Promise or Peril? Exploring Black Adults' Perspectives on the Use of Artificial Intelligence in Health Contexts

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Abstract

As artificial intelligence (AI) is rapidly integrated into healthcare, ensuring that this innovation helps to combat health inequities requires engaging marginalized communities in health AI futuring. However, little research has examined Black populations' perspectives on the use of AI in health contexts, despite the widespread health inequities they experience–inequities that are already perpetuated by AI. Addressing this research gap, through qualitative workshops with 18 Black adults, we characterize participants' cautious optimism for health AI addressing structural well-being barriers (e.g., by providing second opinions that introduce fairness into an unjust healthcare system), and their concerns that AI will worsen health inequities (e.g., through health AI biases they deemed inevitable and the problematic reality of having to trust healthcare providers to use AI equitably). We advance health AI research by articulating previously-unreported health AI perspectives from a population experiencing significant health inequities, and presenting key considerations for future work.

CCS Concepts

• **Social and professional topics → Race and ethnicity**; • **Human-centered computing → Empirical studies in HCI**.

Keywords

Health AI, Digital Health, Participatory AI, Community-Centered Design, Racial Health Equity

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1 Introduction

There has been a rapid increase in the use of artificial intelligence (AI) in healthcare settings for disease detection [2, 25, 57, 62], treatment recommendations [2, 67], well-being promotion [15, 79], and insurance coverage [6, 100]. In parallel, we have seen racial health inequities continue to proliferate in the United States (U.S.) [71]. For example, compared to other racial groups, Black communities experience poorer mental health outcomes [21] and less access to healthcare [71], and they are more likely to have providers fail to effectively manage their pain [64, 110] and to misdiagnose them [31].

Research is only beginning to examine how AI can be designed to reduce racial health disparities [11, 46, 63, 66]. In particular, notably little research has invited Black communities to contribute their perspectives on AI as it relates to health ("health AI"), despite prior work demonstrating that eliminating health inequities requires prioritizing minoritized groups' involvement when designing health technologies [82, 99, 118]. As a result, we know little about how Black communities feel AI should and should not be used to address health and health equity, which impedes the field's ability to ensure health AI research and innovation is fair and responsible.

Addressing these research gaps, we conducted an in-depth research study examining the following research question: *What perspectives do Black adults have on health AI and its ability to support health and racial health equity?* To answer this question, we invited 18 Black adults to complete a survey and a series of qualitative workshops. Our findings shed light on the nuanced outlook that our participants have regarding health AI. In contrast to results from a national sample of adults across racial groups [113], our participants were more enthusiastic about AI, even noting ways that AI could address health inequities. However, our qualitative data reveal the complexity behind participants' AI attitudes, and how in reality, their views on AI's potential range from enthusiasm to resistance. We further show how these views are shaped by participants' critical considerations of the limits and opportunities for AI and their personal experiences of and outlook on structural health barriers: healthcare system failures, racism and bias, and mental health stigma. Participants engaged in critical reflections around opportunities for health AI to address structural barriers to wellbeing, such as by addressing access-related disparities and providing valuable second opinions that help introduce fairness into an unjust healthcare system. At the same time, they also discussed ways that AI can perpetuate and worsen health inequities, for example, by describing what they perceived as the inevitability of bias in health AI and the problematic reality of having to trust other humans to use AI equitably in the healthcare space.

We advance digital health and responsible AI research in HCI and related fields, by illustrating how perspectives on the future of health AI may be more complex than perceiving the technology as 'good' or 'bad'. Instead, our findings articulate previously-unreported perspectives that foreshadow the negotiation of AI potential versus the technological pessimism that can arise when considering constructs of access and disparity that are pervasive for populations that experience significant health inequities. We

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further use our findings to contribute key considerations that can help advance more equitable health AI research and innovation, including:

(1) our participant-surfaced design opportunity of conceptualizing health AI as armor that racially minoritized communities can use as a shield from pervasive healthcare biases,
(2) the value of intention-focused framings of health AI harms (including intended, unintended, and inevitable harms), and how such framings elucidate opportunities to support marginalized groups' wellbeing (e.g., by mitigating intervention-generated inequalities caused by *harmful reliance* on AI),
(3) the value of collectivism as a design and methodological orientation for health AI, and
(4) the need to balance community perspectives and critical scholarship in health AI design and research.

These considerations represent new directions for health AI research, and unrealized opportunities to consider how this technology can be more effectively designed to mitigate pervasive health inequities. We conclude by reflecting on the importance of collaborative design work amongst community, industry, healthcare, and academic stakeholders, to enable the translation of findings such as those in this paper into equitable, concrete shifts in AI innovation.

2 Related Work

2.1 Racial Bias in Health AI

Research has long shown that deep and systemic racial inequities and biases are present in health and healthcare [59, 123]. For example, Black Americans experience heart disease and diabetes at a higher rate than other races [56], and Black communities experience less access to and lower quality healthcare than other racial groups [106]. These racial biases are also oftentimes mirrored in health AI. For example, Huang, et al. report that 67% of papers in their scoping review found racial bias present in machine learning health applications [51]. Jindal [58] also discusses how these biases can be found throughout the process of developing AI-based systems, from biased raw data, data extraction, and data labeling, to biased model implementation. A review of racial and ethnic biases in healthcare algorithms outlined how these biases present challenges to patient privacy, data security, institutional transparency, and health equity [53], as well as overall precision and fairness outcomes [51]. Research by Obermeyer, et al., found that a healthcare algorithm used to predict which patients were in need of additional medical care missed more than half of Black patients who should have been flagged as in need of additional care [76]. The model failed to accurately flag Black patients in need of care because it used healthcare costs as a proxy for healthcare needs, ignoring the systemic barriers to healthcare access and quality care in Black communities, which leads to lower healthcare expenditures in this population. Recent research [88, 108] and government rulings [78] have called for addressing AI biases in healthcare, yet have omitted explicit calls for marginalized groups' participatory engagement in AI development.

Considering how AI might help *reduce* health disparities requires building upon the existing foundation of digital health equity research that is exploring what it might mean for technological interventions to meaningfully intervene on health inequities. For example, critical research in areas such as biomedical informatics and precision medicine highlight the significant importance of considering how interventions can address the systemic drivers of health that are at the interplay of oppression and resultant disparities in care for several populations [30]. Relatedly, Veinot and colleagues [117] convey the criticality of understanding and addressing the societal factors associated with health disparities when designing digital health interventions. This work calls attention to the essential practice of not simply focusing on downstream influences on health (e.g., psychological or behavioral drivers of health outcomes), but rather that addressing health disparities requires confronting the root causes of these inequities in sociotechnical interventions.

Yet, research is only beginning to explore how AI can help reduce health inequities. For example, a recent study by Johns Hopkins Medicine found that clinical sites using autonomous AI screening for diabetic eye disease had greater annual screening rates amongst Black patients than sites using standard (non-AI assisted) screening protocols, suggesting that AI could improve access to care for historically disadvantaged populations [52]. AI is also being used to identify biases in medical curricula, a longstanding issue for medical education [93]. Lastly, researchers are starting to apply AI to better understand diseases that affect Black Americans at high rates, such as sickle cell disease [32], but these explorations are still early. As conveyed by the growing research in this area [30, 84], the critical praxis of addressing systemic drivers of health requires transforming power dynamics through research that helps to inform and effect social change [30]. Thus, to help build more equitable health AI futures, further work is needed to examine if and how AI can address health inequities in Black communities. Our research offers such insights from the perspectives of community members themselves.

2.2 Participatory Methods in Health AI

There is increasing recognition that bringing diverse stakeholders together is necessary to develop ethical and responsible health AI [27, 99], and that eliminating racial bias in health AI necessitates the authentic involvement of impacted communities *and* earning community trust [77, 82]. Extensive research in public health has shown community-based participatory approaches to be crucial for creating health interventions that are both effective [101] and that address racial health inequities [3, 47, 69, 120]. Participatory methods in AI and machine learning research have shown promise for better aligning these applications to historically marginalized patients' "unique worldviews, community strengths, and healthcare goals" [90], also drawing attention to the need to consider not only the inherent bias in datasets, but also the social structures from which data is derived.

Although we have begun to see the use of participatory methods in exploring health AI among various communities [90], including Black communities in the design of health AI remains rare [82]. However, recent research has made important methodological contributions and yielded system design considerations focused on this population [68, 118]. For example, Harrington, et al. found that design workshops with Black older adults had the potential to help participants invest in their own health and address community health concerns [44]. In a study exploring the design of health chatbots with Black older adults, Harrington and Egede found that participants considered chatbots a potentially useful way to seek health information [46]. They also noted that perceived chatbot race, age, and gender influenced trustworthiness and credibility, finding that Black chatbots were more relatable, but simply changing the race of the chatbot's character did little to erase the history of distrust Black people have towards the healthcare system or health technologies. A study by Kim, et al., explored the design of a COVID-19-related chatbot with Black participants, raising important considerations that go beyond surface level design elements, including participants' expectations that the chatbot act as a "trustworthy voice that could represent the Black American community to the medical system" [63]. Our work builds upon this foundation of participatory research methods by contributing a community-focused approach to health AI futuring and also introducing the use of qualitative workshops that explicitly invite participants to consider health AI futures in light of social and structural factors that create racial health inequities.

2.3 Black Americans' Perspectives on Health AI

While some prior work has focused on designing specific types of AI health tools (e.g., chatbots), other work has examined health AI attitudes more broadly [65, 114]. National assessments of the public's attitudes towards health AI have increasingly emerged [8, 16, 34, 65, 85, 113], yet work specifically studying the factors driving Black Americans' attitudes towards health AI–and their perspectives regarding AI's role in addressing health equity–is lacking. Researchers are just starting to engage this community on important topics, such as Lee and Rich's work on medical mistrust that showed Black participants who mistrust doctors and nurses perceive health AI as equally untrustworthy and unfair as human medical providers [66].

Despite this emerging work examining Black adults' perspectives and attitudes towards AI broadly [42] or specific health application areas, a recent systematic literature review found no peer-reviewed studies that directly and broadly examined Black patients' perceptions or acceptance of AI in healthcare [23]. We address this gap by contributing what we believe is the first study to comprehensively examine Black adults' broader attitudes towards health AI, including both expected value and potential harms across a range of health scenarios. Examining perspectives across these scenarios enables us to illuminate issues that must be resolved for health AI innovation to progress equitably. Our work contributes key insights into how Black adults feel AI can, and cannot, go beyond supporting health to supporting *health equity* by rectifying harms that cause poorer health in Black communities. These findings present a diverse set of concerns and opportunities for future work.

3 Methods

As a critical first step to building equitable AI systems, we conducted a mixed-method study to examine Black communities' current perspectives on health AI. From June-July 2024, we engaged 18 Black adults in a series of in-person workshops and online surveys; all study sessions were held in a city within the Southeastern region of the United States. The study was conducted in adherence to Google's ethical, legal, and privacy standards for human subjects research and was reviewed by the Advarra Institutional Review Board and determined to be exempt from IRB oversight. We recruited from Google's pool of individuals who had opted-in to being contacted about opportunities to participate in research studies [39]. Potential research candidates were screened based on our inclusion criteria, that they must: be at least 18 years old; be able to speak, read, write, and understand English; identify as Black/African American or mixed race with Black/African American as one of the races; have at least one of the following: a) heard of, read about, or used AI in some way, *or* b) educational, job, or volunteer experience in healthcare or health/wellness promotion; and lastly, have an interest in the topic of racial equity in health (defined as ensuring people of all racial and ethnic groups have a fair and just opportunity to achieve health and well-being). One hundred and forty-seven people responded to our research announcement and were screened for our inclusion criteria. Forty-seven met the eligibility criteria, and eighteen were invited to participate based on purposeful sampling across age, gender, sexual orientation, healthcare background, and familiarity with AI.

Prior to data collection, we provided a study overview and collected written consent from all participants. The study consisted of two research activities; first, an online survey collecting demographic information and gauging perspectives and experience with AI and health equity, and second, a series of in-person group workshops.

3.1 Data Collection & Analysis

3.1.1 Pre-Workshop Survey. The survey instrument included 25 items including questions from established national survey measures assessing general attitudes towards AI [95], attitudes towards health equity [92, 111], perspectives on AI in health [113], and demographic data including age, race/ethnicity, gender, sexual orientation, and occupation.

3.1.2 In-Person Workshops. After completing the pre-workshop survey, each participant was asked to participate in a total of three workshop sessions (Workshops 1, 2, and 3) spaced approximately 2 weeks apart. Following common practice in participatory design [45, 80], holding workshops across multiple sessions allowed us to mitigate participant fatigue and create activities that further examined and built upon discussions and learnings from prior sessions.

To allow for in-depth discussions, we limited the size of each workshop to a maximum of six participants. This meant that we ran three sessions of each workshop (for a total of 9 workshop sessions across the three Workshops). We followed the same workshop guide across each of the three sessions. Each participant was asked to join one session of each workshop, choosing the session that worked best for their schedule (for a total of three workshops per participant). Each workshop session lasted 2.5-3 hours and had a total of 4-6 participants. Prior work suggests that 2-6 focus group sessions is appropriate for identifying most themes in a data set [41]; by running 9 workshop sessions, we aimed to collect sufficient data to fully examine our research questions.

Each workshop had a different focus and engaged participants in different activities. The first two workshops allowed us to explore our research question, *What perspectives do Black adults have on health AI and its ability to support health and racial health equity?*. The third and final workshop explored additional topics outside of the scope of this paper (e.g., the methodologically-focused topic of how participants felt their communities can be most effectively engaged in the collaborative design of health AI systems). As such, in this paper, we report on our study design and findings for the first two sets of workshops in the series only (a total of six workshop sessions).

During the first workshop ("Workshop 1" below), participants were introduced to foundational definitions of health equity, AI, and machine learning. We held a discussion around the ways AI shows up in participants' everyday lives, the bias that can creep into AI, mental health and pain management disparities, and participants' perspectives on the use of AI in various health contexts and for addressing health inequities in Black communities. To seed these discussions, we showed participants short videos of AI being used in 1) a consumer health context (a chatbot that supports mental health by allowing people to engage in text conversations with the bot about how they are feeling) and 2) a clinical setting (AI-assisted automatic pain recognition through facial analysis). We chose these examples as 1) both mental health and pain management are areas where Black communities experience significant health and healthcare disparities [21, 64, 110], and 2) these were topics that we asked participants about in the survey. The focus groups enabled us to delve more deeply into their perspectives on these use cases.

In the second workshop ("Workshop 2" below), participants reviewed a subset of the aggregated survey results, which assessed participants' perceptions of health AI ahead of the workshops. Participants were guided through a discussion of the results aided with printouts with chart and text summaries, and we asked participants to use stickers to annotate where they felt "encouraged", "concerned", "surprised", or "confused" by the results surfaced across the participants in the study. The group then discussed participant reactions and the reasons behind them, enabling us to further examine participant attitudes towards the use of AI for health and health equity, and limitations therein. Additionally, as we will discuss in our findings below, these group reflections on the survey trends enabled community-centered reflections on the meaning and implications of participants' AI attitudes.

In summary, our study design implemented participatory AI strategies for advancing racial health equity proposed by Parker et al. [82], including not only supporting reflections on AI's relevance for participants' personal lives but also prioritizing community-centered reflections as a way to support design thinking around the structural and social factors that shape health and health inequities. Furthermore, we supported meaningful participation through a) the establishment of relevant health equity and AI background knowledge for our participants before delving into their perspectives on these topics, and b) engaging participants in multiple data collection sessions [82].

3.1.3 Analysis. Our survey and focus group data analysis centered on examining participants' perceptions of and attitudes towards AI's use for health and health equity. Survey questions were analyzed using descriptive statistics. Workshops 1 and 2 produced 16.5 hours of discussion audio, which was transcribed verbatim. We conducted an inductive, thematic analysis of the subsets of these transcripts that were relevant to our research question (Section 1) [13, 14]. We began by reflecting on this data, by listening back to the audio recordings and reading through analytic memos noting preliminary trends and distinctive moments in the data [17]. The first author then inductively coded the transcripts, labeling data snippets related to our research question, and iteratively grouped codes into higher level themes.

During this analysis process, the authors collaboratively examined the data and refined the analysis through 1) regular meetings throughout data collection in which our team discussed preliminary trends, key perspectives conveyed by participants in the workshops, researcher memos, and emergent topics and trends in the data that warranted further examination in subsequent workshops, 2) meetings where we reviewed and discussed the analytic codes, themes, and relationships between the themes, and triangulated our workshop and survey findings, and 3) the collaborative writing and review of the findings reported on in this paper. Regarding this latter point, following qualitative research best practices [20], our analysis process extended into the writing of this manuscript. Specifically, as we wrote about our findings, we clarified and expanded upon our themes and the relationships between them as we considered them further in light of our data and relevant related literature.

Through this collaborative process, our team achieved consensus in our thematic analysis, which produced 301 codes that were grouped into 42 subthemes, which were then grouped into 12 top-level themes. In this paper, we report on a subset of the findings that resulted from this analysis (6 top level themes, 20 subthemes, and 141 codes).

In qualitative research, *data saturation* refers to the point during data collection and analysis "when no additional issues are identified, data begin to repeat, and further data collection becomes redundant" [48]. Researchers have critiqued this concept as being insufficiently defined and noted that there often lacks insufficient guidance regarding how data saturation can be evaluated, while acknowledging that assessments of data saturation will necessarily vary across studies [35]. However, there has been an increasing effort to provide researchers with guidance in assessing whether data saturation has been met [35, 48].

One way of evaluating data saturation is by assessing *code saturation*, that is, the point in data analysis where "no additional issues are identified and the codebook begins to stabilize" [48]. Hennick et al. [48] offer that two measures of *code saturation* are the point in the analysis when 1) most codes have been identified *(code identification)* and 2) most high-prevalence codes have been identified *(data prevalence)*. While there is no definitive threshold for declaring data saturation, Hennick et al. [48] suggest that code saturation may be established as the point at which 80% to 90% of codes have been identified.

We modeled Hennick et al.'s approach to assess code saturation in the analysis conducted and reported on for this paper (the six sessions held across Workshops 1 and 2 and the resulting analysis for this dataset). Assessing our workshop analysis in the chronological order in which the workshops were held, we found that 84% of our codes were inductively developed and applied to our data by the second session of Workshop 2 (our fifth of the six workshop sessions analyzed in total for this paper). We also explicitly examined our highest prevalence codes. Following Hennick et al. [48], we defined the highest prevalence codes as those that appeared in more workshops than the average code. On average, codes in our codebook appeared in 1.6 workshops; thus, we assessed our highest prevalence codes as those that appeared in two or more workshops. We found that 100% of these codes were inductively developed and applied to the data by the second session of Workshop 2 (our 5th of six workshop sessions overall). These findings establish code saturation in our data occurred by our fifth workshop session [48].

3.2 Participants

We enrolled 18 Black Americans from a metropolitan area of the Southeastern United States in our study. This focused sample size is appropriate for our qualitative study design [48], as it enabled us to examine each participant's perspective in-depth to obtain a detailed, rich dataset that captures the nuance in our participants' health AI perspectives. Furthermore, studies with comparable qualitative aims (i.e., of understanding community perspectives and lived experiences as they relate to digital health and health equity) have had similar sample sizes (e.g., [45, 80]).

All participants were asked to join one of three sessions (4-6 participants per session, each of the three sessions of a workshop followed the same workshop guide) in each part of our 3-part workshop series. We took this approach (i.e., splitting participants into these small groups) to ensure we had sufficient time to fully explore each person's perspective. In total, we held 9 workshop sessions across the entire workshop series (3 sessions for each part of the workshop series).

All participants completed the pre-workshop survey, and 16 people participated in the workshops. Participants came from a range of age groups, with most participants falling in the "18-24" group (n=6) and the "35-44" group (n=8). Twelve participants reported as heterosexual or straight and 6 participants reported as queer, lesbian, gay, or bisexual. Four participants reported currently working in the healthcare industry and one participant reported currently working in the information/technology industry. All participants reported having heard of AI prior to our study, and all but one participant had used AI prior to this study, with most (n=10) indicating they used AI "a lot" or "a moderate amount". Most participants (n=13) reported being interested in using AI in their daily lives. Detailed participant demographics can be found in Appendix A, Table 1.

4 Positionality Statement

We find it important to share our positionality as a commitment to reflexivity in HCI research. The authors of this paper are scholars who have conducted several years of research examining how technology can advance health equity. Each author has conducted community-engaged research designing health technologies with racially minoritized and otherwise marginalized communities for at least ten years (primarily Black but also Latinx). All authors reside in the U.S.; two identify as Black American, one identifies as White American. We bring diverse cultural backgrounds, lived experiences as it relates to the social construction of race, and scholarly expertise regarding racial health equity and health technology design to the examination of the current state of, and future directions for, racially-equitable participatory health AI.

5 Survey Findings

In this section, we report our participants' pre-workshop attitudinal survey results alongside data from an independent national sample [113], in order to provide a reference point that highlights similarities and deviations from the general population. Given that our recruitment technique did not match that of a randomized national sample, and with a sample size of 18, compared to 11,004 nationally, we do not make statistical comparisons or conclusions from these survey data. Rather, these pre-workshop survey results were used to unlock deeper qualitative data collection by 1) alerting us to attitudinal trends ahead of the workshops, which helped us craft focus group questions that further examined the trends, and 2) allowing us to show participants their attitudinal data, in aggregate, during Workshop 2, enabling community-focused reflections on health AI. Findings in Section 6 include workshop participants' reactions to these survey results. Detailed results for all survey data reported can be found in Appendix B.

5.1 Overall Perspectives on the Use of AI in Health

Most participants in our study expected that the use of AI in health and medicine would lead to better health outcomes for patients (61%), which is higher than national survey data (38%) [113] (Appendix B, Figure 2). However, 22% reported feeling *unsure* if AI would lead to better or worse outcomes, also much higher than the national data (2%). At the same time, most participants in our study reported concerns that AI could move too fast in health, before the risks are fully understood, but did so at a lower rate than the national population (61% vs. 75% [113]), and 17% of our participants (compared to only 2% nationally) felt *unsure* whether or not they were more concerned about AI moving too fast before risks are fully understood, or AI moving too slow and missing out on opportunities to improve patients' health (Appendix B, Figure 3).

5.2 Bias and Equity in Health and Medicine

In terms of bias and equity in health and medicine, participants in our study reported fewer mixed-results than in previous national research [111, 113]. When asked how much of a problem is *"bias and unfair treatment in health or medicine, based on patients' race or ethnicity,"* 83% reported that it is a major problem, much higher than 35% reported nationally (Appendix B, Figure 4). Similarly, 89% of participants (vs. 31% nationally) strongly agreed that *"it would be unfair if some people had more of an opportunity to be healthy than other people,"* and 100% (vs. 41% nationally) strongly agreed that *"our society needs to do more to make sure that everyone has a fair and just opportunity to be healthy."* (Appendix B, Tables 2 and 3).

5.3 AI's Role in Bias and Equity in Health and Medicine

Most participants in our study expected that *"If AI were used more in health and medicine to do things like diagnose disease and recommend treatments, issues of bias and unfair treatment based on a person's race or ethnicity would ..."* probably (67%) or definitely (11%) get better, which is higher than the national sample (35% and 9%, respectively [113]) (Appendix B, Figure 5).

When asked about AI's potential to improve or worsen specific elements of health and medicine, participants expected that AI would make things *better* at higher rates that previous national research [113] (Figure 1). This included expectations that AI would lead to fairer treatment, reduce mistakes, and improve the quality of healthcare specifically for Black Americans. When it comes to AI's impact on patient-provider relationships, participants had mixed perspectives with 39% thinking that AI would make the relationships *better*, 44% indicating they would be *worse*, and 17% *not much difference*. Participants also reported mixed expectations on whether AI would make the security of patients' personal health records *better* (38%), *worse* (44%), or *not much difference* (17%).

5.4 Perspectives on AI's Use within Different Domains of Health and Medicine

Echoing past research [113], we explored participants' personal desires for AI in three distinct scenarios: determining pain medication amounts ahead of surgery, screening for skin cancer, and chatbots for mental health support. Participants showed mixed desires for AI in pain medication dosing (56% would want it used, 44% would not) and mental health chatbots (39% would want to use them, 44% would not), compared to past research which indicated a majority of Americans would *not* personally want AI used in these scenarios (Appendix B, Figures 6-9). For AI's use in skin cancer screening, a majority of participants in our study (83%) indicated that they *would* personally want this, compared to 65% nationally (Appendix B, Figure 8). Eighty-three percent of participants also reported expectations that AI would make skin cancer diagnosis more accurate, compared to 55% nationally (Appendix B, Figure 9).

6 Focus Group Findings

While our survey findings demonstrate that our participants expressed greater enthusiasm for health AI than in the general populations surveyed in prior work, our qualitative findings shed light into the nuanced outlook our participants expressed regarding the use of AI in health contexts. Their feelings ranged from enthusiasm for AI, to skepticism, to feeling that AI is dangerous. Going beyond prior work reporting quantitative trends in health AI attitudes [8, 16, 34, 65, 85, 113], our qualitative findings further characterize factors that provide context for and shape our participants' perspectives on health AI: the ways in which participants were critically considering AI's role in health, their attitudes towards their fellow community members' perspectives, the structural problems they described as harming Black communities' well-being, and the opportunities and limits they saw for AI in addressing health inequities.

6.1 A Spectrum of Perspectives on the Outlook for AI

6.1.1 AI Openness & Enthusiasm. The openness to and enthusiasm for health AI from our survey was echoed in our focus groups. Some participants described how they had already used AI in their day-to-day lives, and in health-related contexts, such as AI-supported mental health apps (P5, P11). Participants who worked in healthcare described using AI in their jobs, for example to "establish how likely it is someone's going to be addicted to pain medication" (P10) or to assist with patient scheduling based on factors such as whether or not the patient has co-morbidities (P13).

Beyond *using* AI, several participants discussed their *positive outlook* on health AI. For example, some were optimistic about using AI in clinical settings to determine pain medication dosage (P5), enable robotic assistance with tasks like moving patients to and from the bed (P12), and diagnose disease (P5, P1). Some participants went so far as to say that AI could diagnose more effectively than human providers, such as P1, who said the following about skin cancer screenings: *"I know that there are a lot of times mistakes made by humans... I would think that AI has been fed enough accurate data to be able to better diagnose you than a doctor, I guess"* (P1, Workshop 2). Interestingly, P1 felt this way even after our Workshop 1 discussion of how insufficient data can create biased AI tools.

Several participants described how AI can have benefits when more directly used by everyday people, for example, by enabling access to healthcare and health resources (P1, P5, P6, P7, P11, P13)–such as through tools that support mental health, providing recommendations for how to manage one's health (P7, P11), sending smartwatch alerts when one has been sitting for too long (P13), and introducing people to new health concepts (P9). P6 summarized his outlook on AI's potential by saying *"it literally saves your life probably two or three times every day in some way shape or form."*

A Community Outlook. When reflecting on the survey findings, some participants expressed feeling encouraged that their fellow participants were open to AI uses in health. Participants felt that 1) it is important for their community to be open to healthcare options beyond traditional healthcare (P12), 2) AI provides benefits for health (P13, P11), 3) the pervasiveness of computers and smartphones makes health AI something that people can actually have access to (P9), and 4) that others being open to AI would enable AI to *"continue to learn from more diverse groups of people and hopefully get better and better"* (P15, Workshop 2). One participant also discussed being excited to see *"so many people have somewhat of a fear built up for it, but understand that even the pieces of it that they are afraid of can possibly be good for people"* (P6, Workshop 2). These findings convey how participants were not only interested in how AI could benefit themselves or loved ones. They also expressed a genuine sense of care about how others in their broader community felt about AI, not wanting those individuals to miss out on potential AI benefits.

6.1.2 AI Causing Harm. And yet, while our participants spoke to many health AI opportunities, they also described potential harms. Foremost, there was a central concern not simply about AI itself, but rather *how it is used.* Some participants expressed concern about AI being intentionally used against them. P11, for example, discussed her concern about AI coming *"to destroy us,"* indicating

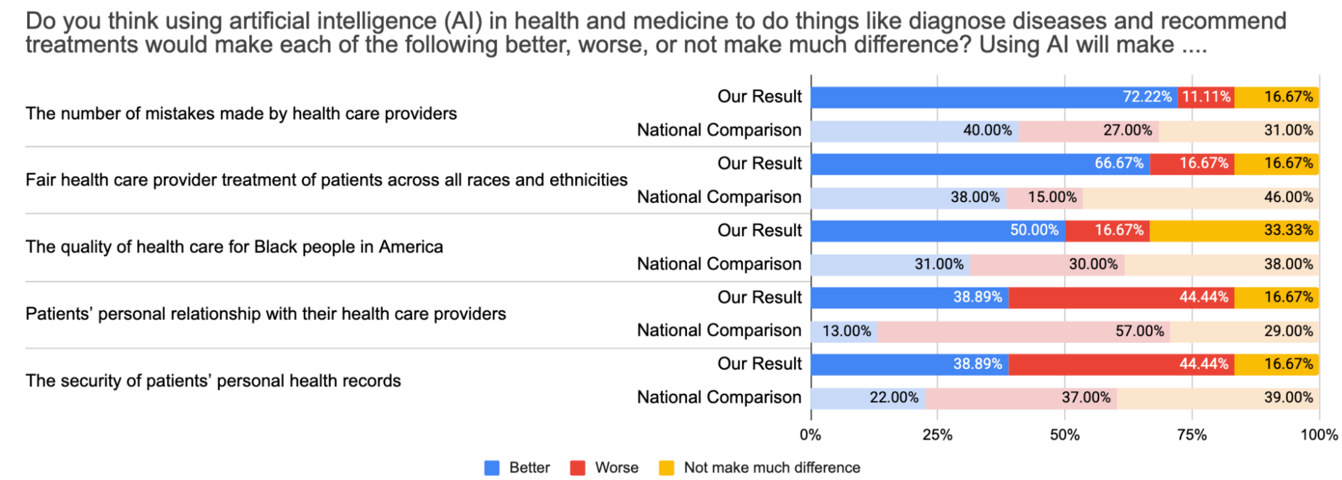

Figure 1: Our study participants' (n=18) perspectives on AIs potential to improve or worsen aspects of health and medicine, shown alongside results from a 2022 national survey [113].

that mitigating this threat required people being cautious about how they use it. P1 (Workshop 2) similarly described concerns of AI misuse, conveying the threat of bad actors creating and using AI that harms, given that *"those who have ulterior motives and wanna do bad things with it can."* P5 (Workshop 2) added to this discussion, conveying that she was *"sure there's people out there using it the the wrong way."*

Participants also expressed concerns about unintended harms. For example, they discussed AI incorrectly assessing the state of one's well-being, leading the AI to not recognize when a person is in distress (P16), provide responses that inhibit the person from getting necessary help (P11, P16), or misdiagnose people (P5, P10, P13). For example, P13 discussed how at his healthcare workplace, providers are so excited about the efficiency that AI is introducing to colonoscopy procedures that they are not having enough dialogue about the threat of misdiagnoses. P13's comments bring light to how a health AI affordance can sit in tension with the risk it presents for harm.

Some participants conveyed the dangers that AI presents as being rooted in the fact that AI is created by humans, with P1 (Workshop 1) noting *"we're not 100% right. So AI can never be 100%"*. P6 (Workshop 2) similarly conveyed that *"at its core, [AI] is gonna be dangerous naturally because of what you said, humans created it. We're dangerous... Look at what we do to the environment around us in the name of comfort."* P6 and P1 speak to a feeling of inevitability of AI posing dangers and limitations.

These concerns about intended, unintended, and inevitable harms, when considered alongside the health AI optimism that several participants expressed, demonstrate the spectrum of feelings our participants held regarding health AI.

6.2 Critically Assessing the Role of AI in Health

In this section, and the ones that follow, we delve more deeply into the factors that shaped participants' appraisal of health AI. Here, we describe how participants were critically thinking through the role that AI should or should not have in addressing health. We describe their nuanced and mixed viewpoints that expressed both hopes and concerns, the caution and hesitation they employed when considering the technology, and how they actively questioned AI's ability to support wellbeing.

6.2.1 Nuanced & Mixed Viewpoints. Participants expressed nuanced takes on the current state and future of health AI, with many feeling *both* optimism for and resistance to AI. This mixed perspective was evident through several survey questions (e.g., Figure 1), and articulated throughout the focus group discussions. Participants expressed feeling *"divided"* (P15) about their feelings around AI's potential for good or bad, with P1 stating, *"I feel like it's a double edged sword. You got great things that can come from it, but you got a lot of bad things that can come from it."* As an illustrative example, P6 (Workshop 1) described how AI could help *and* be detrimental to mental health. When considering to what extent a chatbot could address racial disparities in mental health, he said: *"I believe it can because... you can open up a dialogue that you're not having with anybody else. It can ask you questions, it can make you think."* Here, P6 expresses optimism about a chatbot's ability to open up a space for people to talk about their challenges, and have something that helps them think through these issues. However, just a couple of minutes later, he expressed concerns about the same technology, saying: *"It might create a crutch for you that isn't really there...another further thing that leans us into being addicted to our phones... To where we're not actually working through the problem that's in our reality, versus just telling a computer program what it needs to hear so it can tell us that we're doing ok."*

These two perspectives that P6 shared–the optimism and the concern–reflect a larger pattern that we observed across participants. Indeed, P1 also had dual perspectives on AI for mental health, indicating on the one hand that the technology could help people develop coping skills, but that it would not be helpful in the midst of severe mental health episodes. This pattern further demonstrates the critical way in which participants were thinking beyond surface level likes and dislikes of AI features to interrogate key opportunities and problems that can arise with the technology.

6.2.2 AI Caution & Rejection. These multifaceted views also highlight the larger caution around health AI that several participants expressed. For example, some participants expressed wanting to take a measured, cautious approach to AI, waiting to see more information about AI and evidence that AI was benefiting well-being before they would be willing to use it. For example, P1 (Workshop 2) said: *"I haven't seen a lot of good come from it yet to change my mind...I'm going to have to see these miraculous things happening with AI."* Similarly, P6 (Workshop 2) indicated a need to slow the speed at which we are embracing AI and the well-being recommendations it provides: *"So I'm encouraged that people... will hold up on, on AI, before we just fully submit to what it suggests for us."* Like P1 and P6, P7 (Workshop 2) also discussed the criticality of being fully informed before rushing into health AI use: "*You can't be the first one to take this on without a good measure of, research. Gotta do your homework.*"

Beyond caution, and building upon participants' discussion of AI harms in Section 6.1.2, some participants also expressed reluctance and flat out refusal to engage with health AI. For example, P6 (Workshop 2) indicated he is *"not going all in just yet"* and P1 (Workshop 2) said he would not want AI to be used if he had surgery, stating he would want to *"just do it the regular way"*. P5 (Workshop 2) also conveyed the limits of her use of AI, stating her openness to using chatbots for writing support, but not in other contexts: *"Am I relying on it for emotional support? Absolutely not!"* These examples further map the spectrum of attitudes held by our participants towards AI.

A Community Outlook. Just as we saw participants encouraged by others' openness to health AI in Section 6.1.1, some participants were encouraged to see (through our survey data) that others in the community were being cautious and considering *"the potential risks when using AI"* (P15, Workshop 2). Furthermore, sometimes *not* seeing that caution reflected in the survey data led to concerns. For example, P3 and P14 (Workshop 2) expressed concerns with the survey results, with P3 stating: *"technology that's in infancy...I'm just thinking about, you know, everything that could go wrong. And to me it's a little concerning as to, you know, how much blind faith there is into the all of this."* These concerns were rooted in the view that AI has not yet reached a level of maturity to warrant the faith that the survey data suggests many participants have in the technology.

6.2.3 Health AI Skepticism. Beyond the need for caution, some participants expressed doubt and disbelief that AI has the capabilities necessary to truly support well-being. For example, P8 (Workshop 1) questioned AI's ability to carry out the automatic pain detection reflected in the video we showed during the workshop, stating, *"Oh, I don't think that's great technology. I think they need to go back into the laboratory on that one...[it] may not be able to see the pain."*

Participants' questioning of AI's abilities primarily focused on its use in mental health contexts. P13 (Workshop 1) described the limitations of mental health chatbots that rely on textual interactions between the AI and the person: *"There's so much nuance that's missing... It's providing you data based on the text that you're prompting. Not necessarily the inflections in your voice or–because that really tells you, it kind of gives you insight into what's really going on with the person."* Building upon P13's critiques, P1 (Workshop 1) also felt that this technology would fail to help him when he is in significant distress: *"I go to therapy. I take medication...when I'm in that kind of serious need, I, I'm gonna be honest with you, the people around me don't really help. So to think about something on my phone- that's not, that's not enough help for me."* P1's quote together with the other findings in this section show that our participants' AI attitudes were not simply shaped by their preferences, but more fundamentally, *by what they believed AI has the capacity to do.*

6.2.4 Over-reliance on Health AI. Lastly, as participants conveyed shortcomings, some described how relying on AI to address health issues was unwarranted and problematic. For example, P1 (Workshop 2) discussed how, while he can appreciate "the vision" of using AI in health, he questioned, *"is it realistic right now to completely depend on the, you know, AI system?"* P11 (Workshop 2) conveyed similar concerns fearing that people may stop relying on their own ability to assess their well-being or where they *"get to the point where [AI]'s all they rely on"* and they *"don't even want to go see a doctor."* P11 further felt that over-reliance on AI poses a threat, as she felt generative AI may not be giving people the truth but rather, *"chat GP[T] is like...just telling you what you want to hear. And people might just, you know, overuse it or rely on it too much."* This quote emphasizes P11's concern that if AI starts catering to what people want to hear, people may be motivated to keep using the technology even if it is providing information that may be detrimental to their health. In sum, these over-reliance concerns are rooted in participants' concern about AI's maturity and the consequences of turning over one's healthcare to technology.

Our findings regarding participants' critical assessments of health AI provide context for the spectrum of AI perspectives shared in Section 6.1. In particular, they demonstrate how the dangers that many participants felt health AI presents are partially rooted in feelings of caution, skepticism towards AI's capabilities, the critical questioning of AI that participants were engaged in, and their concerns around over-reliance on the technology.

6.3 Structural Concerns for Black Adults' Well-Being

We now turn to a discussion of how our participants' health AI perspectives were shaped by their views on the ways that structural factors–healthcare systems, racism and bias, and stigma–have created barriers to well-being in the Black community, and the opportunities and limits of AI for addressing those factors.

6.3.1 Healthcare System Failures. Our participants described various ways that the healthcare system has failed them, their families, and the Black community.

Ineffective Care. Several participants (P4, P5, 12, P14, P16) discussed personal experiences receiving ineffective care. As P14 highlighted:

> "I had to have an ambulance to pick me up. But the doctors and stuff were like, are you faking this or like...you should stand up... I'm like, I can't even move my leg... I had to wait for the doctors to go do an X-ray, do an MRI, see that [the disc in my back] was popped,

> and then they came in there with a different tune. And like, 'oh, well the the pain medicine [is coming], sir. Really sorry'... it [took] like four hours... for me to have like pain medicine." -P14, Workshop 1

P4 (Workshop 1) also expressed how she received insufficient pain medication when having her wisdom teeth extracted, saying, *"I was like literally wincing in pain at home. Like, dude, I need something."* Both P4 and P14 had to endure physical suffering while they waited for healthcare providers to believe their need.

To feel like a doctor disbelieves your pain is dehumanizing, and some participants further expressed frustration with what they felt was a lack of humanity from providers who fail to spend sufficient time with them (P5, P12). P5 (Workshop 1) said that when in the hospital, *"you are just another body in the bed and [doctors are] trying to diagnose you, treat you... because the next body needs to come."* P5 feeling like "just another body" highlights how a lack of provider care reduces one to feel like they have been stripped of their person-hood. Indeed, these frustrations echo research showing Black patients are less likely than White patients to feel the doctor has spent sufficient time with them [18].

Access Barriers. Participants also described fundamental concerns about healthcare access, particularly mental healthcare. For example, P10 described not having health insurance as a barrier to using AI-enabled mental health tools, given that she felt such tools should be used together with therapy. Her concern is a reminder that even as consumer health AI tools are introduced, their efficacy may be hindered if people lack financial resources to seek complimentary care from a health provider. P5 (Workshop 1) further described the challenge of healthcare access, conveying how she felt specialized mental health and substance abuse resources were less accessible for Black communities than other groups: *"A lot of different other races, I'll just say that, they go to treatment centers and facilities and I'm like where is these facilities for us?... it's very rare you see African Americans, you know, afforded that type of luxury."* P5's comments speak to well-documented inequity of Black populations having less access to vital health services than other groups [124].

Medical Mistrust. As a result of these healthcare failures, some participants expressed feelings of medical distrust. For example, when reflecting on the survey finding that 61% of participants were most concerned that healthcare providers will move too fast in using AI (Appendix B Figure 3), P5 (Workshop 2) concluded she and her fellow participants were *"all on the same page"* in terms of having a *"distrust with health care providers"*, something she described as concerning. P5 further conveyed her limited trust of the healthcare system when considering the use of AI to automatically detect pain, saying even *"if [the AI] did what it needed to do by identifying the pain, I still have to rely on the medical staff to do their part. And that makes me a little shaky."* P10 (Workshop 1) further described the issues of medical mistrust amongst Black individuals, and the implications for an AI-assisted mental health tool such as a chatbot: *"Trust is a large issue in the Black community when it comes to healthcare. I know most people my age... they're not gonna trust an app on their phone. They're gonna say, oh maybe my therapist is reading this or maybe...I'm gonna be locked up."* These findings echo prior work reporting medical distrust in the Black community intersects with their perspectives on health AI [66]. We also go further, to highlight how for some, it is not simply that healthcare mistrust transfers to mistrust of the AI, but that the AI is distrusted *precisely because* they recognize that they would have to still trust healthcare providers to use the AI in a way that is fair.

6.3.2 Racism & Bias. Our participants described in detail the medical bias that negatively impacts Black communities. They spoke to the legacy of Black communities experiencing racism (P13), the present day persistence of racism and health inequities in Black communities (P11), how such inequities are rooted in unequal access to resources (P11), how *"bias against people of color... is passed down"* from generation to generation (P1), and how bias appears in healthcare scenarios like pain medication prescribing. For example, P8 (Workshop 1) discussed how doctors are *"more likely to give a white female painkillers rather than give it to a Black person."* She discussed how this inequity occurs due to unconscious bias that causes doctors to see her and think: *"[She's] a black lady. [She's] probably a drug addict... They're unconsciously thinking that... And so they're gonna be more likely to give the white, my white counterpart... the pain medication."* Indeed, prior work has demonstrated that doctors do not treat pain equitably across racial groups, with Black patients less likely to get the pain medications they need [64, 110].

Building on these discussions of persistent racial bias against Black communities, P13 (Workshop 2) described how he felt that the Black community, *"we're more willing to trust a faceless, nameless, you know, system than to trust [White providers], you know, I mean, because we know the history of, you know, that demographic of people, right?"* P13 speaks to the history of harm that Black communities have experienced in the United States (including the robbery of freedoms, wealth, resources, and opportunity by a White-dominated society), harms that persist to create poorer health outcomes for Black populations today [4, 60, 124]. In P13's view, these injustices position many in the Black community to trust AI more than they would a doctor. P12 (Workshop 1) echoed these sentiments, indicating that given the state of race relations in the United States, Black communities can feel like *"I just come out better by, you know, going the AI route or... at least having something to check the doc."*

6.3.3 Mental Health Stigma. Lastly, echoing research documenting the role of stigma in mental health inequities [22, 121], several participants spoke to mental health stigma as a structural barrier to well-being in Black communities. In a mental health context, stigma refers to the "stereotypes, prejudice, and discrimination that accompany being labeled 'mentally ill'" [107]. Researchers have described the disproportionate prevalence of mental health stigma in Black communities [22], and the negative impacts of stigma, such as those who are diagnosed with a mental illness being ostracized and alienated by their social networks [107]. Furthermore, research shows that when people believe that a) they are likely to receive a mental health diagnosis and that b) they will be discriminated against because of that diagnosis, they are less likely to pursue professional mental health support [96]. The prevalence and consequences of stigma in Black communities begins to convey why our participants felt that mental health is *"just not really talked about...we just got kind of power our way through it"* (P5, Workshop 1). Indeed, researchers have discussed how one barrier to mental health help-seeking in Black communities is the normative belief that one must project an image of strength, concealing struggles with mental health challenges [107]. In line with this prior work, our participants discussed how, in their communities,*"people are not prioritizing it for themselves or the whole community"* (P7, Workshop 2) and that *"there's a lot of stigma in Black communities"* around mental health (P15, Workshop 1), such as the perpetuation of the myth that *"it's not even [a] real"* issue. P1 (Workshop 1) conveyed how, because of stigma, *"we can't always in the Black community go to people to ask for help."*

In summary, many participants expressed concerns about structural health barriers in Black communities, echoing our survey finding that 100% of participants felt that "our society needs to do more to make sure that everyone has a fair and just opportunity to be healthy" (Section 5).

6.4 Will AI Ameliorate or Perpetuate Structural Threats to Health and Well-Being?

Each of the issues discussed in the previous section–healthcare system failures, racism, bias, and stigma–create barriers to well-being (barriers disproportionately experienced in Black communities [71]), that AI has the opportunity to dismantle, perpetuate, or worsen. Our participants shared their perspectives on each of these possible outcomes.

6.4.1 AI Rectifying Harms. Several participants described ways that AI can not only support health broadly, but also specifically address factors that contribute to health inequities in Black communities.

The first opportunity that our participants saw for AI was in countering access-related health inequities. Addressing the fact that Black communities experience less access to healthcare than other racial groups [124], and building upon the AI optimism discussed in Section 6.1.1, participants discussed how AI opens up opportunities for greater access to healthcare and health resources (P5, P7, P11, P12). Some participants expressed their visions for AI being able to support greater access to health information, including localized information about *"resources in your area that you can follow up with"* (P7, Workshop 1). P6 (Workshop 1) described mental health chatbots as being a useful bridge to therapeutic care, because it could provide a *"safe space in between the sessions, where you might not be able to reach your chosen professional, but you can at least get some thoughts off of your mind."* P6's quote speaks to the value AI could provide in filling gaps in care in between healthcare visits, enabling more continuous support.

Second, participants expressed ways that AI can help to counter the medical bias that disproportionately harms Black communities (P1, P12, P13, P16) [59, 71, 106, 123], and how AI can garner more trust than healthcare providers (P5, P6, P12). These participants felt that AI lacks the biases of healthcare providers and thus could be used to counter medical discrimination. For example, P13 (Workshop 2) discussed how AI benefits from being *"race-less, no ethnicity, right? So it's able to somehow come in and bypass all of those, you know, pre-perceived notions about bias."* P1 (Workshop 2) expanded upon this idea of AI being without bias to say why he felt that AI would treat him fairly: *"I think that when you're dealing with AI, it's a system... it's not a person. So it's not gonna naturally discriminate against me. I have better chances with, you know, AI than I would if I went to a white doctor."* While research has pointed to racial biases existing in health AI [49, 76] and we discussed such biases in the workshops, P1 felt that he was more likely to receive just treatment from AI than a white doctor, given the significant racial bias against Black Americans that exists in healthcare. Upon seeing in our survey findings that most participants (61%) felt that "the use of AI in health and medicine to do things like diagnose disease and recommend treatments would lead to" better outcomes, P12 (Workshop 2), described feeling encouraged by AI's potential for mitigating racial bias for Black patients, saying that AI could help address: *"whatever the stigma is or whatever they're [the doctors] doing wrong...this shows an alternate form of, of, you know, having a fair chance of getting diagnosed properly."*

P12 expressed that AI could help introduce fairness into the currently unjust healthcare experience for Black individuals. While acknowledging that there was still a risk with using AI, he indicated that *"you wanna take better risk than others."* Relatedly, P5 (Workshop 1) expressed: *"If the AI also went back and you know, did a follow up like, hey, did this person receive what they needed?...Then maybe it may be a little bit better for me. Like if I knew it was something checking to make sure that that individual did what they were supposed to do."* P5 raised this potential of using AI to check the decisions made by doctors, providing a kind of second opinion, as a way to boost her comfort with healthcare. P12 (Workshop 1) further described how AI could enable tools that help minimize the barriers Black communities face to receiving effective care: *"As far as Black, Black people wanting to just check on even, even the little minor mental health or whatever...just something that helps them know that I get a fair shake and you know, I won't be judged or I won't be punished... that's why this could be beneficial."* P12 brings light to the various fears that can arise in a medical context for Black communities who face disproportionately poor treatment–concerns around being judged, not being treated fairly, or even punished–and the potential for AI to reduce the chances of receiving poor treatment.

Lastly, some participants felt that AI could help combat mental health stigma. For example, P1 (Workshop 1) stated it would be helpful to have *"something like AI or something that can... make that barrier a little easier to then want to go get help."* Echoing P1's proposition that AI might help ease access to mental healthcare, P13 (Workshop 1, Group 1) described how using AI-assisted mental health tools could help with *"removing stigma, which would then hopefully kind of do a soft introduction to actually getting help, speaking to someone, you know, in person."* While P13 opens his statement with the framing of AI "removing stigma", his explanation in the remainder of his statement speaks more-so to AI helping people *overcome* the barriers to care that stigma introduces. Stigma creates barriers to mental health help-seeking by, for example, leading people to believe there will be negative social consequences if they pursue help and when people experience pressure from others to *not* seek help [107]. Prior work has demonstrated how these stigma-induced barriers inhibit mental health help-seeking in Black communities [107]. As such, P13's comment conveys his belief that AI could make it more comfortable for someone to begin the process of obtaining support (providing a "soft introduction"), by creating a space for help-seeking (i.e., with the chatbot) that is shielded from the social forces of stigma one can experience when pursuing help in traditional healthcare environments. Eliminating public and structural stigma is a complex undertaking that requires significant societal change [109]. Importantly, P13 and P1's perspectives do not convey the perspective that AI can do away with the barrier of mental health stigma itself, but rather a feeling that AI may help people overcome barriers to help-seeking that mental health stigma creates. Given the prevalence of mental health stigma in Black communities [22, 107], their perspectives demonstrate a belief that there may be opportunities for AI to help counter the impacts of a structural force shaping health inequities–stigma.

6.4.2 AI Perpetuating & Worsening Health Inequities. While several participants were hopeful that AI could help to address health inequities, others were concerned about its potential to perpetuate or worsen these inequities (P5, P6, P11, P13, P15). In particular, participants described concern over AI perpetuating racial biases. As P11 (Workshop 2) said about AI: *"We need for those things not to be biased because that's what's already happening with face to face interactions. We don't need the machine to feel the same way about us."* P11's quote highlights the ways that Black Americans have to go through their lives navigating how others see them, and the potential for those views to result in discrimination. P11's comment reflects her desire for Black communities to not have to *also* navigate how technology feels about them.

Other participants (P3, P6, P11, P12, P15, P16) further described the threat of health AI embodying racial biases, specifically the biases of those creating the technology. P6 (Workshop 1) explained, *"it's like Black [people's] pain is a myth that even the computers, or the coders, or the people putting it in there, they have that same, like I said, biased thought process. So that's what's going into it."* P11 further conveyed P6's concerns about AI perpetuating racial biases, saying that if AI is used in pain medication prescribing, which it already is [126], there is the threat of it perpetuating racist and debunked beliefs in the myth that Black individuals experience less pain due to having thicker skin [50].

In addition to concerns about AI *embodying* and *perpetuating* racial biases, P5 questioned its ability to *counter* these biases. When considering the video we showed depicting the use of AI-driven facial recognition to automatically detect pain, and to what extent that technology could address racial inequities in pain management, P5 conveyed her doubt:

> "The AI is not giving the person the medicine. So, so it's just like it's the medical staff. So does that stop their bias or is that just identifying oh, they're in pain and it's up to you to figure out what you're gonna do?... And, that's when we're expecting people to be human. But a lot of times they don't act in such a way... that's where I feel like a lot of the trust is gone in the community as we're dealing with, you know, an actual human being, which is sad." -P5, Workshop 1

P5 conveys that while one would expect providers to be human, and act in ways that are morally just, this often does not occur. This quote echoes our earlier discussion of participants feeling that providers fail to express a sense of humanity (Section 6.3.1). P5 conveys how her outlook underscores the unfortunate reality that for many in the Black community, trust in healthcare providers has been eroded.

In summary, each of our participants' concerns around structural health barriers in Black communities, their hopes for AI futures that counter these inequities, and how technology could perpetuate, worsen, or fail to address inequities conveys opportunities and challenges for future health AI research that aims to more effectively advance health equity.

7 Discussion

Despite widespread health inequities in Black populations and parallel widespread integration and study of AI in healthcare contexts [74], research has rarely examined how Black communities feel AI might impact the health of their communities [82, 91]. Creating equitable AI systems requires direct participation in AI visioning (including articulating opportunities and risks) from groups experiencing inequities [10, 28]. Our work takes this approach, addressing the paucity of health AI research with Black communities and going beyond broad public assessments of AI attitudes common in prior work [8, 16, 34, 65, 85, 113]. Specifically, we contribute a qualitative characterization of our sample of Black adults' attitudes towards the use of AI for health and health equity. Our findings convey nuanced factors shaping our participants' perspectives–including their views on structural health barriers and critical reflection on AI's role in health. As a result, we explicate how participants embraced some AI aims currently motivating the field [1], like using AI to increase healthcare access (Sections 6.1.1, 6.4.1), while having mixed views on aims like using AI to counter medical bias (Sections 6.3, 6.4). We conclude with considerations for future equity-focused health AI research.

7.1 Health AI as Armor: A Path towards Health Equity?

Prior work has extensively documented the optimism of researchers, scientists, and clinicians regarding the power of AI to revolutionize healthcare [2, 15, 25, 57, 97, 100]. Increasingly, research has also recognized the importance of examining the public's attitudes towards and comfort with AI being used in their healthcare [61, 97, 113, 116]. This work has documented public trust in AI-assisted health technologies [116] and beliefs in the benefits of AI tools for supporting health (e.g., enabling more accurate and efficient diagnoses and treatment, and healthcare access [61, 72]). Within HCI, research has documented lay people's belief in AI's ability to support their personal health, for example by bootstrapping their health decision making [116] and enabling personal reflection that enhances mental well-being [103].

However, beyond such perspectives, we have little insight into how the public–especially racially marginalized populations–feels AI might help to counter health inequities. And yet, while improving health generally and reducing health inequities specifically are related, they are distinct topics. Gathering communities' views on the potential for AI to combat inequity requires longitudinal qualitative explorations that help participants consider the health inequities that exist, what creates them, AI's power and pitfalls, and their ideas for how AI might be leveraged to combat inequities [82]. By engaging with such qualitative research, our participants were able to describe the potential they saw for AI to go beyond helping them personally achieve well-being to address the broader societal issue of health inequities.

Taken together, our findings conveyed how participants felt AI could serve as a kind of protective armor that helps their communities shield themselves from the pervasive healthcare biases that cause disproportionate harms for Black communities. This idea of AI as a form of protection from existing healthcare is distinct from much of the common visions of health AI, which laud AI values such as accuracy, precision, optimization, efficiency, and cost reduction [2, 25, 122]. In contrast, by framing AI through the lens of protection from healthcare harms, our participants discussed AI as presenting new opportunities for Black communities to access unbiased and nonjudgmental treatment and accurate diagnoses–such as through tools that verify that a patient has received fair and appropriate treatment (P5, P12). Such ideas address the widely-documented pattern of Black communities being more likely than other racial groups in the U.S. to receive ineffective treatment and inaccurate diagnoses and to be disbelieved, disrespected, discriminated against, and unfairly judged by their providers [38]. Future work should further examine how health AI tools can be designed to activate and advance communities' power to protect themselves from healthcare system harms. While the ultimate ideal is a radically transformed healthcare system that is free of bias, such transformations require extensive institutional and societal shifts that take time. We offer that there may be value in exploring ways for AI to offer support alongside efforts to more fundamentally address the equity issues within healthcare institutions.

The values driving much of the health AI visioning to date (e.g., AI as enabling accuracy, efficiency, and precision in medicine [2, 25, 122]) are insufficient for achieving health equity, as prior work has shown that eliminating health disparities requires directly addressing the social and structural determinants of health that create disproportionate barriers to well-being in populations [4, 55]. Recognizing this, a growing body of work has sought to articulate the specific ways that AI can advance health equity [37, 54, 75, 82, 105]. Within HCI, such work is still nascent [82], and thus we lack a full appreciation of the ways in which our field can contribute to human-centered AI research and innovation that advances health equity. As HCI continues to rapidly increase its focus on AI broadly, it will be essential to not only ask the question of how AI can be used as a tool to advance health, but also how it can advance health equity by targeting the underlying, fundamental causes of inequity.

As HCI researchers, there are opportunities to examine how AI-driven tools can be designed to help intervene amidst health injustices (as discussed above), and how it can be used to support the study of and advocacy around health equity issues. For example, prior work has discussed the value of using AI to help scientists study the multifactorial causes of health inequity, given AI's ability to surface correlations in complex datasets that can give better insights into the way that health inequities come to be [40]. While this work did not examine the opportunities for interactive system design, as HCI researchers, we have further opportunity to examine how interactive systems can be created to not only help scientists and clinicians, but also the broader public understand what health inequities exist and why, and how to engage in advocacy efforts that combat them. This work would build upon the rich body of citizen science and civic technology research in HCI and related fields [86, 94], helping extend this work to identify the unique opportunities that AI presents for the study of and advocacy work around health equity issues.

7.2 Confronting the Range of Health AI Harms

And yet, while our participants conveyed some optimism for using AI to advance health equity, they also communicated concerns. As discussed above, our participants surfaced the need to ideate how health AI could mitigate *intended*, *unintended*, and *inevitable* harms. Our findings build upon literature in AI ethics that helps developers and scientists understand the various ways that algorithmic systems can cause harms [5, 89, 98, 102]. This prior work provides frameworks, taxonomies and definitions of harm that offer ways of thinking concretely and systematically about how algorithmic systems can hurt people. Shelby et al. [98], for example, discuss *the types of problems* that AI can cause for people, such as through allocative harms that lead to the loss of resources, information, or opportunities in marginalized groups. Rebera et al. offer another framing of harms, encouraging researchers and developers to acknowledge *hermeneutic* harms–the psychological and emotional hurt people experience as they struggle to make sense of their unexpected and problematic experiences with AI [89].

Our findings build upon this prior work by introducing yet another framing of harm, raised by our participants, that is of particular relevance to health AI systems. Our participants' discussions highlight the importance of examining the *intention* underlying AI harms; they recognized that beyond understanding the technology itself, there is a need to contend with *how the technology is used*–with what intention. Their discussions reflected a delineation of health AI harms as sometimes *intended* (i.e., cases when AI is used maliciously by bad actors to purposely hurt certain populations), other times *unintended* (i.e., AI being taken up with good intentions but still causing harms, for example, through flaws in the technology), and in some ways *inevitable* (dealing with the reality that AI is created by humans, and as humans are flawed, AI is also destined to be flawed). Each type of harm suggests a different remedy.

7.2.1 Intended & Unintended Harms. First, intentional and unintentional health AI harms require legal and technical safeguards to prevent the malicious use of AI to harm populations. The complex legal landscape for assigning liability when health AI causes harm make this an incredibly challenging space to navigate [12]. It is important that, as lay people are engaged to brainstorm health AI futures, they are supported in co-establishing an understanding of the potential legal recourse–and the limits therein–they may have if the designs they envision are created, and then used to intentionally or unintentionally cause harm. Such context is essential for supporting meaningful and informed health AI design thinking. Mitigating both intended and unintended harms further requires engaging and building upon existing toolkits and design processes for mitigating health AI harm that prior work has introduced. While such tools are being increasingly developed [5, 36, 102], resources that emphasize a focus on directly addressing both intended and unintended harms that threaten health equity are sorely needed. It is essential that future work ensures health AI design and implementation toolkits, frameworks, participatory design approaches, and other resources are tailored to consider the particular threats and healthcare harms that marginalized groups already experience and that they are posed to further experience as health AI is intentionally and unintentionally used to cause harm [82].

For example, while our participants expressed some optimism that chatbots could be used to address mental health disparities in Black communities, these tools also stand to cause unintentional harm when they miss key signals of distress, make recommendations that inhibit people from engaging in needed formal mental healthcare-seeking, or provide other ineffective, inappropriate, or harmful responses to those experiencing mental health concerns [19, 26, 70]. Another point of harm would be introduced if the technology attempts to act in a therapeutic role but fails to facilitate the kind of relational interaction needed to build rapport and trust that is essential for effective therapeutic support [19]. Alternatively, chatbots designed for mental health support may create an inappropriate emotional attachment, sense of trust, and reliance [29, 70]. Such impacts could cause new forms of psychosocial harm or demotivate a person with mental illness from seeking out needed human support and care [29].

Indeed, even as our participants conveyed optimism around AI-driven mental health platforms, they also shared concerns around the limitations of such tools. If these tools provide suboptimal or harmful care and become disproportionately relied upon within Black communities while other racial groups continue to have greater access to and utilization of professional care from human providers, then the technology could further worsen disparities. We see this scenario creating a new form of *intervention-generated inequality*, that is, disproportionate harm experienced by a population as a result of a health "innovation" [119]. Veinot et al. [119] detail several ways in which digital health interventions can cause harm to already marginalized populations, such as when the intervention is more heavily used by, or more effective for, socioeconomically advantaged groups.

Considering the harms that mental health AI could introduce, we offer that an additional form of intervention-generated inequality is that caused by what we term *harmful reliance* on AI, where a digital health platform a) *is more heavily used by populations experiencing disparities* than by populations with greater socioeconomic advantage, b) *negatively impacts well-being*, c) is *less effective than traditional healthcare*, and d) *exists within a societal context where traditional healthcare is more accessible to, utilized by, or effective for socioeconomically advantaged populations.* These co-occuring conditions create a scenario in which even a well-intended health AI tool can cause serious unintended harm. Such problematic outcomes must be thoroughly mitigated in digital health design and evaluation.

For example, a key step in the design and evaluation of health AI tools should be critically examining the uptake of these tools across populations. Rather than marginalized groups' high uptake of these technologies being accepted as an unquestioned, default indicator of success, we must critically investigate the implications of this uptake, to what extent the technology is being used to a higher degree in marginalized groups, positive and negative impacts of such use on health outcomes, the broader impact of this uptake on disparities in outcomes between populations, and how populations are differentially impacted when they vary in their overall reliance upon the technology versus traditional healthcare.

7.2.2 Inevitable Harms. Beyond unintended and intended harms, something less contended with in prior work is the idea of inevitable health AI harms–that no steps taken (be they legal, social, or technical) can prevent the threats that AI could present for health equity. If these harms are in fact inevitable, the question must be asked: should the technology be created at all? Further reflection is needed regarding a potential moral imperative to call for limits to be placed on what kind of AI tools get created. Such efforts would build upon human-centered computing research calling for work that establishes when *not* to create technology because it is deemed too problematic [7, 83]. AI tools that are created in a world where health inequities abound and as actors increasingly seek to limit the work done to counter such inequities, it is crucial to weigh the costs of introducing technology that will inevitably cause harm with the potential benefits that technology may also introduce.

As researchers increasingly engage lay populations in ideating health AI futures, it is essential to scaffold participants' considerations of intended, unintended, and inevitable AI harms–what kinds of problems participants foresee in each category, how these harms can serve as a threat to health equity, and potential sociotechnical solutions for mitigating these harms. Future work may explore design ideation around explainable AI and seamful design in AI as opportunities to counter each form of harm by illuminating how the technology works and flaws therein, expanding upon prior work [36, 89, 102, 125]. Such research can help build a comprehensive understanding of the unique affordances of different design approaches for addressing the notion of intentionality underlying health AI harms.

7.3 Attending to Community-Oriented Perspectives on Health AI

One striking finding was the degree to which our participants expressed care for their fellow participants' health AI perspectives (Sections 6.1.1 and 6.2.2). From concern to encouragement over participants' survey responses, we saw our participants' reactions being rooted in a desire for their community to be safeguarded from the potential harms of AI and to be able to reap the benefits of the opportunities AI presents. Our findings regarding the structural barriers to well-being that our participants face provide context for these views, demonstrating the weight of their caution and desire for their communities to be supported and not harmed by AI. These findings show the importance of not only studying marginalized groups' views on how AI can benefit their own health or even that of their loved ones, but also exploring how their attitudes exist in relation to their communities.

Prior work has discussed the importance of *collectivism* in Black communities–how values of interdependence and collective well-being are often highly resonant in Black cultural contexts [81]. Engaging members of the Black community in focus groups to both interrogate and ideate on health AI allows for people to collectively consider design solutions that center their identity and shared values [43] in a way that might lead to directives at the community level and that could be shared as *collective knowledge* at a critical time of addressing AI literacy. Collectivism as seen in community focus groups or other forms of community discussion forums can promote *community resilience* and *agency* [104, 115], as signaled by our participants' ability to critically assess the impact of AI in health. Guiding participants through reflecting on individual participant survey responses helped to facilitate conversation about individual versus collective community impact, which has particular relevance for the progression of equitably integrating AI in health [82]. Our work builds on this prior work regarding what such collectivism might mean in a health AI context, and we encourage future to further examine such opportunities for centering collectivism as a design and methodological orientation for participatory health AI efforts.

7.4 Balancing Community Viewpoints and Critical Scholarship on Health AI

Our findings speak to the optimism, hesitation, and concern that our participants felt regarding the role AI can play in health promotion, and specifically in addressing health disparities in their communities. Much of our participants' critique of AI's limits and also the harms it can cause were rooted in the discussions we scaffolded around AI harms. Following Parker et al.'s strategies for racially equitable participatory AI research [82], we grounded our workshop discussions in activities aimed at supporting co-learning with participants regarding how AI can cause harm.

It is notable that even amidst these discussions of harm, many participants still expressed a positive outlook regarding the beneficial role that AI can play in the wellbeing of their communities. As discussed previously, they conveyed how they felt AI could be used as a form of armor in protecting them from healthcare system harms. This optimism could be critiqued by arguing that participants lacked a full understanding of how AI can and already is causing harm to racially minoritized communities. Additionally, prior research conveys the criticality of considering how political ontologies of race shape the development and use of AI systems [24]. If participants were given further knowledge about the politics and corporate interests that shape decision making regarding the design and use of AI, and other precipitators of harm, then perhaps they would feel less optimistic and would change their minds about how they want to see AI used in health promotion. This critique would underscore how essential Parker et al.'s strategies of co-learning and longitudinal design are in participatory AI efforts [82]. In particular, this critique suggests that future work may need to conduct even longer-term co-design engagements than done in our study, to enable further co-learning about not only the opportunities but also the critical harms that can occur with health AI technology. At the same time, this critique risks invalidating participant perspectives, by prioritizing the viewpoints of scholars over those outside of academic settings.

Indeed, we offer that participants' persistent, yet cautious and nuanced optimism should also be seen as a valid belief and hope that even amidst health AI's shortcomings, there may still be opportunities for this technology to be used in equitable ways [42, 73]. While one might argue that this optimism comes from a lack of understanding current processes of model training or the range and breadth of harms, recent work in critical studies points to *Black optimism* [42] and even *Afro-skepticism* [73] to acknowledge the ways participants may find joyful existence in re-imagining technologies that have historically caused harm. Our analysis presents an entry point for considering health AI and the future of health AI from the perspectives of both possibility and refusal, alluding to critical frameworks such as technoskepticism, which highlight the possibilities that can be generated by technology skepticism [73]. The skepticism and outright rejection mentioned by our participants draw attention to the power of refusal and resistance in shaping innovation and encouraging scientific paradigm shifts [112]. Engaging Black adults in community-oriented conversations of health AI's promise and potential impact created space for a more structured critique of how health AI *should* exist and the current ways AI development and design is exclusionary to marginalized groups such as Black Americans. We can take from participants' discussions not only the concrete design directions that they envisioned but also the underlying hope that these ideas reflect. That is, by expressing optimistic resistance for the future, participants showed that they are not rejecting the idea of AI in their communities outright, but instead are maintaining hope that such tools can be used for good.

Interpretivist epistemologies have long argued that individuals' perspectives are inherently subjective and that they are valuable to understand precisely because of that subjectivity–their viewpoints help us understand how a person's context, experiences, and values shape how they interpret, think about, and act in the world [9, 87]. We use qualitative methodologies because we want to understand this sensemaking and action [9], and thus even when participants' perspectives stand in tension with critical scholarship, we must treat them as empirically valid and valuable data for helping us produce an emic understanding of the populations studied. The question then for HCI–a field interested interested in not only studying human phenomena, but also determining how to act on those understandings through the design of (and decisions not to design) new technologies–is: *considered in concert, what does the measured optimism of our participants and the increasing literature documenting AI harms in Black communities imply for how we should move forward?* Should we discount participant optimism given the critical studies literature? Should we prioritize participants' optimism over the critical scholarship, using it to motivate continued research that creates AI that addresses health disparities? We argue for a more nuanced approach.

Specifically, even as participants express their thoughts on health AI and the role it can play in their community, just as with speculative design efforts, we can take these participant ideas not *only* as concrete products to build. Rather, we can also treat participants' ideas as reflective of the futures they want to see realized. A participant conveying that they see opportunities for AI chatbots to support mental health in Black communities conveys not simply that they want to see a particular kind of chatbot built, but more fundamentally a desire to see mental health AI addressing disparities in Black communities. The futures that participants convey thus establish guiding endpoints, values, and measures of success for researchers, practitioners, designers, policymakers, and other AI stakeholders–the ideals that they should pursue and use to determine if their work is on the right track and serving the interests and priorities of those who the technology is meant to impact. It is our role as HCI scholars and designers to bring together lay perspectives and critical scholarship to generate recommendations for paths forward that give thorough consideration to both sources of knowledge, making sure to honor, and not devalue, lay perspectives.

7.5 Limitations and Future Work

While our study provides previously-unavailable, deep, qualitative data on Black adults' perspectives on AI within health and health equity contexts and in relation to their communities, it is not without limitations. Notably, our research was conducted with a racial community–Black adults–from a single metropolitan area within the Southeastern United States, and thus, was designed to provide contextual generalizability. Our participant pool differs from the national population in several ways: skewing younger than average, with a significant proportion identifying as queer, lesbian, gay, or bisexual (33%), and 22% having significant experience working in health care.

We sampled and recruited participants to reflect the diverse community population that our participants came from, which includes varied intersectional identities and perspectives. There is a possibility that our participants with healthcare experience had a greater ability to understand the potential opportunities and limitations of health AI. We intentionally sampled for participants with and without healthcare experience to explore a range of outlooks from varying levels of expertise. While we also sought to ensure diverse representation in our sample across social identities such as sexual orientation (reflecting the makeup of the city in which the study was conducted), our current analysis does not speak to the ways in which the intersection of racial, sexual orientation, and other identities shapes health AI attitudes. This is an important line of inquiry for future work.

Additionally, our survey data was designed to inform focus group topics, by showing aggregate survey results directly to participants *during* a workshop, which fostered a more concrete and pointed discussion among participants. Our study's sample size and location within a particular geographical location, while appropriate for our research aims [45, 48, 80], also precludes us from providing statistically generalizable findings regarding the perspectives of Black adults across the United States. Further research is needed in order to examine statistically generalizable data comparing attitudinal measures amongst various communities and populations. Additionally, further community-engaged research is needed to gather qualitative insights regarding the perspectives of Black adults from community contexts beyond those studied in our research.

Finally, while we believe our research can serve as a model for how participatory, community-engaged health AI research can occur within an industry setting, additional research may support our findings being applied to improve health AI models and systems. Partnerships between community-based organizations, healthcare organizations, academic institutions, and technology companies will be essential to continue this work and ensure the translational application of research. These partnerships can enable a pipeline that enables community priorities to shape health AI design priorities, development practices, and product creation in companies, and the use and evaluation of these technologies in health contexts.

However, such partnerships can be incredibly complex and difficult to navigate. For example, Erete et al. [33] detail challenges that can arise in design collaborations between nonprofit organizations and businesses, such as the delicate process of negotiating the non-disclosure agreements that technology companies typically require their partners to enter into, when those agreements stand in tension with the nonprofit organizations' values. Introducing healthcare organizations into a design partnership brings even greater complexity, for example, as additional legal and regulatory constraints may further complicate collaboration and the additional values and priorities of these organizations may stand in further tension with those of community members and technology companies.

And yet, given the concentration of AI model development in technology companies and the notoriously black-box nature of these models, the rapid integration of AI into healthcare contexts, and the essential perspectives that community members have to offer for the equitable design and use of AI, these stakeholder groups must be in direct conversation with one another to translate findings, such as those presented in this paper, into practical shifts in how health AI is created and used. Despite the constraints and tensions that can arise in multi-stakeholder efforts, these collaborations are vital to ensure that community perspectives drive improvements in the AI foundation models used by billions of people each day and the health systems that leverage these models. A starting point for such work is emergent research offering up reflective practices for design collaborations between technology companies and community-based organizations [33]. This research details questions that stakeholders in industry-community collaborations can reflect upon, such as the power dynamics at play in their collaboration, to enable more equitable partnerships. More research is needed that builds upon this prior work to articulate strategies for successful industry-community-academic-healthcare partnerships in AI design contexts, where there are specific inequities and structural barriers to well-being that need to be mitigated.

8 Conclusion

Racial health inequities are pervasive and persistent–they require concerted effort to dismantle. With AI rapidly transforming healthcare, we must deliberately investigate how the technology can be used to close gaps in health outcomes and ways it may stand to exacerbate them. It is essential that the voices of the racially minoritized drive such investigations. The findings in this paper represent a crucial step forward. Much more work is needed to examine the multifaceted, diverse perspectives on health AI held within Black communities and in other marginalized groups–and to use those learnings to guide future health AI innovation, use, and decision making.

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A Participant Details

Table 1: Participant demographics

PID	Age	Gender	Occupation Industry	How much have you heard or read about artificial intelligence (AI)?
1	35–44	Man	Health care and social assistance	A moderate amount
2	55–64	Woman	Banking, finance, accounting, real estate or insurance	A lot
3	18–24	Man	Transportation	A little
4	18–24	Woman	Retail and trade	A moderate amount
5	35–44	Woman	Banking, finance, accounting, real estate or insurance	A lot
6	35–44	Man	Health care and social assistance	A moderate amount
7	35–44	Man	Information/Technology	A lot
8	45–54	Woman	Property management	A lot
9	18–24	Woman	Banking, finance, accounting, real estate or insurance	A moderate amount
10	18–24	Woman	Health care and social assistance	A moderate amount
11	35–44	Woman	Not working	A little
12	35–44	Man	Transportation	A lot
13	35–44	Man	Health care and social assistance	A lot
14	35–44	Man	Hospitality, service, arts, entertainment and recreation	A lot
15	18–24	Woman	Not working	A moderate amount
16	25–34	Man	Hospitality, service, arts, entertainment and recreation	A moderate amount
17	18–24	Woman	Media/Communications	A moderate amount
18	25–34	Man	Media/Communications	A lot

B Detailed Survey Results

B.1 Section 5.1 Details: Overall Use of AI in Health

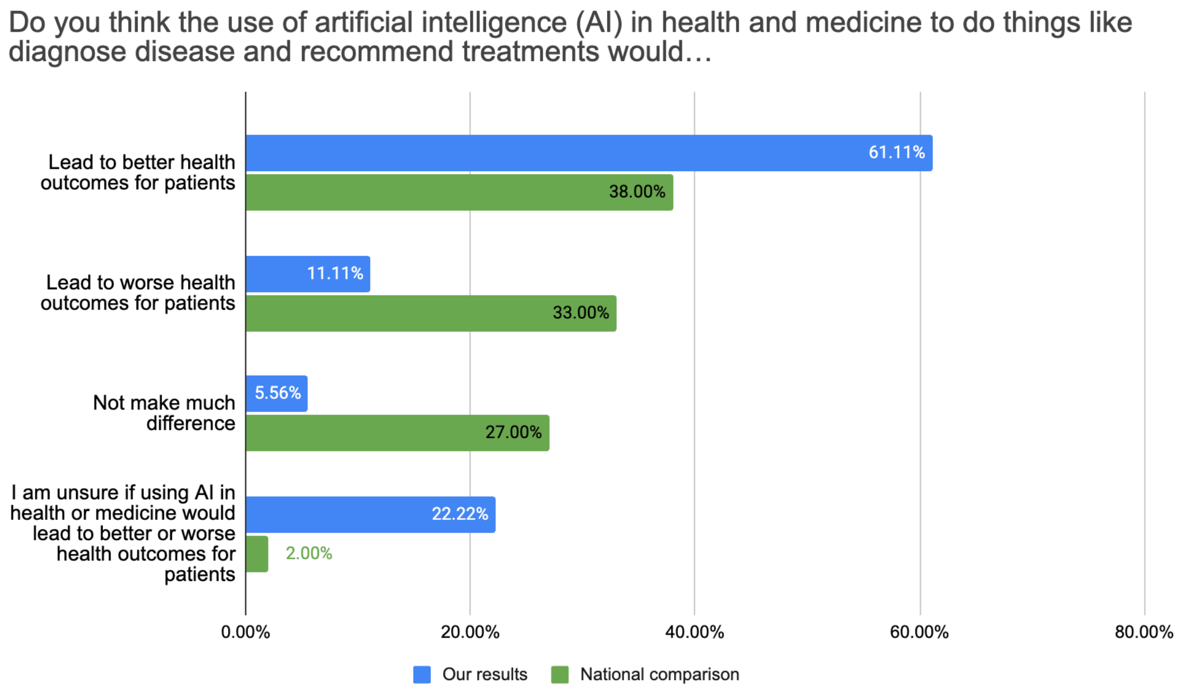

Figure 2: Black study participants' perspectives on AIs potential to improve or worsen health outcomes, shown alongside results from a 2022 national survey [113].

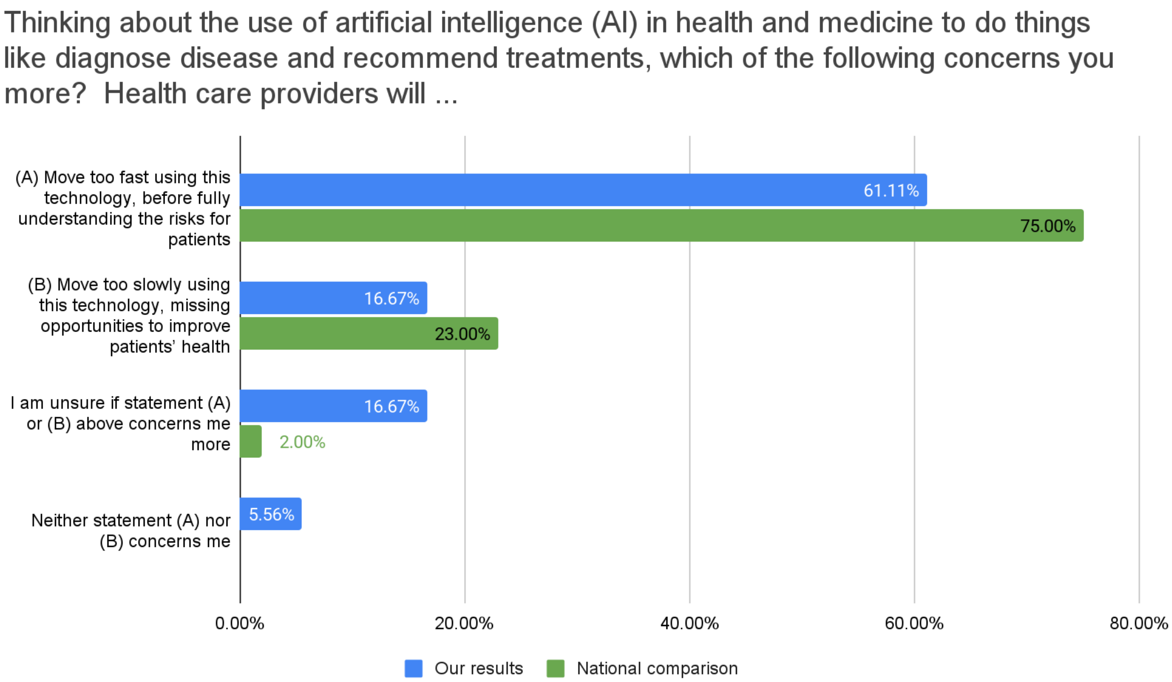

Figure 3: Black study participants' perspectives about AI moving too fast or too slow, shown alongside results from a 2022 national survey [113].

B.2 Section 5.2 Details: Bias and Equity in Health and Medicine

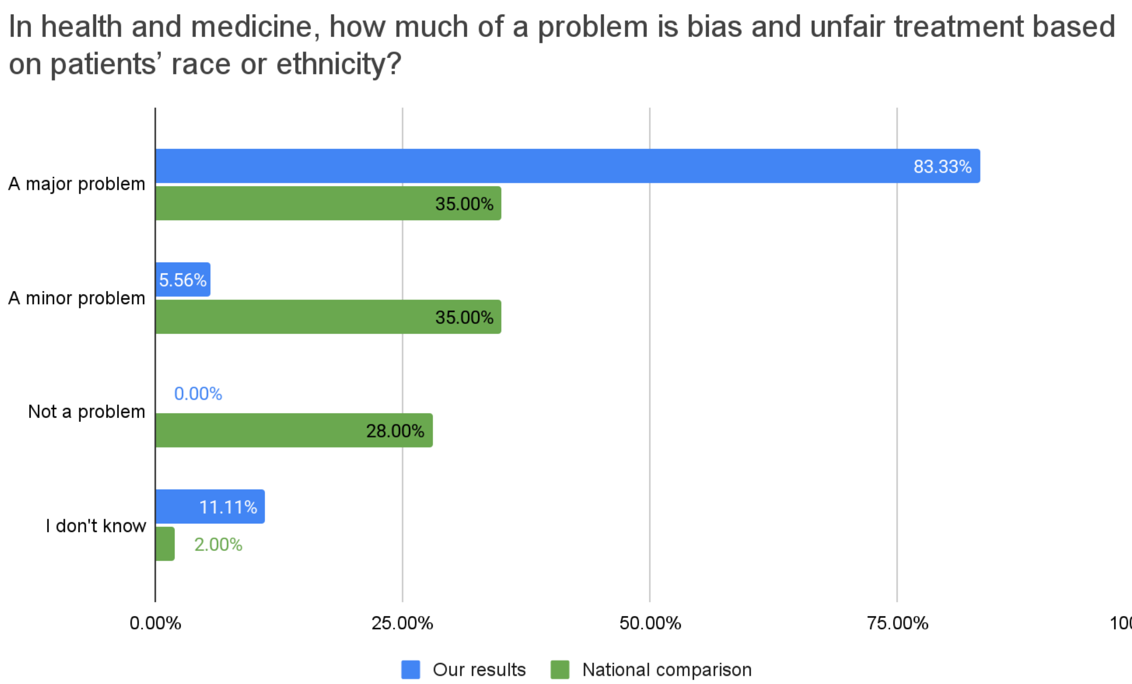

Figure 4: Black study participants' perspectives on how much bias and unfair treatment based on patients' race or ethnicity is a problem in health and medicine, shown alongside results from a 2022 national survey [113].

Table 2: Black study participants' perspectives on whether or not it would be unfair if some people had more of an opportunity to be healthy than other people. Results are shown alongside data from a 2018 national survey [111], which reports data on the percent of respondents endorsing highest response category.

Please state how much you agree or disagree with the following statement. It would be unfair if some people had more of an opportunity to be healthy than other people.	Results		National comparison
	N	%	%
Strongly agree	16	88.89%	31.30%
Somewhat agree	1	5.56%	
Neither agree nor disagree	0	0.00%	
Somewhat disagree	1	5.56%	
Strongly disagree	0	0.00%	

Table 3: Black study participants' perspectives on whether or not society needs to do more to make sure that everyone has a fair and just opportunity to be healthy. Results are shown alongside data from a 2018 national survey [111], which reports data on the percent of respondents endorsing highest response category.

Please state how much you agree or disagree with the following statement. Our society needs to do more to make sure that everyone has a fair and just opportunity to be healthy.

	Results		National comparison
	N	%	%
Strongly agree	18	100%	40.8%
Somewhat agree	0	0.00%	
Neither agree nor disagree	0	0.00%	
Somewhat disagree	0	0.00%	
Strongly disagree	0	0.00%	

B.3 Section 5.3 Details: AI's Role in Bias and Equity in Health and Medicine

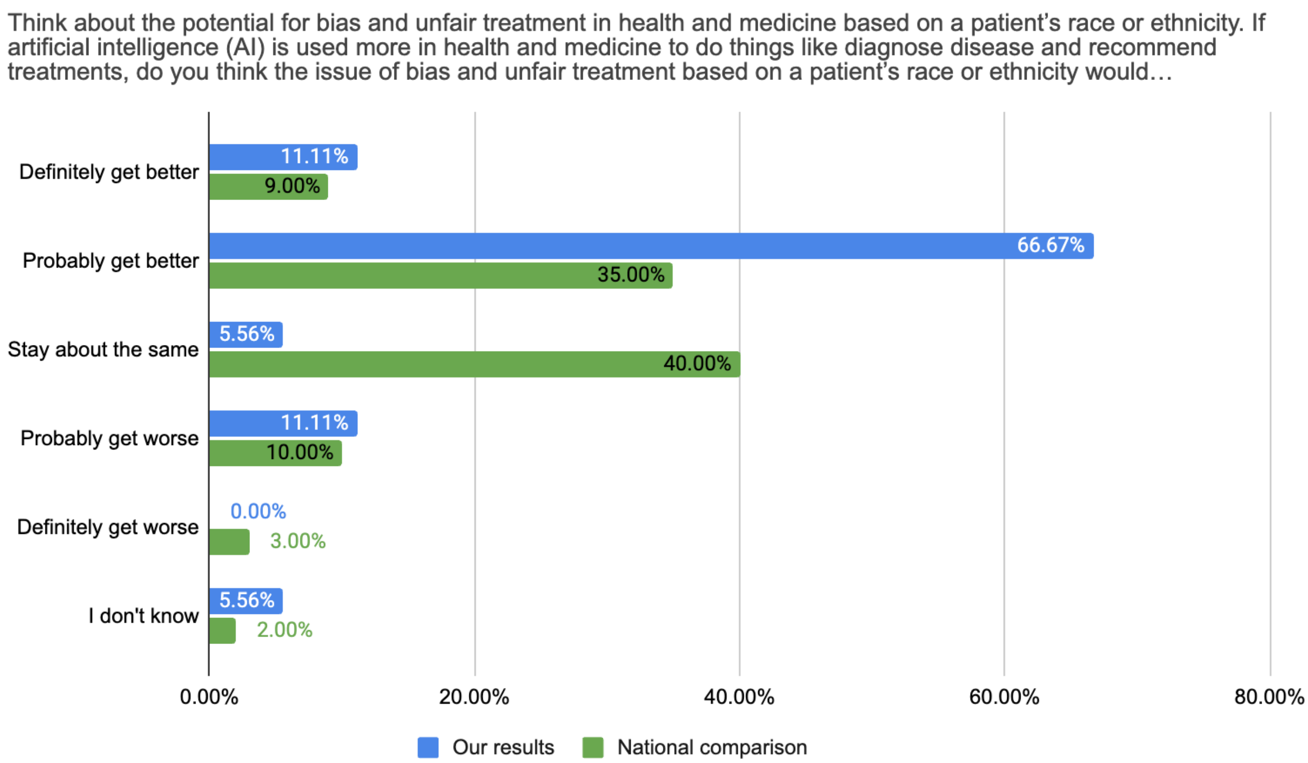

Figure 5: Black study participants' perspectives on whether the issue of bias and unfair treatment based on a patient's race or ethnicity would get better or worse with AI, shown alongside results from a 2022 national survey [113].

B.4 Section 5.4 Details: Perspectives on AI's Use within Different Domains of Health and Medicine

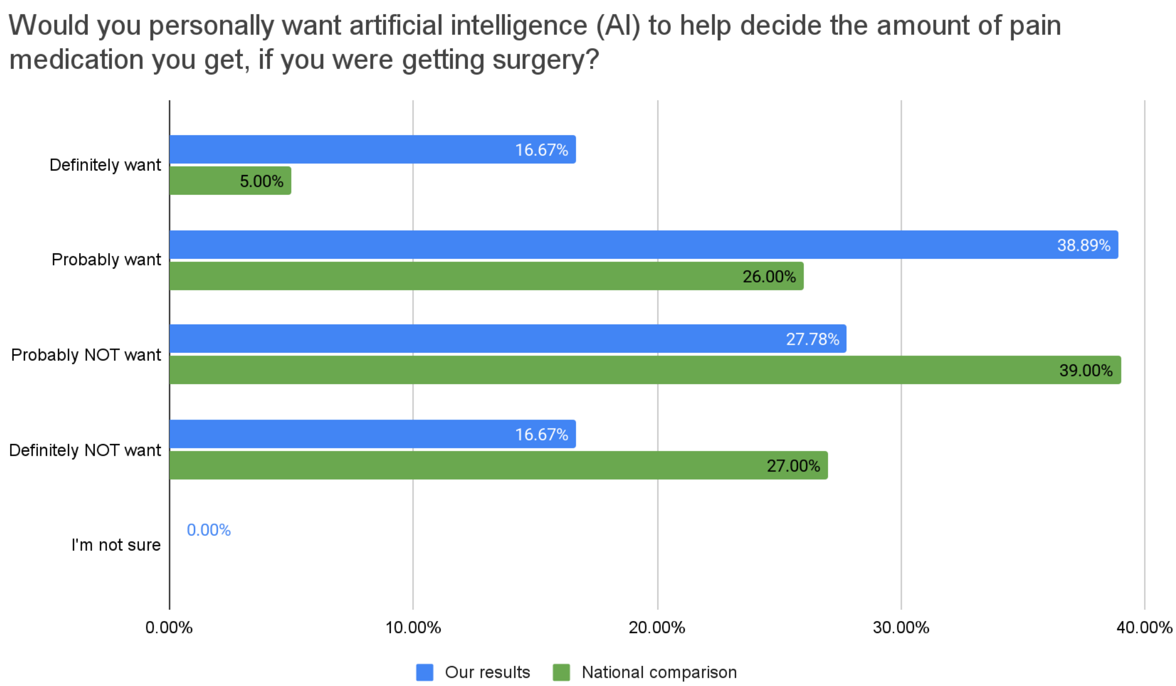

Figure 6: Black study participants' personal desires for AI used to determine pain medication amounts, shown alongside results from a 2022 national survey [113].

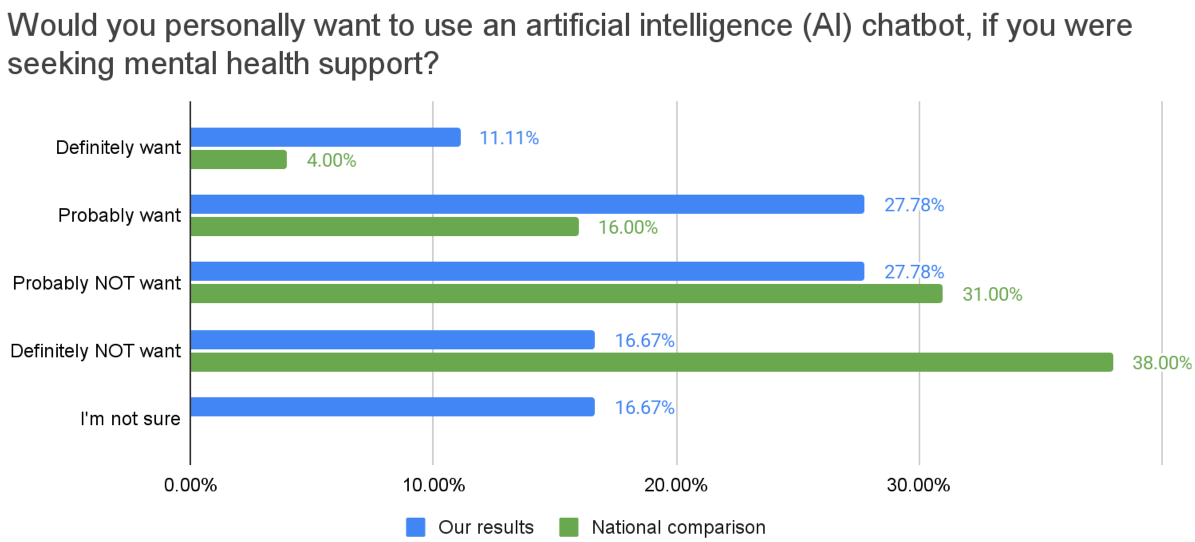

Figure 7: Black study participants' personal desires for AI used in chatbots for mental health support, shown alongside results from a 2022 national survey [113].

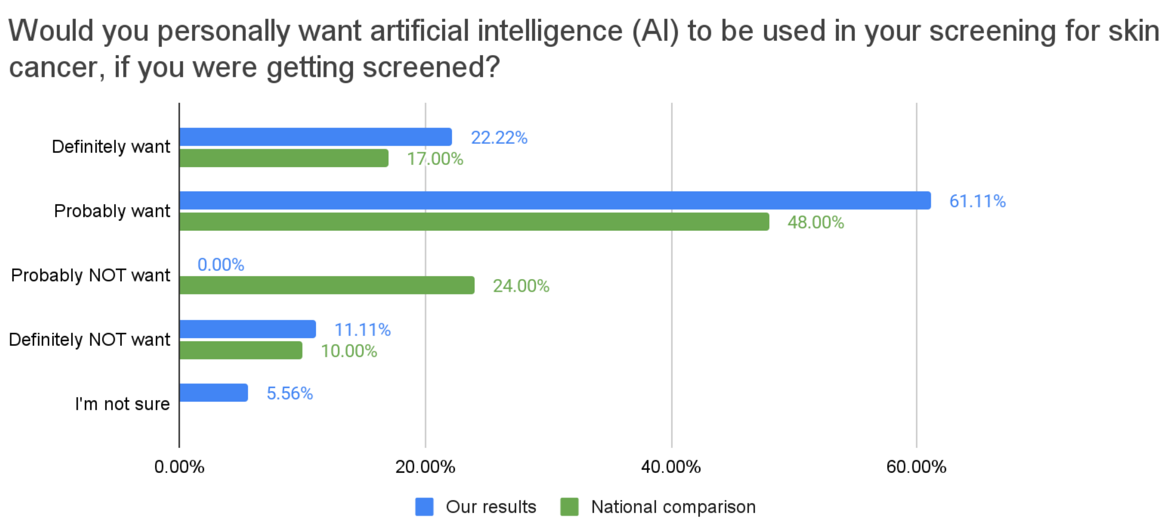

Figure 8: Black study participants' personal desires for AI used in screening for skin cancer, shown alongside results from a 2022 national survey [113].

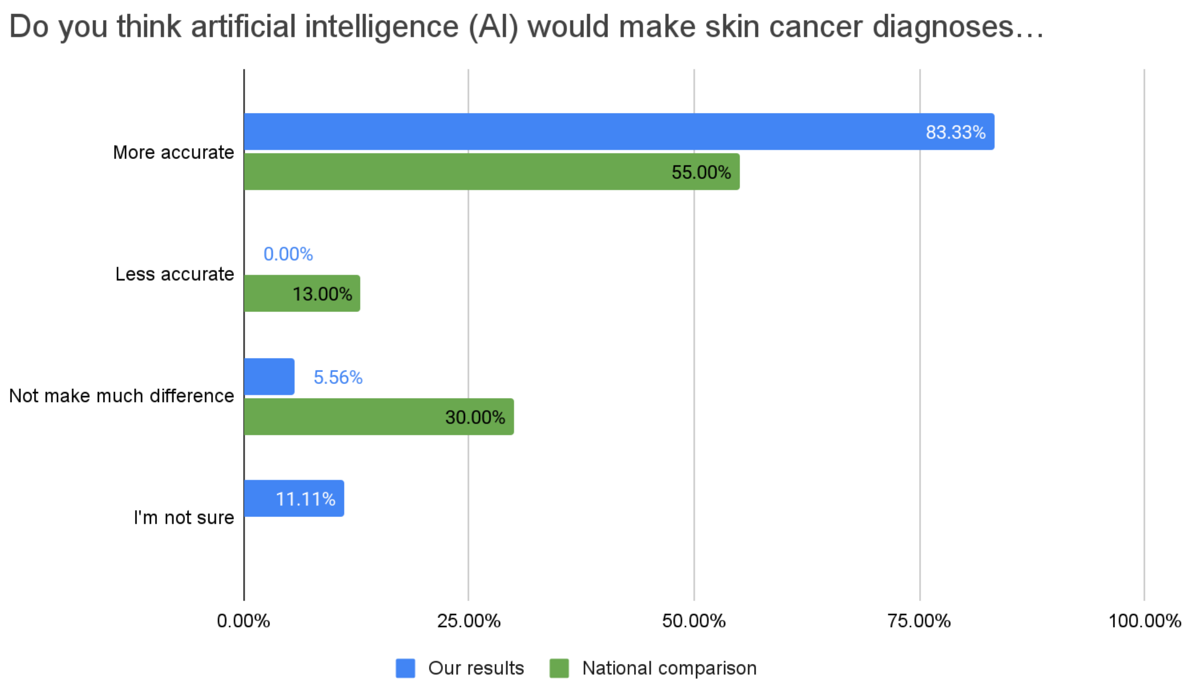

Figure 9: Black study participants' perspectives on whether AI will make skin cancer screening more or less accurate, shown alongside results from a 2022 national survey [113].