI systems. Together, these pillars form a progression: from critical reflection, to structural analysis, to collective responsibility, and ultimately to action. These pillars provide a foundation for liberatory AI engagement that is both critically informed and community-centered.

Finally, this paper argues that while historical considerations are widely acknowledged within critical studies of sociotechnical systems, historical analysis as a method has not yet been systematically integrated into AI assessment and auditing practices for youth[6, 74]. The aim of historical analysis is to develop a deeper understanding of the social, cultural, economic, and political forces that shape how AI systems are designed, deployed, and experienced[23, 90]. [74] proposes incorporating historical analysis within assessment protocols to: (1) expand the harm discovery phase, (2) inform research questions and (3) substantiate and communicate findings. This paper builds on this aforementioned work by examining how AI education must be reimagined not only as technical training, but as a site of systemic transformation, which actively returns agency and a radical imagination to minoritized communities [94].

2.2 Resisting AI Solutionism

While expanding AI literacy is important, these initiatives overwhelmingly emphasize learning how to build or use AI systems, with far less attention to when AI should not be used[49]. This imbalance reflects a broader ideology of AI solutionism, in which complex social injustices are reframed as technical problems awaiting computational fixes[8]. Critical scholarship has long challenged such technosolutionist thinking[36]. Historical reexaminations of the Luddites, for example, show that resistance to technology has often been a rational response to tools deployed to dispossess workers and consolidate power, rather than opposition to innovation itself[52]. Scholars have shown how AI systems frequently treat symptoms rather than causes, reproducing inequality while appearing neutral or objective[35].

A number of scholars have attempted to articulate what it actually means to resist AI solutionism[27, 32, 51]. [71] describes the following actions as forms of AI resistance: disrupting, questioning, and working around systems or destroying. One concrete articulation of this appears in the Feminist Manifest-No, which offers 32 commitments of refusal and action in relation to data practices, several of which map directly onto critiques of solutionist AI. For example, the Manifest-No asserts that [18]:

(1) "*We reject tech solutionism as a moral cover for punitive data logics (e.g., always-on facial recognition, default data capture,*

racist predictive policing) and instead pursue feminist problem-solving that treats data practices as reflections of power rather than neutral tools.

(2) *We reject the claim that data systems are too technical for those most affected by them to understand, and instead commit to making systems intelligible, tangible, and controllable to the public.*

(3) *We reject extractive work about minoritized communities, committing instead to data practices that are consensual, reciprocal, and rooted in "working with and for" those communities.*

(4) *We commit to radical disruption for social transformation, rather than incremental fixes that leave underlying power relations intact.*

(5) *We reject data logics that hyper-value the quantitative and "objective", committing instead to methodologies that center subjective, embodied, political, and affective knowledge. We refuse the idea that only generalizable, numerical forms of evidence count."*

Collectively, these commitments demonstrate that resisting AI solutionism is not only about saying "no," but about re-orienting data and AI practices toward accountability, community control, and social transformation.

3 Methods

3.1 Participants

The Data Activism Program included 34 high school and college students (ages 14–20). Twenty students participated in person (18 high school, 2 college), largely recruited through local youth employment programs, and 14 students participated virtually (6 high school, 8 college). All students identified as having African ancestry. The program functioned as paid summer employment: in-person students received $1200 through worksite programs, and virtual students received a $1200 scholarship upon completion. Written consent/assent was obtained from students, parents, and community organizers prior to data collection.

Participants were recruited through multiple pathways. We partnered with local youth employment agencies, which distributed the opportunity through their existing applicant pools, and we also worked closely with leaders of youth summer programs who shared the study with students that applied to their programs. In addition, we collaborated with HBCUs to extend recruitment to college-aged participants. The primary selection criterion was demonstrated interest in social justice and data science. No prior coding experience was required; we sought students with a willingness to think critically about systemic injustice. Applicants were asked three questions covering their prior coding experience and familiarity with discussions about racism and systemic oppression.

We recruited four social justice organizations through outreach to local and national nonprofits. Each prospective community partner participated in an approximately one-hour informational session covering study requirements and their experience working with youth. The sole eligibility criterion was a commitment to engaging youth in using data science to address systemic oppression, including supporting them in developing research topics and providing feedback on their data activism projects throughout the program.

3.2 Data Activism Program

The Data Activism Program is a 120-hour AI and data science curriculum delivered over six weeks (4 hours per day, 5 days per week). Youth learned to collect, clean, analyze, and present data through the lens of "liberatory computing," a framework that equips minoritized students to use computing skills(e.g., Python and Pandas) to mitigate systemic oppression[91]. Liberatory computing is grounded in five pillars: sound racial identity, critical consciousness, liberation-centered academic identity, collective obligation, and activism skills[30, 91]. This paper focuses on three components of the program: historical analysis, Responsible AI design, and community-driven final research projects (see Figure 1).

3.2.1 Historical Analysis. Before engaging in Responsible AI design, students were taught how to conduct historical analysis through three foundational lessons: "AI Ain't I a Woman?", "Discriminatory Design", and "13th". In "AI Ain't I a Woman?", students examined Dr. Joy Buolamwini's film on facial recognition bias, learning how skewed training data disproportionately misidentifies darker-skinned women[15]. "Discriminatory Design" introduced students to how systemic biases are embedded in everyday objects and technologies[7]. Students analyzed examples such as biased hiring algorithms, pulse oximeters' inaccuracy on darker skin, and exclusionary urban planning, concluding that seemingly neutral design choices encode cultural values. Finally, through Ava DuVernay's film, "13th", students traced the historical roots of racial inequality, the legacy of slavery, and mass incarceration[1]. Together, these lessons provided a shared historical foundation for understanding how present-day AI systems perpetuate longstanding forms of oppression.

3.2.2 Responsible AI Design. After building historical context, students were introduced to Responsible AI principles and anti-AI solutionism. The COMPAS algorithm is used in U.S. courts to predict recidivism but has been widely criticized for racial bias, with Black defendants more often misclassified as "high risk" and white defendants as "low risk"[48]. In the "Intro to COMPAS" lesson, students examined how the tool shapes legal decisions, analyzed racial disparities, and inspected the arrest-based datasets and input variables that produce biased outcomes[62]. Also, they connected these harms to the legacy of slavery and mass incarceration discussed in the "13th" lesson. These lessons positioned students as evaluators and redesigners of AI systems, rather than as passive users.

3.2.3 Final Research Projects. In the culminating phase, students completed community-driven research projects with partner organizations, using data science to address systemic oppression and imagine how AI could support minoritized communities[93]. Students learned Python and Pandas throughout the program, building the technical skills needed to collect, clean, and analyze community data. The full curriculum, including detailed descriptions of the pedagogy and final projects, has been documented in prior publications[93]. Students designed studies, collected community data, conducted historical analyses of relevant harms, and produced research briefs, intersectional data visualizations, and data drawings. Critically, these were not simulated exercises. The projects created lasting change by generating real deliverables that community partners used for advocacy, public education, and policy

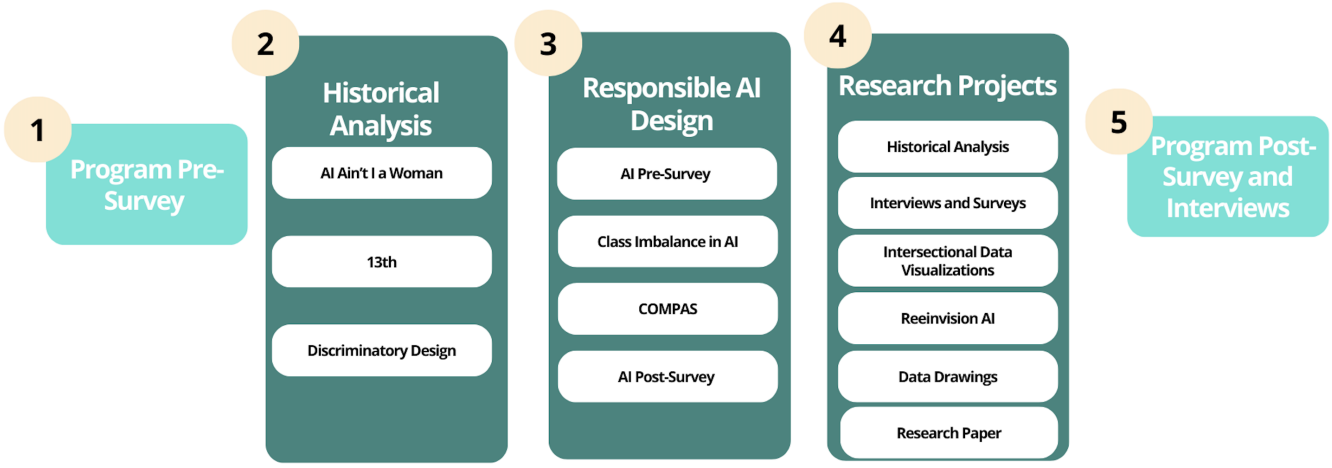


Figure 1: Timeline of lessons from the Data Activism Program that discussed AI.

work. For instance, students' work with the Algorithmic Justice League on mass surveillance in schools contributed to a document that helped shape New York City public schools' policy on how students and teachers could use AI. Students collaborated with four social justice organizations (AfroPink, the Vera Institute of Justice, the Algorithmic Justice League (AJL), and Sea Grant) on projects aligned with each organization's mission. In partnership with AfroPink, students visualized racial disparities in breast cancer outcomes; with the Vera Institute, they explored relationships between school discipline, dropout rates, and incarceration; with AJL, they audited mass surveillance in schools; and with Sea Grant, they analyzed how ocean acidification disproportionately affects minoritized communities. As part of their final research reports, students also responded to the prompt "How do you want to use AI to support your data activism project?". The responses to which are analyzed in Section 4.1 using reflexive thematic analysis.

3.3 Surveys

We report on three survey items related to AI solutionism. Findings from other survey questions administered throughout the program have been reported in prior publications[93]. The first survey item functioned as a pre- and post-measure, given to students on the first and last days of the program (see question 1 in Table 1 in Appendix 1). Survey items 2 and 3 were administered before the lessons on Responsible AI and after that specific lesson in Week 2 (see Table 1 in Appendix 1). These surveys included Likert-style items measuring students' confidence in Responsible AI concepts. For the Responsible AI quiz, 33 students completed both pre- and post-assessments. A total of 34 students completed both the survey administered at the start of the class and the survey administered at the end.

3.4 Semi-structured Interviews

We conducted post-program interviews with 28 students (Table 2, Appendix 2). Each semi-structured interview was 90-minutes. As this study is part of a broader project examining youth and activism, we focus here on three interview questions related to students' perspectives on AI (see Appendix 2), with the remaining questions analyzed in separate publications. The three interview questions explored how students' views on AI had evolved over the course of the program and how they believed AI could be used to support African American communities. Follow-up questions were used to confirm our understanding of students' responses or to prompt further elaboration. The first author conducted all interviews, with a second researcher present to take notes, and all sessions were recorded. Each transcript for the 3 interview questions was approximately 1 page per person.

3.5 Data Analysis

Regarding the interviews and their final activism projects, the first author transcribed the data using a transcription service and checked it for accuracy and organized the data that was already written for their final data activism projects. We analyzed the data using reflexive thematic analysis, an iterative approach focused on identifying meaningful patterns in qualitative data[11, 12]. We conducted the thematic analysis by using inductive approaches[10, 19, 39, 54]. The first author developed inductive codes based on emerging themes in the data (see Table 3 in Appendix 3 for the codebook). Coder 2 then independently reviewed the same excerpts, consulting the codebook for code definitions without referencing Coder 1's specific coding decisions. Following this independent review, the two coders calculated percent agreement, then met to discuss each excerpt where they had assigned different codes, explaining their reasoning until reaching at least 80% agreement. As differences arose in how we initially applied certain codes, we engaged in collaborative discussions to revise the codebook definitions. Collaborative discussions between coders served to resolve discrepancies and ensure consistent application of the codebook across the data.

To support the credibility of our findings, we drew on Luttrell's (2019) reflexive model of research design[53], grounding our validity criteria in two principles: authenticity, confirmed by asking students

whether our analyses accurately represented their experiences, and reciprocity, evidenced by students' sustained engagement with reflexivity beyond the program. Our sample of 34 students from a single context is intentionally bounded, and we make no claims of broad generalizability. Rather, we offer this work as a replicable model for youth-adult partnerships in justice-oriented AI education that others can adapt across contexts. To assess the differences between specific pre- and post-survey results, we used the Mann-Whitney U test.

4 Findings

Our findings are organized into three main themes: (1) youth perspectives on decentering AI solutionism in their data activism projects; (2) the value of historical analysis in AI assessments for youth; and (3) ambiguity in AI's role for supporting Black futures. To substantiate these themes, we draw on surveys, students' final projects, and post-program interviews.

4.1 Youth's Perspectives on Decentering AI-Solutionism

As part of their final projects, students worked in small groups of approximately eight to respond to the prompt: "How do you want to use AI to support your data activism project?" The same question was posed to students individually in their interviews. This section (4.1) draws on data from both their final project artifacts and individual interviews. We analyzed interviews and students' final research papers as artifacts, from which two themes emerged in response to research question 1 and the aforementioned interview question: (1) groups exemplified a critical stance on AI solutionism(¾ groups), and (2) a group whose critical perspectives on AI were emerging but not yet fully articulated in their final projects(¼ groups). In what follows, we examine how each of the four groups fits within these two themes:

4.1.1 Exemplifying a Critical Stance on AI Solutionism. A critical stance on AI solutionism involves recognizing that AI is not a neutral or automatic fix for complex social, political, or historical problems. The following three groups(Algorithmic Justice League, Vera Institute of Justice, and AfroPink) each articulated this stance in distinct ways throughout their final projects:

Algorithmic Justice League

The first group expressed a clear critical stance on AI solutionism. These students partnered with the Algorithmic Justice League on a data science project examining the use of military-grade surveillance cameras that have AI recognition features in their public high schools. This section focuses on how they responded to the question, "How do you want to use AI to support your data activism project?" Their community-engaged research ultimately concluded that AI should not be used in school surveillance, citing risks of targeted harm, limited transparency, and broader safety concerns. These findings were shared with the Algorithmic Justice League and contributed to policy discussions on AI use in the New York City Department of Education, shaping broader debates around surveillance and algorithmic fairness. Participant 1 reflected on these concerns, stating,

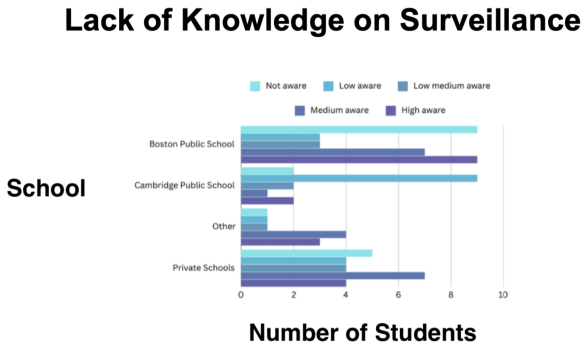


Figure 2: Algorithmic Justice League Group: Bar graph showing survey results indicating low awareness of surveillance and lack of transparency in AI data use

> *"In our school district, as far as we know, AI does not have a place yet, but it easily could, and I feel like making sure that there isn't any particular AI bias helps make sure that we don't have issues with AI use in the future"*

This response illustrates the theme of enacting a critical stance on AI solutionism: students framed AI refusal not as a rejection of AI outright, but as a precautionary stance grounded in historical awareness. Students recognized that surveillance technologies have historically harmed minoritized communities by disproportionately tracking and disciplining them, reinforcing the school-to-prison pipeline, which is a pattern also documented in prior research.

This critical stance extended beyond the question of surveillance alone. Across the group, students consistently drew boundaries around when and how AI could be appropriately used. The AJL group conducted over twenty interviews with students, principals, and teachers about mass surveillance in their local schools. While these interviews produced rich qualitative data, students noted that conducting qualitative analysis was time intensive. Although the group ultimately chose not to use AI directly in their thematic analysis, they reflected that AI might be useful for locating datasets or supporting data cleaning under carefully defined constraints. Participant 2 explained,

> *"Although it has the potential to be biased, it can help to better understand graphs and charts, assist with collecting data, and make research more efficient"*

This quote exemplifies an anti-technosolutionist orientation. Rather than embracing AI as a comprehensive solution, the student acknowledged its limitations while identifying a narrow, carefully bounded role for it in low-stakes analytical tasks. This decision further illustrates how students exercised reflexive judgment by distinguishing between contexts where AI use could meaningfully support their work and contexts where it risked undermining the justice-centered commitments at the core of their research.

Vera Institute of Justice Group

The Vera Institute of Justice group's position centered on a critical view of AI solutionism. Students collaborating with the Vera Institute of Justice investigated how systemic inequities (underfunded schools and poverty in minoritized areas) contribute to high



Figure 3: Vera Institute of Justice Group: Mapping Inequality with ArcGIS: High-Dropout Schools Cluster in Areas with Elevated Incarceration Rates

school dropout rates in Baltimore City, and how addressing these factors could reduce mass incarceration among African-American students. Their analysis found a moderately positive correlation between incarceration and dropout rates, with high-dropout schools concentrated in higher-incarceration areas. Similar to other groups, they took a critical stance on AI solutionism, arguing that AI alone cannot address structural problems. Participant 4 explained:

> *"I think AI should not be used to directly answer our research goals especially because information generated from AI is not always entirely true and can be fabricated data. One thing I noticed was that for a lot of datasets that we found there was some missing data, so my fear is that directly asking AI to solve these research goals would result in some fabricated data. I guess that in using AI, ethical standards of how it should be used should be considered before any action is taken."*

This reflection demonstrates an in-depth understanding of how missing data, and uncritical reliance on AI outputs can lead to inaccurate or harmful conclusions. Overall, rather than rejecting AI outright, students articulated a nuanced position: AI should not be used to automate judgment or prediction in contexts shaped by systemic injustice, but might be cautiously leveraged for supporting data collection and cleaning. As the Participant 5 reflected,

> *"AI can analyze large datasets to uncover patterns, trends, and disparities related to inequality in Baltimore City."*

This stance reflects an emergent form of AI refusal grounded in historical analysis and technical fluency, rather than disengagement from AI altogether. This collaborative sense-making process was evident when one student initially proposed using AI to predict outcomes such as school success or likelihood of incarceration. Through group discussion, however, students collectively recognized that such predictions rely on deeply biased systems and oversimplify the structural conditions shaping these outcomes. This exchange illustrates how collaborative deliberation, rather than individual insight alone, assisted students with having a critical stance on AI solutionism.

AfroPink

The AfroPink group was notably skeptical of AI solutionism from the outset. Students partnered with AfroPink, a nonprofit organization, to illuminate breast cancer disparities, noting that although Black women have lower incidence rates, they experience disproportionately higher mortality rates[96]. Their research revealed racial disparities in breast cancer mortality, with Black women facing higher death rates in poorer counties compared to Caucasian women. Participant 6 reflected on the limited and carefully bounded role AI could play in their research, stating,

> *"AI should not be used as a basis of notable research because a lot of the information tends to be flawed and can often use evidence without providing a source.... Although it can't be used to conduct research, it would be very useful for the more tedious tasks like inputting numbers and organizing data, which I used it for. Google Sheets has AI that is very useful."*

This response demonstrates students' understanding of how AI systems can amplify harm when they rely on poorly sourced data. Participant 7 articulated a more skeptical stance toward AI's role in research, stating,

> *"I personally don't believe that AI is necessarily good for any specific part of a project. I think that it can incite laziness and can result in a lack of authenticity. Also, as we have discussed throughout much of this program, having some sort of connection to whatever group or community you may be researching is important. I do think that AI can be used to organize and sort data that a researcher has found themselves."*

In regards to having resistance to AI solutionism, this response foregrounds the importance of relational commitments over technical efficiency, emphasizing that meaningful research emerges from sustained engagement with communities rather than from AI solutions. The student's reasoning aligns with a core principle of anti - AI solutionism, namely that non technical work is essential. Policy change, reciprocity, reflexivity, and relationship building are often more impactful than AI interventions alone[64]. Rather than viewing AI as a default solution, the students prioritized authenticity and collective obligation as foundational to responsible AI research practice.

4.1.2 Emerging Critical Perspectives on AI. The Ocean Acidification group demonstrated an emerging critical perspective on AI, though it remained in its early stages. While their final project did not explicitly engage with anti-AI solutionist frameworks, subsequent interviews and surveys from the students in this group revealed that critical perspectives were beginning to develop:

Ocean Acidification

The Ocean Acidification group was the only group that were in the beginning stages of articulating a critical stance on AI. This group was asked to consider whether AI could support their research on mitigating the harmful effects of ocean acidification on minoritized communities. In response, students described several ways in which they used or envisioned using AI in their project. Their final project slides stated,

> *"We used generative AI to extract the coordinates of towns and cities where carbon capture facilities were*

> *placed. We also used generative AI to develop our three dimensional model of our stamp, which we used to make the T-shirts. We think that AI could be used to monitor the levels of acidity in the oceans of America."*

While these responses do not explicitly reflect an alignment with anti AI solutionism, subsequent surveys and interviews with students in this group indicate that they did, in fact, agree with many of its underlying ideas. In response to other interview questions, students emphasized that AI should be used as a supporting tool rather than treated as a primary solution, and that addressing ocean acidification ultimately requires structural environmental justice policy.

The ocean acidification group's emerging critical perspective on AI stemmed in part from the limited research available on how ocean acidification affects minoritized communities, particularly in their own neighborhood. While some students had general experience with environmental injustice, they were less familiar with ocean acidification and its potential impacts on seafood, local economies, and community health, which made it more difficult to grasp the systemic issues involved. In the discussion section, we elaborate on why connecting projects to students' lived experiences is crucial for assisting them with evaluating whether AI should be used and for recognizing how power operates within specific contexts.

4.2 The Value of Historical Analysis in AI Assessments for Youth

This section addresses research question 2 by examining which design elements of the Data Activism curriculum supported students in critically engaging with AI solutionism and extending those insights beyond the program. The responses analyzed here are drawn from interview question 2: "How have your views on AI changed over time, especially since you first started learning about it? What experiences or information influenced those changes?" (see Table 2, Appendix 2). Most students (n = 22) began with limited or predominantly positive views of AI, but became more aware of AI-related harms over time. A smaller group (n = 6) entered the program already aware of AI bias and reported that the curriculum reinforced and deepened their understanding. Historical analysis played a central role in how students came to understand AI's social and political implications. Many students identified specific historically-grounded lessons, such as those examining the COMPAS algorithm or facial recognition bias, as pivotal in shaping their views(see Methods section for full description).

4.2.1 From Positive Views to Critical Awareness of AI Harms. Most students entered the program with a limited and mostly positive view of AI shaped by tools such as ChatGPT, but began to recognize that AI can also be misused, deployed without transparency, and embedded in everyday surveillance infrastructures (e.g., airport facial recognition). Participant 8 explained:

> *"I walked into the program not knowing much about AI other than ChatGPT. But it was interesting to see how it can be used for good, but also how it can be misused, even if it's being used with good intentions, because there can still be bias behind it. Like now at airports they have facial recognition. They say it's so no one steals your identity from your passport or anything. But a lot of people just agree to it, and you don't really know what it's being used for. This experience made me think more about what things in my day-to-day life are having a bigger impact or being used for other purposes."*

In response to a question about which lesson changed how Participant 8 thought about AI, the student added:

> *"I think the COMPAS lesson… There are always going to be the views of the creator being put into those algorithms, whether it's intentional or not."*

In short, the student moved from seeing AI as a helpful consumer tool to viewing it as a sociotechnical system shaped by power, history, and human decision-making. These insights were strengthened by the historical analysis integrated into the program, including watching "13th", which contextualized COMPAS within the legacy of slavery, mass incarceration, and anti-Black criminalization. By pairing algorithmic analysis with historical analysis over six weeks, students learned to connect biased outputs to the histories and data structures that produce them.

Another student's understanding shifted after being exposed to observable examples of AI harms (e.g., facial recognition failing to detect darker-skinned faces) and gaining hands-on experience with the technical aspects of AI (e.g., coding and data science). Participant 9 explained:

> *"I hadn't really thought specifically about AI biases before the program. I knew it was a thing, but I never thought about it in depth or how it affects marginalized groups. That was definitely something I learned more about and became interested in, to the point where I started doing my own personal research. Learning the actual data science behind it, how people code these AI systems to work the way they do and how bias gets implemented, was also really helpful. It's one thing to hear about AI bias from a social perspective versus seeing how it actually works on the technical side."*

When asked which lessons assisted Participant 9 in understanding AI bias, the student pointed to both coding practice and historical examples of racialized AI failures:

> *"Yeah, there were the Python coding lessons. And there was also a video we watched early on that showed a side-by-side comparison of how AI bias works. It showed an African American person with darker skin try a facial recognition tool and it didn't recognize them, and then someone with lighter skin tried it and it worked. Seeing that visual comparison of AI bias in real life really put things into perspective for me and shaped how I think about AI bias, along with a lot of the other things we did in the program"*

Participant 9 highlights two important instructional components: (1) technical grounding, which helped them understand how bias enters systems through design and data, and (2) historical evidence, which made racialized AI harms visible and concrete. Together,

these experiences supported students with connecting computational processes to social harms.

Notably, the student also described continuing to research AI issues on their own time, demonstrating how the six-week Data Activism Program fostered sustained curiosity and critical engagement beyond the classroom. This aligns with broader goals of critical AI literacy, which emphasize not only teaching students about AI harms, but also equipping them with the technical skills (e.g., Python, data analysis) to investigate these systems themselves. Without this technical grounding, students may understand that AI can be harmful, but lack the agency to analyze how and why those harms occur.

4.2.2 Building on Existing Critical Awareness of AI Bias. For a smaller cohort of six students, prior awareness of AI bias served as a foundation that the curriculum extended. Participant 10 reflected on their increasing desire to continue to use AI as a form of social justice after the program ends:

> *"Before coming into the program, the only thing I knew about AI was ChatGPT and a few videos about how AI could influence software. I never really got into the activism part of how AI could impact people's lives. Last year we learned about how security cameras and facial recognition couldn't detect Black people's faces, but other than that I didn't really know what else AI could do … After the program, the whole data science aspect was really fascinating, and now I'm looking into majors that have machine learning, AI, or human–computer interaction."*

This student participated in an earlier version of the Data Activism Program in 2023, which only briefly discussed AI bias. In contrast, the 2024 cohort engaged with AI and racial bias over a six-week curriculum that integrated historical AI analysis, technical instruction, and community research. The increased depth and duration appeared to support more sustained engagement, to the point where the student began actively exploring AI-related majors.

Survey findings aligned with this qualitative pattern, revealing increases in youths' understanding of AI bias, class imbalance (a condition in which certain groups are underrepresented in training data, causing AI systems to perform less accurately for those populations), and structural inequality (see Table 1 in the Appendix). Students reported more frequent reflection on issues such as racism and AI bias after the program (p = .05183; pre-survey: n = 9 strongly agreed; post-survey: n = 17 strongly agreed), suggesting a positive, though not statistically significant, trend in critical awareness. Items tied to technical and socio-technical concepts showed statistically significant increases. Students demonstrated stronger understanding of why the COMPAS algorithm is biased against African Americans (p = 4.18E-07; pre-survey: n = 4 strongly agreed; post-survey: n = 15 strongly agreed) and greater confidence explaining how imbalanced datasets affect machine learning performance (p = 2.49E-05; pre-survey: n = 4 strongly agreed; post-survey: n = 18 strongly agreed). These results indicate that historically grounded AI instruction can simultaneously strengthen technical fluency and socio-technical reasoning. Future research will examine how students specifically engaged with the COMPAS lesson, including moments of confusion about training data, how the algorithm interpreted the data, and how students made sense of predictive models amplifying anti-Blackness. This work will show which scaffolding approaches are most effective in cultivating deeper critical AI literacy.

4.3 Ambiguity in AI's Role for Supporting Black Futures

This section contributes to research question 1 by examining how students engaged with AI solutionism beyond their data activism projects, drawing on responses to interview question 2: "How do you think AI should be used to uplift African American lives beyond your final project?" (see Table 2, Appendix 2). While Section 4.1 examined students' critical stances on AI within their final projects, this section asks them to speculate about AI's broader role in supporting African American communities. Three themes emerged: (1) students acknowledged AI harms but struggled to identify concrete beneficial applications, often expressing that they saw potential for AI use but had no clear application; (2) some emphasized the need for more diverse AI creators to meaningfully shape AI's social impact, and (3) a smaller subset envisioned AI as a tool for expanding research and creative inquiry. Together, these themes illuminate how youth imagine or hesitate to imagine AI in service of Black futures.

4.3.1 Recognized AI Harms, Limited Applications. The majority of students "saw potential for AI use, but no clear application", meaning they were open to the idea that AI might be useful in certain contexts in the future, but did not view it as a reliable or just tool at present. Participant 1 explained:

> *"Right now, when AI is used in certain ways, like facial recognition, it negatively impacts people of color because of biased data. We need to focus on that first. After that, the next step is really educating the population… Systemically many [African Americans] don't have access to this information based on where they live. From personal experience, a lot of my family doesn't feel connected to technology and wants to stay away from it because they don't understand it… Communities are an important part of building a better AI future."*

This student's response highlights how historical and structural inequalities in access to knowledge shape who feels capable of engaging with AI. For many participants, these inequalities had become newly legible through the program's historical lessons on redlining and environmental racism, which showed how one's zip code can predetermine access to well-funded schools, healthy food, transportation, and other conditions that structure quality of life. Even though this student did not identify a concrete application for AI, they emphasized the need for community education, engagement, and representation as prerequisites for imagining beneficial uses of AI for African American communities.

Similarly, Participant 8 doubted that AI could address anti-Blackness on its own, though they supported efforts to make it more inclusive. Without such changes, they struggled to see beneficial AI applications. They stated:

> *"I don't have a super amazing vision for the future off the top of my head, but I think more changes can be made within the AI that's already being used. Like when we were talking about the poem and the video 'AI Ain't a Woman,' there's still so much change that has to happen for current AI to be more inclusive and representative of everyone around the world."*

Their response highlights an important distinction among participants: rather than imagining new AI futures, some students prioritized repair and inclusion within current systems. Essentially, they understood how algorithmic harms are disproportionately borne by minoritized communities.

4.3.2 Strengthening Representation in AI Development. Participant 11 stated that increasing diversity in AI development is essential for achieving more equitable outcomes:

> *"I feel like one way we can use AI to uplift lives is not how it's used now with policing or predicting crime rates in certain areas. If we're using it for unjust reasons, that's because of who's behind it and who's making the programming. I just feel like if we had more people of color, or really just more culturally sound people working on things like that, it would be better for everyone and not just one community"*

This response resonates with prior research underscoring the importance of diverse, culturally competent teams in shaping more equitable AI systems[29]. Diversity does not solve AI fairness, but it provides an important foundation for more justice-oriented outcomes[41]. Although the student did not specify a concrete application of AI, they clearly identified the social conditions under which AI could become beneficial, namely, when development teams include individuals from different backgrounds who can anticipate cultural and racial harms. Their response also highlights a skill emphasized in the Data Activism Program: learning how to collaborate across differences and articulate why diverse participation matters in AI design, a competency rarely foregrounded in mainstream critical AI education[69].

4.3.3 AI as a Tool. Participant 12 articulated a more fully developed idea about how AI could be used to support their community, particularly in educational settings:

> *"AI can be very helpful when it comes to providing tutoring...I know a lot of the time tutors are very expensive and some schools might not have the best resources."*

Overall, while few students articulated concrete future applications for AI, the consistent pattern across all three themes was that students grounded their reasoning in historical analyses, which is a finding we elaborate on in the Discussion section.

5 Discussion

Cultivating critical AI literacy (CAIL) among youth calls for future-oriented design practices that resist AI-solutionism[3, 89]. Our program created opportunities for youth to explore AI within alternative socio-cultural landscapes. Below, we discuss the opportunities and challenges that emerged from the Data Activism Program, offer actionable design recommendations based on our findings, and discuss broader implications for CAIL and CCI. We note that while students' final projects demonstrated their capacity to articulate anti - AI solutionist perspectives on AI, the curriculum could better highlight how researchers and minoritized communities are actively leveraging AI, particularly small language models, in ways that preserve data sovereignty and support community needs. The following design recommendations for developing anti-AI solutionist fluency in future CAIL interventions are grounded in our empirical findings. These guidelines emerge directly from what we observed students engaging with, grappling with, and accomplishing throughout their AI projects, and are further informed by existing literature where noted:

1. **5.1 Design Guidelines for Navigating AI Harms, Community Needs, and Black Speculative Traditions**
   - (a) Use historical analysis as a research method for AI evaluation.
   - (b) Engage students in conversations about resisting AI solutionism.
   - (c) Show students examples of AI being used to support minoritized communities.
   - (d) Introduce Afrosurrealism (and related Black speculative traditions) as analytical tools.
2. **5.2 Design Guidelines for Young Adult Development and Economic Opportunity (YYADEO)**
   - (a) Position youth as AI researchers and knowledge producers.
   - (b) Provide paid training and work experience for AI evaluation.
   - (c) Establish youth-led local boards for resource allocation for AI policy.

5.1 Design Guideline 1: Navigating AI Harms, Community Needs, and Black Speculative Traditions

This study shows that teaching data science through a critical, historically grounded curriculum can assist students with resisting techno-solutionist thinking.

5.1.1 Engaging Youth in Resisting AI Solutionism. Importantly, students thought of ways to mitigate systemic oppression that did not rely on artificial intelligence as the primary site of intervention, such as transformative justice[78]. These findings align with prior critiques of AI solutionism, which caution that technical systems cannot resolve fundamentally social, political, or historical problems[46]. Yet, while an increasing amount of the literature warns against uncritical adoption of AI[24], few studies demonstrate how youth can learn data science while simultaneously analyzing the historical conditions that shape racialized technologies[69]. Our results extend work in CCI by showing that youth are capable of interrogating algorithmic harms and of understanding and redeploying AI for more just and inclusive ends. Such capacities hold potential for influencing public policy on complex and longstanding social issues.

5.1.2 Highlighting Community-Centered AI. A notable implication of this work concerns students' evolving ideas about AI's role in

supporting Black communities. When asked whether AI could address issues affecting African American communities, most students expressed skepticism or uncertainty. From one perspective, this indicates a productive resistance to AI solutionism because students did not assume that AI could "fix" systemic oppression. By contrast, it also suggests that students were not yet familiar with how small, context-specific AI models are being used to support minoritized groups (e.g., language models built for journalists documenting feminicide)[81]. Future instruction should ensure that students understand both the risks of AI and examples of non AI solutionist, community-driven, small-scale AI practices, so that students do not conflate "critical" with "anti-technology"[71]. One compelling example of community-centered AI is the Te Hiku project, led by a Māori nonprofit radio station in New Zealand. Te Hiku developed its own natural language processing tools to support Māori language revitalization while maintaining full community control over their data[40]. Central to this work is the principle of kaitiakitanga, or guardianship, which shaped a data licensing framework that restricts access to organizations that respect Māori values and return benefits to the community. Notably, the people building and maintaining the system are themselves members of the Māori community, and the project actively cultivates the next generation of Māori data scientists through internships and junior positions. This example illustrates how AI can be developed in ways that position communities as co-creators and decision-makers rather than passive data subjects.

5.1.3 Afrosurrealism as an Analytical Lens for AI. Prior work in HCI has explored Afrofuturism, speculative design, and constructionism as strategies for guiding youth to imagine alternative technological futures[42, 46]. These studies show that speculative worldbuilding can expand students' sense of agency and support more inclusive imaginaries of technology[47]. However, we observed that even when students understood systemic oppression and AI harms, their speculative futures still reproduced worlds in which oppression persisted and needed to be eliminated. This aligns with literature suggesting that futuring practices are shaped by who has historically been allowed to imagine the future, which can constrain speculative thought among minoritized groups[41].

To address these constraints, we propose integrating Afrosurrealism as a complementary pedagogical approach. Whereas Afrofuturism imagines liberation through future sci-fi worlds and advanced technologies[13], Afrosurrealism situates itself in the absurd, dreamlike realities of the present, treating the "future-past" as already here[55]. This framework offers distinct affordances for helping students grapple with the surrealism of Black life, historical trauma, and systemic violence without assuming that technology must be the mechanism of liberation. Scholars such as Octavia Butler and N.K. Jemisin have long used speculative fiction to critique racial violence, and HCI scholars like Woodrow Winchester argue that Afrofuturism can motivate inclusive design[25]. Yet, to our knowledge, no AI education studies have examined how Afrosurrealist practices, such as rewriting personal experiences with absurd or dreamlike elements, might support critical AI literacy.

Future work should explore how Afrosurrealism can be integrated into AI education to broaden students' imaginative capacities beyond both utopian "AI for good" narratives and dystopian refusal. For example, students could read Afrosurrealist writers, such as Henry Dumas or Amiri Baraka, or rewrite historical events through surreal lenses to analyze how oppression manifests in the "absurdity" of everyday life[56]. Crucially, this historical engagement should serve a dual function: excavating histories of harm and centering histories of resistance, so that students encounter Black intellectual and creative traditions as sources of radical imagination and agency rather than solely as documentation of subjugation. By connecting historical analysis of AI assessments and Black speculative traditions, future research can improve students' ability to develop a more expansive critical imagination, one that recognizes that problems such as anti-Blackness are not technological problems to be optimized away, but social and political realities that require collective, creative, and culturally grounded responses.

5.2 Design Guideline 2: Young Adult Development and Economic Opportunity (YYADEO)

Our findings demonstrate that long-term, community-centered engagement with AI enables youth, particularly minoritized youth, to move beyond narrow narratives of "AI literacy" toward restorative justice perspectives. In contrast with models of AI education that center technical upskilling alone, our study shows that youth can function as researchers, theorists, and policy advocates capable of interrogating the conditions under which AI should or should not be used in their communities.

5.2.1 Youth as AI Researchers. A key contribution of this work is the demonstration that youth can lead AI and data science research processes rather than occupying peripheral roles (e.g., auditors, testers, or advisors)[5, 99]. Prior educational research has often placed students in simulated professional roles around AI systems[46]. Our results show that young people can define research problems, conduct AI harm assessments, produce evidence, and present policy recommendations to decision-makers.

This finding aligns with and extends Youth Participatory Action Research (YPAR) frameworks, which conceptualize youth as theorists, designers, and activists engaged in iterative research and action[2, 3, 16, 67]. Students' final projects demonstrated that historical thinking increased their ability to scrutinize whether AI systems (e.g., predictive policing or automated education platforms) were feasible, ethical, or desirable within specific sociopolitical contexts. This suggests that young people are capable not only of recognizing harms, but also of situating AI within long-standing histories of racialized surveillance, exclusion, and underinvestment, an analytical competency rarely examined in K–12 AI curricula[60].

5.2.2 Policy Implications. In addition to AI education contributions, this work has implications for youth civic participation and technology governance. Students in the Data Activism Program presented their findings to municipal leaders, senior K–12 district officials, and a former federal technology executive, advocating for investments in Responsible AI and community-informed policy. These interactions supported prior research showing that youth political efficacy increases when students see policymakers as approachable rather than inaccessible figures, and when research is

positioned as a tool for influencing change rather than solely as an academic exercise[57].

Our results also resonate with broader reimaginations of youth development. Whereas existing workforce development systems disproportionately emphasize short-term job placement, we observed that youth benefited most from long-term research experiences that built liberatory computing skills[30, 93] and other capacities that extend beyond technical training[92]. This aligns with proposals such as the Youth and Young Adult Development and Economic Opportunity (YYADEO) model, which frames youth not merely as workers, but as community leaders and decision-makers capable of shaping economic and technological futures[85, 86]. It guarantees paid training and work experience, establishes youth-led local boards for resource allocation, provides holistic support from 7th grade to age 26, and adopts an equity-driven approach aimed at addressing systemic barriers. Both the Data Activism Program and YYADEO center holistic support, political agency, and long timelines rather than short-term labor market alignment.

Our results raise a critical systems-level question: *How can we redesign institutional support so that youth can engage in AI research and policy on a long-term basis, rather than only through isolated programs?* Prior research on YPAR suggests that continuity drives transformative impact, but most computing and AI interventions remain short in duration[3, 46]. Addressing this issue may require institutional rather than programmatic change, which connects directly to emerging federal and regional efforts focused on youth leadership and economic opportunity.

Building on these results, we identify several promising directions for future work. For example, just as youth participatory budgeting initiatives have given young people a voice in municipal resource allocation, analogous youth participatory AI initiatives could enable youth to meaningfully shape the procurement and adoption of technologies in their schools and cities [4]. Another priority is developing collaborations between universities, youth development agencies, and school districts to scale historically grounded AI curricula. Universities possess research capacity and infrastructure that K–12 teachers often lack, and structured partnerships could redistribute expertise and resources more equitably. Overall, our study contributes to growing calls for reimagining AI education as historical, political, abolitionist, and youth-led[41, 58].

Scaling these initiatives to ensure sustained youth involvement in AI decision-making will require coordinated investment across nonprofits, universities, and government institutions. This model is best positioned to expand in cities that already have existing infrastructure, such as youth employment programs or participatory budgeting initiatives, where civic relationships and institutional capacity already exist, as establishing anew presents a significant challenge. This will also require developing AI literacy skill progressions that are standards-aligned and attentive to students' holistic wellbeing. Ultimately, realizing this vision depends on sustained funding, cross-sector partnerships across nonprofits, government agencies, universities, and school districts, and policy environments that treat youth as legitimate stakeholders in shaping the AI systems that affect their lives.

6 Conclusion and Future Work

This study shows that when youth are given data activism skills beyond default AI use, they produce research and policy ideas that center justice. Historical analysis played a key role in how youth interpreted AI's social and political implications. We extend research on youth, data science, and AI by showing that young people can be researchers and policy designers who assess when AI should be adopted. However, the absence of positive, non–AI-solutionist examples may have constrained their ability to imagine alternative sociotechnial pathways. Future work should explore how Afrosurrealism can be integrated into AI education to broaden students' imaginative capacities.

7 Selection and Participation of Children

Participants were high school and college youth recruited through a publicly advertised summer program in partnership with youth employment programs. Enrollment was voluntary with no academic or technical prerequisites, and assent/consent was obtained from youth and caregivers verbally and in writing. Data collection included student-created artifacts, classroom observations, and anonymized interviews, with privacy maintained through de-identification and encrypted storage. Participants received direct benefits including paid training, technical skill development, and opportunities to present to community stakeholders. All procedures were IRB-approved, and we continued supporting students after the program through recommendation letters and public art exhibitions of their projects.

8 Limitations

Several limitations should be acknowledged. First, voluntary and compensated participation may have introduced selection bias toward students already motivated by social justice issues, meaning those with less prior interest or greater barriers to participation may not be represented. Second, given the six-week duration of the program, extended follow-up data is needed to assess whether students' critical AI fluency persisted over time and translated into sustained activism beyond the program. Finally, the ocean acidification group's more limited engagement with anti-AI solutionist frameworks suggests that curriculum effectiveness may vary depending on how closely project topics connect to students' lived experiences with racial injustice, and that projects more distant from students' communities may require additional scaffolding.

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9 Appendix

9.1 Appendix 1

Table 1: Survey items with associated p-values

Week	Survey Item	p-value
1	I frequently reflect on issues of inequality, such as racism and AI bias.	0.05183
2	I understand why the COMPAS recidivism algorithm is biased against African Americans.	4.18×10^{-7}
2	I can explain the impact of an imbalanced dataset on the performance of a machine learning model.	2.49×10^{-5}

9.2 Appendix 2

Table 2: Interview questions about AI and student projects

Q#	Interview Question
1	How do you want to use AI to support your data activism project?
2	How have your views on AI changed over time, especially since you first started learning about it? What experiences or information influenced those changes?
3	How do you think AI should be used to uplift African American lives beyond your final project?

9.3 Appendix 3

Table 3: Codebook for Students' Views on AI Use in Final Projects, Broader Applications, and Changes Over Time

Question	Code	Definition	Count
1. Youth's Perspectives on Decentering AI-Solutionism	Data Analysis	Mentions of AI being used to analyze data, identify patterns, trends, disparities, predictions, summaries, or visualizations.	10
	Data Collection	References to AI supporting the identification, gathering, verification, or sourcing of data.	4
	Data Cleaning	Use of AI for organizing, sorting, correcting, or preparing datasets prior to analysis.	3
	Edit Writing	Mentions of AI supporting writing tasks without generating original research content.	5
	Inspiration	Use of AI for brainstorming, idea generation, or general background knowledge.	2
	Exemplifying a Critical Stance on AI Solutionism	Explicit skepticism or resistance toward AI as a solution, emphasizing its limitations, risks, bias, ethical concerns, or inability to replace human judgment.	3 groups out of 4
	Emerging Critical Perspectives on AI	Students were beginning to question AI's role and limitations, but had not yet fully connected these concerns to broader structural or historical frameworks of AI solutionism. Their critical awareness surfaced primarily in subsequent interviews and surveys rather than in their final project deliverables, suggesting it was still developing at the program's conclusion.	1 group out of 4
2. The Value of Historical Analysis in AI Assessments for Youth	From Positive Views to Critical Awareness of AI Harms	Participants entered the program with minimal, neutral, or optimistic views of AI and, through the course, developed a more critical understanding of AI's harms, risks, or negative societal impacts.	22
	Building on Existing Critical Awareness of AI Bias	Participants had prior awareness of AI bias or harm before the course, and the program reinforced, deepened, or provided concrete examples that strengthened those existing views.	6
	COMPAS Lesson	Participant explicitly referenced the COMPAS algorithm or lesson when discussing AI bias, fairness, or harm.	5
	Discriminatory Design Lesson	Participant explicitly referenced the discriminatory design lesson, including examples of technology designed to exclude, control, or harm minoritized groups.	1
	Faulty Facial Recognition Lesson	Participant referenced lessons, videos, or examples demonstrating racial or gender bias in facial recognition systems.	10
	Predictive Policing Lesson	Participant referenced lessons or discussions about AI used for crime prediction or policing, particularly its disproportionate harm to minoritized communities.	1
3. Ambiguity in AI's Role for Supporting Black Futures	Strengthening Representation in AI Development	Participant emphasized that AI bias can be linked to who designs AI systems and highlighted the importance of greater racial, gender, or experiential diversity among AI developers.	5
	AI as a Tool	Participant described AI as a useful tool for brainstorming, generating ideas, locating sources, or supporting data-related tasks, while often maintaining a critical stance toward overreliance or accuracy.	11
	Recognized AI Harms, Limited Applications	Participant shows strong critical awareness of AI harms and emerging efforts to translate that insight into meaningful, contextually grounded uses, though these applications remain in early stages of development.	15

9.4 Appendix 4

Student Application Questions for the Data Activism Program:

(1) *Coding experience:* Do you have any prior coding experience? If so, please describe the languages and courses you have taken. Note that lack of coding experience will not affect eligibility.
(2) *Discussion experience:* This program relies heavily on discussions about racism and systemic oppression. Have you participated in similar conversations before? If so, describe your experience and comfort level. If not, what motivates your interest in exploring how racism has affected your life?
(3) *Personal experience with oppression:* Have you encountered instances of oppression, such as racism, on a personal or systemic level? If so, how did you navigate that experience?