Designing Chatbots with Black Americans with Chronic Conditions: Overcoming Challenges against COVID-19

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ABSTRACT

Recently, chatbots have been deployed in health care in various ways such as providing educational information, and monitoring and triaging symptoms. However, they can be ineffective when they are designed without a careful consideration of the cultural context of the users, especially for marginalized groups. Chatbots designed without cultural understanding may result in loss of trust and disengagement of the user. In this paper, through an interview study, we attempt to understand how chatbots can be better designed for Black American communities within the context of COVID-19. Along with the interviews, we performed design activities with 18 Black Americans that allowed them to envision and design their own chatbot to address their needs and challenges during the pandemic. We report our findings on our participants' needs for chatbots' roles and features, and their challenges in using chatbots. We then present design implications for future chatbot design for the Black American population.

CCS CONCEPTS

• **Human-centered computing → HCI design and evaluation methods**; • **Social and professional topics** → *Race and ethnicity*.

KEYWORDS

Black American community, chronic condition, chatbot, COVID-19, participatory design

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1 INTRODUCTION

Chatbots, text-based, computer-generated animated or embodied characters that utilize conversational interfaces to interact with humans [18], are widely deployed throughout different healthcare sectors. For example, they can be found in mental health smartphone applications (e.g. Woebot [117], Replika [88]), which educate patients about healthy behaviors [13, 36] and health literacy [71], diagnose physical or mental illnesses [57, 84, 121], and deliver interventions for chronic conditions or mental disorders [10, 32, 55, 90]. In many cases, chatbots have proved useful and generated high satisfaction and acceptance from patient users [103, 112] because of their ease of use [6, 58], user-friendliness [16] and presentation of instant information [16, 64].

Despite the benefits of chatbots, they can be problematic when their design does not consider the cultural context of a particular population [86], which can lead specific populations to engage less with the chatbot out of a lack of trust and rapport [72]. This issue can exacerbate healthcare inequality when chatbots are utilized as a low-cost alternative to delivering healthcare [1]. The importance of understanding the cultural context is especially salient for marginalized populations, who prefer healthcare providers that share similar cultural backgrounds [22]. As potential healthcare providers, chatbots must therefore also understand and contextualize the user's culture in order to generate trust and rapport for higher engagement.

Such culturally informed health technologies can also address the digital divide often seen among marginalized populations [49]. Understanding culturally perpetuated behaviors and needs allows the designed technology to be useful for a range of individuals within the culture [43]. For instance, Grimes and Grinter [43] pointed out how a smartphone game called OrderUp! can be effective for the Black American population because of how it embeds the idea of community into the game design, which is considered important for the population's culture. Other technology design examples have also demonstrated how comprehending the cultural context of marginalized populations has resulted in positive outcomes in terms of delivering practical health information [52, 79]. However, these technologies have been limited to mobile health technology, without being extended to chatbots.

To help address this lack of cultural context in the chatbot design, we examined how chatbots can be designed specifically for the Black American population. In particular, we focused on Black Americans with chronic conditions against the backdrop of COVID-19. Black Americans are disproportionately affected by COVID-19 compared to other ethnicities in the United States [89] as a result of socioeconomic factors: education [4], healthcare literacy [11],

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poor housing conditions [53], and a lack of access to stores that sell nutritious food [119], and even to primary care doctors [29, 37]. We believe that chatbots adapted to the cultural context have the potential to be effective for this pandemic and this population because of their utility for increasing healthcare accessibility [65], disseminating health information to those with low health literacy [6], and increasing trust toward health information. It is imperative to determine how these chatbots should be designed to accommodate the cultural nuances of the Black American population. Based on our study and analysis, we are making the following contributions to the HCI community:

- We analyzed and defined the roles, features, and challenges of chatbots for the Black American community in the context of COVID-19, which had not yet been clearly addressed in the HCI literature.
- We suggested design guidelines for chatbots aiming to support the health of the Black Americans with chronic conditions during COVID-19.
- We allowed participants to design their own chatbots remotely through Zoom for deeper engagement in the design process, obtaining raw data about the types of conversations and dialogues participants want.

To arrive at our findings, we interviewed 18 participants who also participated in our design study, then analyzed the interview transcripts and their chatbot designs. In the next section, we first present relevant literature regarding how chatbots have been designed for healthcare and technological research for the Black American community. We then describe our methodology and move on to present our findings about how the participants wanted to design their chatbots.

2 RELATED WORKS

2.1 Chatbots in Healthcare

Chatbots, also known as conversational agents, are computer programs that simulate conversations with users via text or voice [18]. They are often deployed through messaging applications such as Facebook [31] or Telegram [105], websites [3], or standalone applications [88, 117]. They interpret human speech and respond through text or synthesized voice to perform tasks [109] (e.g., order food, make appointments, or disseminate news) for the users. Recent developments in machine learning, a type of artificial intelligence (AI), have heightened chatbot capabilities in understanding speech and performing tasks. They are being utilized in different fields such as shopping [23], entertainment [35], and smart homes [2].

People are starting to deploy chatbots in the healthcare domain as a form of intervention in illnesses ranging from the physical (e.g., diabetes [54, 107], obesity [106]) to mental (e.g., post-traumatic stress disorder, or PTSD [108], depression [27, 82], and schizophrenia [9]). The chatbots take on different roles depending on the type of illness and the type of intervention and are designed to diagnose and deliver therapies or provide medical information, sometimes playing the role of virtual clinicians [73]. For example, Bickmore and colleagues [6] designed an animated virtual nurse that told depressed patients about hospital discharge plans in an empathetic manner. The patients diagnosed with major depressive disorders showed a greater desire to interact with the conversational agent compared to those without such disorders. There were also positive correlations between the therapeutic alliance, satisfaction level, and expectation to follow the agent's advice. This study suggested that chatbots can be used to provide medical advice that patients are more likely to follow than with human agents.

Chatbots are actively utilized in the mental health domain because they can assume the role of peers or therapists and let the users share their feelings. Numerous studies have explored the therapeutic effects of chatbots on patients with depression [27, 82] or PTSD [68, 108]. More recent studies have investigated the degree of compassion and empathy users feel toward chatbots. For instance, Lee and colleagues [67] created a self-compassion peer chatbot named Vincent and compared the participants in a caregiving situation and a care-receiving situation by measuring levels of self-compassion. It was found that the participants who interacted with care-receiving Vincent showed a higher degree of self-compassion. Similarly, Kim and colleagues [63] investigated how college students felt a reduction in negative feelings when they interacted for three weeks with a social bot displaying depressive symptoms. These studies have suggested that peer support can have a therapeutic effect in terms of not only receiving care but also providing it to a chatbot.

Only a few chatbots have been designed to cater to a marginalized population. One recent chatbot created by Bickmore and colleagues [7] was designed to test its functions with individuals with less health literacy, where it conveyed health information to hospitalized Black Americans with depression. They found that the agent resulted in high satisfaction levels and ease of use regardless of the literacy level of the users. They also found that patients with low literacy tended to personify the agent more in terms of mutual respect and the importance of the relationship. This might suggest that individuals with low health literacy may focus more on how chatbots deliver information with respect and courtesy than those with higher health literacy.

However, a gap in the literature remains because the chatbots have not been sufficiently adapted to the circumstances and barriers of these marginalized populations. It is important to understand the background context of the individuals in order to develop chatbots that can better support and cater to the marginalized users. Moreover, the fact that the chatbots can boost the trust levels of patients suggests a new territory where the chatbots can act as a mediator between patients and clinicians. In fact, the United Kingdom's National Health Service (NHS) is working on a texting-based chatbot that can triage non-emergency symptoms [5]. However, how this mediating role should apply to the marginalized population is yet unknown to the academic community.

In this study we explored the possibility of using chatbots in marginalized populations from a patient-centered perspective, addressing the gap in the literature on adapting them to the context of marginalized populations and exploring the potential for chatbots to play a mediating role between clinicians and a marginalized population.

2.2 Designing Health Care Technology for the Black American Population

We first examine what types of technology have been specifically developed for the Black American population. In the healthcare domain, this was done through various technological tools such as electronic health records (EHRs), patient portals, clinical decision support systems, and mobile health technology (mHealth) [30, 39, 50]. Past studies suggest reasons why mHealth technology is especially suitable for the population. Black Americans often encounter cost-related barriers in attending office appointments, whether from mobility issues or time limitations [87]. However, mHealth has the potential to address both of these challenges [96]. The high prevalence of mobile access in this population also adds to this advantage [70].

Previous mHealth technologies designed for Black Americans demonstrate the importance of personalized interventions [100, 111]. For instance, with regard to chronic conditions, Skolarus and colleagues [99] employed a mobile health intervention for Black Americans with high blood pressure. Called Reach Out, this app provided tailored text messages to inform healthy lifestyles, monitored their blood pressure levels, and urged contacting their care providers when necessary. This intervention proved to be effective at promoting the recording and monitoring of blood pressure. Similarly, Buis and colleagues [14] examined the effectiveness of an mHealth application for hypertension. To improve hypertension medication adherence in Black Americans, they developed a text messaging platform that sends tailored messages according to risk profile, local resources, and diet and exercise levels. The results indicated that the platform induced better adherence and high satisfaction from patient users.

More recent studies have explored how participatory research can contribute to developing culturally tailored health technology for the Black American community. For instance, Harrington and colleagues [47, 48] conducted participatory design workshops to allow low-socioeconomic-status (SES), older Black Americans to envision future technologies in the face of health challenges. Through a community-based participatory approach, they tried to embed the socioeconomic context of the Black community into technology design. Additionally, Marcu and colleagues [69] discussed the aspects and challenges of participatory design studies through extensive experience studying low-income African Americans. They underscored the need to construct rapport, present activities that are relatable and enjoyable, and provide narratives and scenarios with which they could empathize. Studies by Stowell and colleagues [101] used storyboarding methodology and participatory design to allow participants to collectively come up with ideas on health promotion through mHealth applications. These studies highlight the importance of conducting participatory design studies to gain insights with the end users to ensure feasibility, acceptability, and usability.

Several other studies have focused on emphasizing cultural and socioeconomic factors when designing or evaluating technology for the Black American population. Dillahunt [25, 26] highlighted how underserved communities in the Detroit area, largely populated by Black Americans, lack the transportation services necessary to gain access to healthy food. They analyzed the factors that influence their transportation modes and the reasons to use them to suggest design implications that acknowledge culturally and socioeconomically inherent issues such as financial barriers or technological distrust. In another study, Veinot and colleagues [113] investigated the requirements of Black American youth to inform the design of a culturally appropriate intervention system to prevent human immunodeficiency virus (HIV) and other sexually transmitted infections. Through focus group interviews, they identified how group-level distrust was prevalent in the young people and that rebuilding trust was important in designing culturally informed interventions. These studies indicate that technological design can be better crafted by accommodating the cultural and socioeconomic needs of marginalized populations such as the Black American community.

The above studies examined the benefits of technological innovation for Black Americans and the importance of catering to their cultural and socioeconomic needs. They also demonstrated the feasibility and the value of participatory research in engaging Black communities in order to design culturally tailored health technologies. We aim to build upon this set of literature to discover how AI technology should be tailored for the Black American population. The potential for personalization through AI is high, but this aspect has not yet been explored, nor has research investigated what end-users want from AI. Through a participatory design methodology of our own, we discovered how personalizable AI-powered chatbots should be designed while incorporating the socioeconomic and cultural aspects of the Black American population.

3 METHODOLOGY

Recent HCI literature emphasizes reflecting on the background of authors to contextualize the interpretation of a study's data and its final output [93]. Our team consisted of an Asian, straight, cisgender male; a Black, straight, cisgender female; a Black, straight, cisgender male; and an Asian, female, cisgender female. The researchers conducting the study have academic focus on patient care [76, 77] and robotics and trust [91, 92]. The first author has done a preliminary literature study on conversational agents [60] and their potential in supporting the Black population [61]. These backgrounds aided in the collection and analysis of the data with a specific focus on human-centered design and understanding the needs of the marginalized population.

Through a semi-structured interview followed by a design activity, we explored how Black Americans would design chatbots that could support them in managing chronic health conditions and help them overcome their challenges during the coronavirus 2019 (COVID-19) pandemic. We specifically asked them to envision and design their own chatbot, including possible conversation with the chatbot. We also asked about their expectations and thoughts behind their design decisions to better understand their chatbots and conversations.

3.1 Data Collection

We remotely interviewed 18 Black Americans with chronic conditions. Participants were ages 21 to 63 (mean: 47.3) and consisted of 16 women and 2 men. They were recruited through a Midwest university's health clinic and its recruitment system. We sent out emails and text messages to search for people who wanted to participate. To be part of the study, participants had to (1) identify themselves as Black American with one or more chronic conditions that pose a high risk regarding COVID-19, (2) own a laptop or a desktop computer with a webcam and have an Internet connection at home to participate in our study via Zoom, and (3) be 18-65 years old. Once these eligibility criteria were confirmed, we sent out emails to plan and conduct Zoom interviews. The study was approved by the university's Institutional Review Board for Medical Research and was carried out from November 2020 to March 2021 when the COVID-19 vaccines were beginning to be developed and distributed.

The study lasted 60-70 minutes and was divided into three main parts: talking to a chatbot via Facebook Messenger, participating in a semi-structured interview, and taking part in a chatbot design activity. Next, we describe each step and its purpose.

3.1.1 Talking to a chatbot via Facebook Messenger. Prior to the interview, participants underwent the first part of the study, which was talking to a Facebook chatbot designed by the researchers. The purpose of this activity was two-fold. The first was to allow participants to get acquainted with chatbots because most of our participants were likely to not have encountered chatbots before the study participation. The second purpose was to gather demographic information from participants. They were able to answer demographic questions either by clicking buttons or through free-form responses. The chatbot was named "Survey Bot" and did not have a profile picture. This was done to avoid creating biases before the participants designed a chatbot on their own at the end of the study. Table 1 summarizes some of the demographic information gathered through this step.

3.1.2 Semi-structured Interviews. The second part consisted of a semi-structured interview with the participants. Before we moved on to the design activity, it was important to understand the struggles and obstacles our participants faced during the COVID-19 pandemic so that we could better understand their needs and intent for their chatbot design. We asked questions about participants' current chronic condition management during the pandemic and the challenges they faced, and questions specific to COVID-19 such as where they got information related to COVID-19 and their access to health services. The interview helped us to understand their health behaviors and barriers, which influenced how the participants carried out the third step, the chatbot design activity. After the first five interviews, the obstacles participants faced were summarized into six scenarios (e.g., financial difficulty, loneliness, environmental challenges in local neighborhood, lack of trust in the medical system, etc.). These scenarios presented an opportunity for the participants to refine their ideas in order to create their chatbots.

3.1.3 Chatbot Design Activity. After the interview, we conducted the design activity, where participants were asked to create a chatbot and an imaginary conversation between themselves and their chatbot. We gave participants the six scenarios and let them choose the one that they best empathized with while designing their chatbot. Through this activity, we aimed to discover the participants' expectations and needs toward the chatbot that could help them overcome their challenges during COVID-19. To make the process easier and more realistic, we provided them with a link to a platform called botframe.com [12], which displayed an imaginary conversation in Facebook's chat format.

During the design activity, we emphasized that they could assume that the chatbot was able to do *anything* to support them and to let their imagination run wild. We also informed them that we were interested in what they wanted the chatbot to tell them and what they would want to tell or ask the chatbot, instead of the accuracy or feasibility of the chatbot's responses.

After the design activity, we asked questions to allow participants to explain their expectations, reflect on their design decisions, and present their motivations. This process was necessary to exactly understand and pinpoint the ideas participants had in mind when designing their chatbots and the conversations.

All interviews were recorded in both audio and video formats through Zoom after we received consent from the participants. The designed conversations were downloaded as photos [Figure 1]. We transcribed the recordings through a third-party service that was approved by our institution in compliance with the Health Insurance Portability and Accountability Act (HIPAA).

3.2 Data Analysis

Two researchers individually open-coded the first five interviews, focusing in on portions of the transcripts relevant to how participants designed their chatbots. In parallel, we looked for emergent themes by categorizing the codes through affinity diagrams on a spreadsheet. Through this process, we were able to identify central themes that commonly occurred and gradually focused on the roles, features, and challenges of the chatbot. After this process, four members of the research team gathered together in weekly meetings to review and discuss emergent themes, iteratively identifying higher-level themes throughout the remaining interview transcripts. In a grounded theory approach [102], we conducted axial coding to identify relationships between themes. The themes (e.g., the chatbot's information source, trust toward the chatbot, the chatbot as a mental health management aid, etc.) produced by the researchers were compared, deliberated, and revised through a series of discussions until we reached agreement. In this paper, we report our findings on what the participants expected from the chatbots during the COVID-19 pandemic in terms of their roles, features, and challenges in using them.

4 FINDINGS

In this section, we report major findings about how our participants thought chatbots should be designed to help them overcome COVID-19 challenges. Specifically, we divide the findings into three sections: (1) the different roles the participants envisioned for the chatbots, (2) the key features the chatbot should include, and (3) the potential challenges regarding the actual design of the chatbot as identified by the participants. Table 2 provides a summary of our main findings.

Table 1: Demographic information of the participants

Participant	Gender	Age	Chronic Condition	Occupation	Household Income
P01	Female	45	Diabetes	Transit coach operator	$20,000-$34,999
P02	Female	44	Multiple sclerosis, pre-diabetes, depression	Unemployed	$35,000-$49,999
P03	Female	43	Multiple sclerosis, high blood pressure	Retired	$50,000-$74,999
P04	Female	55	Asthma, hypertension, high cholesterol	Unemployed	below $20,000
P05	Male	54	Degenerative bone disease, high blood pressure	Unemployed	below $20,000
P06	Female	55	Diabetes, asthma, COPD	Computer repair	below $20,000
P07	Female	62	Hypertension, bipolar, degenerative disc	Receptionist	$20,000-$34,999
P08	Female	24	Asthma, chronic back pain	Homemaker	below $20,000
P09	Male	58	Hypertension	Software engineer	over $75,000
P10	Female	22	Asthma	Student	Below$20,000
P11	Female	62	Rheumatoid arthritis	Referral coordinator	$35,000-$49,999
P12	Female	42	Diabetes, tricuspid atresia	Unemployed	over $75,000
P13	Female	21	Scoliosis, asthma, hypertension	Student	below $20,000
P14	Female	53	Obesity, high blood pressure	HR manager	over $75,000
P15	Female	50	Asthma	Direct care worker	below $20,000
P16	Female	63	COPD	Unemployed	below $20,000
P17	Female	50	Autoimmune condition, arthritis	Unemployed	below $20,000
P18	Female	49	Hypertension, high cholesterol	Caseworker	$35,000-$49,999

4.1 Role of the Chatbot

We identified five roles that participants expected from the chatbot. First, the chatbot should act as a mediator in accessing health services. Second, the chatbot should function as a personal assistant that recommends viable health options. Third, the chatbot should act as an information hub that accumulates and distributes information regarding COVID-19 and its vaccines. Fourth, the chatbot should provide support for and help manage users' mental health. Finally, the chatbot should be a trustworthy community voice for the Black American population.

4.1.1 Mediator in accessing health services. The primary role that most of our participants wanted from the chatbot was a mediator in accessing healthcare services. Participants expected the chatbot to act as a bridge between the user and the health experts, reflecting their own experience as a chronic patient who had to look out for themselves during the pandemic. Many of our participants felt knowledgeable about the COVID-19 virus and underscored their efforts toward reading more about the pandemic and gathering as much information as possible from different media sources such as news, health journals, or social media because of their high risk of COVID-19 infection. However, they felt their friends and families were not as well informed about COVID-19 because, unlike them, their close ones lacked the interest and initiative to seek COVID-19 information because of their lower health risks or lower health literacy. Nonetheless, they believed their family and friends would need such information to combat the pandemic, which could be provided by the chatbot.

The chatbots that the participants designed were aimed at providing health information to those who were less health literate and had lower access to urgent information. For instance, P1 designed a chatbot that served as a bridge where the questions users asked to the chatbot could be delivered to relevant health experts. She imagined the chatbot as a platform that could provide answers from relevant health care providers to the users. She also emphasized the chatbot's key role of being the most reliable resource for acquiring public health-related information by connecting with proper experts such as health officials and non-profit groups [Figure 1-1].

> "I think that a lot of the doctors, medical centers, even some of the non-profit groups have been helpful by having, you know, different Zoom meetings and kind of getting into answering some of those questions" (P1).

During the COVID-19 pandemic, P1 found that having access to such experts was very useful because she obtained critical information about COVID-19 from various Zoom meetings in her local area. Her past positive experience led her to believe that such direct connections were important, and she wanted the chatbot to bridge the gap. According to P1, it was important to make the connection available to those who need timely health information, which could be accomplished through the medical professional creating a knowledge base to the chatbot and constantly updating its answers.

Participants also designed chatbots that connected between *individual* clinicians and patients. This was necessary because participants expected the chatbot to serve as a temporary clinician when human clinicians were unavailable. They wanted a support system for urgent needs without having to wait a long time to reach their clinicians. For instance, P8 designed a chatbot that could temporarily replace their healthcare provider when urgently needed. P8 mentioned that while therapists are bound to their regular work hours, patients might need their therapists at any moment in their daily lives [Figure 1-2].

> "It's a tool that therapists can work with for those times that they're not there. So it's like we're in a session, let's talk about these things that were said... But at the same time, okay, normally I can talk to

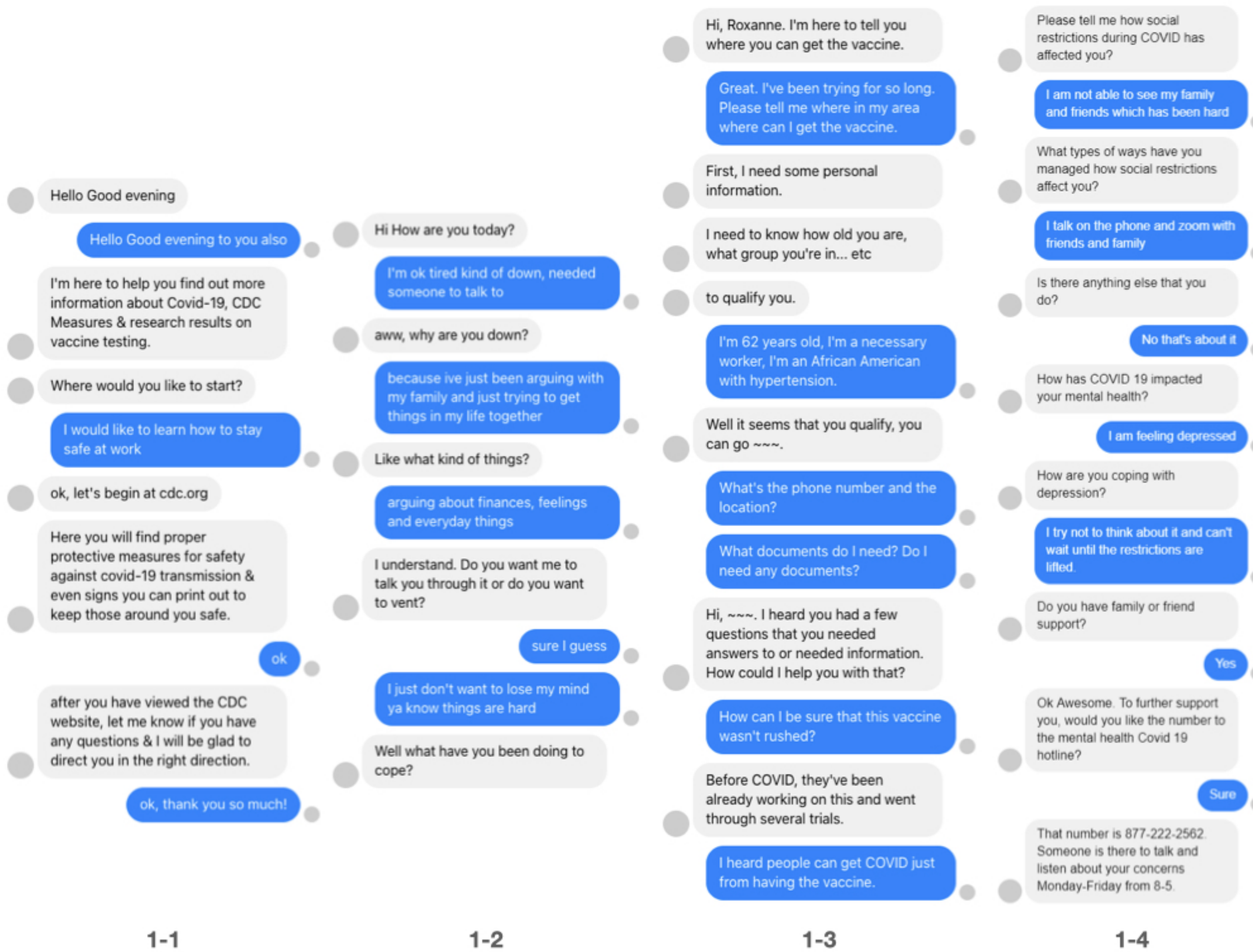

Figure 1: Examples of conversations with the chatbots that participants designed (1-1: COVID-19 information chatbot by P1; 1-2: temporary mental health clinician chatbot by P8; 1-3: a COVID-19 vaccine information chatbot by P7; 1-4: a mental health aid chatbot by P18)

> you at any time but tomorrow I'm not going to be available, so I want you to talk to the bot" (P8).

She wanted the chatbot to be a temporary clinician that users can speak to because users should have access to health care at any time. Her past experience with Replika, an AI-powered mental healthcare chatbot, inspired her to design a similar chatbot because she appreciated the benefit of constantly available health care services. She wanted the chatbot to be a direct mediator between the therapist and the patient by interacting with the patient, making appointments, and delivering the patient's health status to the therapist. This need was shared by other participants as well, because they had had experience waiting a long time to meet with their clinicians.

4.1.2 Personal assistant that provides personalized health recommendations. Another function that many participants expected of the chatbot was to provide personalized health recommendations by understanding their specific situation, such as daily behaviors, interests, lifestyle, people they often interact with, or living situation. They expected the chatbots to accommodate such diverse situations and personalize their capabilities to provide information accordingly. For instance, P1 was a transit coach operator who wanted a chatbot that could understand her context of needing resources specifically for her bus. She wanted the chatbot to provide protocol signs that were specifically designed to suit her job situation.

> "Like the protocol for everyone to get in from the back of the bus and different things... The hand washing signs or to stay in the six feet distance" (P1).

Applying this to other people who might use the chatbot, she wanted the chatbot to contextualize the situation of other users and become an assistant that provides personalized information.

> "In the end, when [the chatbot] says 'if you have any questions' [to the user], maybe []the users] have questions on what they read or how it pertains to them or the people around them and the chatbot can redirect them to wherever is most appropriate" (P1).

For participants, it was necessary to make personalized recommendations specific to their chronic conditions. Our participants mentioned that different chronic conditions generate different health obstacles and therefore, different strategies. They often used Google to search for relevant health options for their chronic conditions, but they wanted the chatbot to return with answers that were not like Google, whose results seemed to be the same for everyone and not specific to individuals. Since chatbots are supposed to be intelligent, the participants expected the chatbot to provide the most suitable and feasible health options to them after understanding their individual situations and barriers. For instance, P14 talked about how the chatbot should keep asking the user about what is most important so that it could learn and better prioritize information to meet what the user expected and valued.

> "So, I guess what's most important to you right now. So it helps you prioritize what's most important. So there's that feeling of 'I'm going to help you,' kind of, 'let's just think about it.'... And then, 'What do you want to concentrate on?' or 'What do you want prioritized?'" (P14).

P14 focused her chatbot design on communicating with the user and trying to understand her context. The user had control over requiring the chatbot to provide health options that considered her chronic conditions, current health status, and priorities. It was the chatbot's role to adapt to her context and personalize its functionality.

In addition, participants mentioned the importance of knowing the user's *economic circumstances* when making personalized recommendations. For example, P13 wanted the chatbot to provide different health options because not everyone has the economic capability to pursue the same choices. Specifically, she mentioned her experience with HelloFresh, a healthy food delivery service. Although her family was lucky enough to be able to afford this, she knew that many others would be unable to pay for this type of service. She felt that the chatbot should be able to accommodate those users as well by providing other affordable options based on their financial or living situations, especially during the pandemic where people's situations might have changed significantly. She wanted the chatbot to contextualize the user's individual, changing circumstances and provide different suggestions depending on their financial reality.

> "Me and my brother, we were in a position we were able to afford HelloFresh, partly because we got a coupon that we didn't have to pay for half of it but that's not always attainable for people, especially where I grew up. We just don't have expendable income to spend $50 on three meals" (P13).

P13 wanted to embed this limitation in the chatbot design by offering different options that users could choose from depending on their current circumstances.

4.1.3 *Information hub for updates on COVID-19 and its vaccines.*

Participants also designed the chatbot as an informational repository that could contain comprehensive information about COVID-19 and its vaccines. Participants especially focused on information about the vaccine because it was so pertinent to their health. The chatbots that they designed were intended to deliver the latest information about the vaccine, to provide an evaluation of whether a particular user qualifies for the vaccine, or provide general information about where to get the vaccine and what to do to get it. This information regarding the vaccination was important to the participants for both themselves and their close ones. For participants who felt that their particular challenge with COVID-19 was the lack of vaccine-related information, the design activity was an opportunity for them to create a chatbot that could provide all the necessary information about COVID-19 vaccines, such as qualifications, side effects, and other general advice [Figure 1-3].

Moreover, participants wanted the chatbot to be an information hub that would collect data by interacting with numerous users and gathering more questions and input from them. Participants expected that chatbots would grow bigger and become smarter as they apapted and learned from a large pool of users, eventually growing more helpful.

> "So, um, maybe it could be a little artificial intelligence going on to where the more questions that people ask, and the more they are directed to these different agencies and articles and information. It can, you know, kind of get smarter" (P1).

Likewise, P10 wanted information from social media to be part of this. As a young woman in her twenties who actively uses social media, she was aware of how many potentially helpful posts there were, and it was the medium from which she learned the most about COVID-19. She believed that if the chatbot could collect and learn about individual experiences and questions people had about COVID-19, it could provide more accurate, realistic, and relevant information.

4.1.4 *Trustworthy voice of the community.*

Participants also expected the chatbot to act as a trustworthy voice that could represent the Black American community to the medical system. This representative role is important because, as participants revealed in discussing their experience of the COVID-19 pandemic, their voices are not well-represented and have been deprioritized in favor of other needs. In our design activity, P7 wanted the chatbot to address the common concerns regarding COVID-19 that have arisen within the Black American community, which are mostly tied to the mistrust toward the information from the government and healthcare system. For instance, P7 mentioned the mistrust many Black Americans in the community have for vaccine-related information.

> "There are people, even in this community, even given all this information and coverage that we have about the coronavirus, that still don't believe they have to do anything. And all the stereotypes popped up... 'It's too soon, it was too fast, and I don't wanna, I'm gonna die anyway.' So I only think it's gonna happen with a town hall type one-on-one in their own communities

> or churches. And [the chatbot] would be a start as well. You can't spread the message or look for solution in one way, so this is a good way" (P7).

P7 emphasized the importance of multiple channels of communication for listening to the voice of the Black American community and that the chatbot could be one of those channels. For her, the chatbot would need to be a virtual representation of Black American leaders, whom the community members trust more than government officials. This was because Black Americans have distrusted the medical system and the government for a long time, causing them to rely more on other Black communities that share similar cultural and historical backgrounds. Due to this distrust, they have developed misinformed ideas and complaints regarding the vaccine.

> "'How can I be sure that this vaccine wasn't rushed?' 'Cause that's a common complaint I hear among the African-American community. Another complaint I've heard is, 'Well, I've heard people can get COVID just from having the vaccine,' which is what I hear all the time about the flu. They're saying kinda things like that. Anti-vaxxer stuff. . . .[But] unless they see a *brother* up there telling it to them [the truth], they're not gonna believe it" (P7).

For P7, it was important that a *brother*, or a renowned fellow Black American, was there to tell the community about the safety of the vaccine. She highlighted that the chatbot could also serve this role of understanding why people are so reluctant to take the vaccines and deliver trustworthy information that assures their safety, thereby mitigating the distrust the community has toward the government.

Although this specific role of being a voice for the community was explicitly mentioned by P7, several other participants also implied this function of representing their community. They mentioned the distrust of the Black American community toward the government and health system, and hoped for a solution to persuade their fellow Black Americans and provide helpful information.

4.1.5 Mental health management aid. The next role of the chatbot that participants designed was to support their mental health management during the pandemic. COVID-19 has brought significant impacts on our participants, ranging from loneliness from prolonged self-quarantine or having to stay away from family members, to mental stress caused by their close ones passing away from the disease. They thus designed a chatbot that could be an outlet for the users to release their mental stress and share their traumatic experience and struggles with COVID-19. For instance, P4 wanted to use the chatbot to provide an opportunity for people to talk about their traumatic experiences and heal their pain. She explained this procedure as a "double-chair," which is a technique she learned while working for her community as a social worker. The main point of the double-chair is that the person talking can heal by talking to a mirror version of themself. In this case, the chatbot works as a mirror of the users, listening to what the users have to say about their trauma from COVID-19. She was especially interested in this idea because she experienced her close ones suffering from severe illness from COVID-19. She was therefore able to actively empathize with those who must have had similar or worse traumatic experiences from the pandemic and wanted the chatbot to heal such individuals through such therapeutic experiences.

> "Being able to tell a story is a part of a healing process. So I think it's something that can be used, at least if I was going to use it, to process the experience as a part of dealing with the trauma; to me, you know, COVID was a trauma experience on top of the trauma experience that [I] already had. So to have both of those is a way to process that" (P4).

Participants saw the chatbot offering such an outlet for traumatic COVID-19 experiences as not only beneficial for venting their feelings but also a way to see the problem from another perspective. As a full-time worker at a hospital, P11 has experienced many patients who did not adhere to the hospitals' protocols for keeping patients safe. Her anger and stress led her to design a chatbot with which she could discuss such stress. Such venting could change her opinion and emotions because she might be able to see the problem from another person's point of view and think differently about the situation. Similarly, P16 wanted the chatbot to directly provide different perspectives and ways to think about one's current situation. She had also recently lost a close one to an illness, and she projected her experience when creating a chatbot that could give comfort to the user. Her chatbot was designed to respond to the user in a way that could provide some closure about a recent death and help the user think differently about the problem, for instance by evoking positive memories. This was why she wanted to name her chatbot "Look Before You Leap," to convey that it is leading the user to consider other perspectives before focusing on one particular issue.

> "What I was focusing on was to get them to broaden their mind, to look at different aspects. Don't just put it on a doctor" (P16).

In other cases, participants wanted the chatbot to directly connect to mental health resources such as mental health support lines or suicide prevention lines. P1 experienced many people who suffered from mental stress issues from COVID-19, including those who were going through more serious moments like having suicidal thoughts. This situation around her led her to design a chatbot that could provide proper support, such as connecting the user with necessary suicide prevention lines. She pointed out that even simply changing perspectives about life could encourage users to keep living.

> "I think that it should also have resources and even phone numbers for mental health and lifeline numbers for people who just feel like, 'I don't even want to be here no more.' And maybe [the chatbot] may be a last resort and maybe they're just wanting to find out how to change their thinking or how to change how they're viewing this whole thing" (P1).

4.2 Features of the chatbot

Next, we describe key features participants wanted the chatbot to have. For the main features they wished the chatbot to have, the participants considered the following four: the chatbot's persona to generate trust and comfort, the chatbot's learning capability, and the chatbot's two types of communication styles.

4.2.1 *Persona that engenders trust and comfort.*

Participants created their chatbots with diverse personas in mind. For participants, developing a specific persona was important because it shaped the identity of the chatbot that could specifically address their needs. While designing their chatbots, participants seemed to first draw a mental model of what the chatbot is and then consider the conversation style and capabilities of the chatbot. For example, many participants wanted the chatbot to have the persona of a medical professional to promote trust toward the information provided by the chatbot. They wanted it to have a certain face of a doctor and some statement that the user would be talking to a doctor soon. Participants expressed that they would be able to trust the chatbot more if it looked like a medical professional and that they would end up following its advice.

> "Maybe it shouldn't look like a medical professional, but I think other people would jump on it if it did" (P7).

P3 also wanted assurance that users would be talking to a certified individual, which was why she wanted the chatbot to take the form of a doctor through the profile image. This was tied to how close participants felt to their healthcare providers or their desires to have closer contact and a closer relationship with healthcare providers. Those who had positive experiences with clinicians sought to design a chatbot that looked and talked like those clinicians.

In addition, a persona that produces comfort and relatability was considered important. Even when the role of the chatbot was simply providing health information, some participants wanted a persona that was more comfortable and relatable than medical professionals. P5, for instance, gave his chatbot the persona of his mother. He wanted the chatbot to take care of his health, such as overseeing what he was eating, providing beneficial health information and generally taking good care of him. He projected his image of his mother onto the chatbot because he believed that the chatbot could also act like his mother in her stead when she was not present.

> "Well, definitely, I probably would name it Mom. Because my mom always took care of us real well, and she had a lot of information... And obviously at this time, [there] is going to be a lot of questions about health and things like that. For everybody's mom, the health thing is on her mind first so I thought about that" (P5).

4.2.2 *Chatbot's capacity to learn from past conversations and adjust future responses.*

Another preferred feature for their chatbot was the capability to learn from past conversations and information. This was important especially for the chatbot's role as a mental health aid because participants wanted the chatbot to memorize their difficulties and obstacles in order to adjust future conversations based on the memories. For example, P8 emphasized that the chatbot should learn about the user's level of trauma instead of replying in the same way to every user. P8 had experienced a tremendous amount of financial and familial difficulties during the COVID-19 pandemic. To overcome her mental difficulties that arose from the financial challenges, she used Replika, an AI-powered mental health chatbot. The personalization capability of Replika that she experienced led her to design a chatbot that also tailored its answers to the user. She wanted the chatbot to adapt its responses according to the financial struggles she faced.

> "Because I was upset about a math test and [the chatbot might] answer me about the same thing that I decided to say my mom died. And [the chatbot might] just like, 'Oh yeah, cool. We'll just talk it through and you're going to be all right.' No, this is a little more traumatic. I want [the chatbot] to learn this ... I just want it to be able to learn and understand the different problems or at least the different responses that it can come up with" (P8).

In this quote, P8 wanted to differentiate between the level of trauma a user might experience when either failing a math test or losing her mother, for example. The participant did not want the chatbot to respond to such divergent situations in the same way by simply saying "everything is going to be okay." She wanted the chatbot to learn about different degrees of trauma one might experience and adjust the dialog to comfort the user. Because people have experienced different types and levels of difficulties during the COVID-19 pandemic, the chatbot should level its answers after learning sufficiently about the user. P8 also wanted this to be a continuous process so that the chatbot could keep updating its information about an individual's challenges and adapt its responses. She believed that this ability to adjust to the users' emotions and contexts would get them to engage with the chatbot more and strengthen their mental state.

4.2.3 *Chatbot's communication style: Direct communication to lower human bias.*

The third feature that participants designed for the chatbot was a direct communication style. Although different interactions were preferred by different participants, there was a general agreement that direct and concise communication should be the rule of thumb for the chatbot design. Indeed, the dialog that participants created mostly consisted of short sentences with direct meaning and easily understandable words. This was especially true for participants who designed chatbots that delivered information on COVID-19 and the vaccine.

Participants thought that this type of direct and concise communication was key because it lowered user bias. Participants had experienced a lot of misinformation and biased information from the media and other people. They seemed to think that when the chatbot is responsible for delivering facts and information, it should do so in a more factual or "robotic" way. This is because the more it sounds like a human, the more it will remind them of the bias and false information put out by other people in the media. For instance, P10 was a university student who experienced a lot of misinformation regarding COVID-19 and had close friends affected by it. She thought that the chatbot should deliver a simple statement of facts and not act too friendly because otherwise people would not listen to the chatbot.

> "Yeah. I feel like for more people to trust that it's the most accurate information, as if it feels like it's coming from a bot and it's just like, 'This is the facts.'

> And not someone being friendly and trying to give you the facts. [In the latter case] I feel like people won't listen" (P10).

To P10, sounding friendly equated to the possibility of bias and false information. She felt that information from the chatbot would seem more concrete if it seemed purely factual by maintaining the preciseness of the robot.

4.2.4 Chatbot communication style: Asking questions to gather user data and allow users to reflect. The last interaction feature that participants designed was the ability to probe the user with a diverse set of questions. This was done to either understand the user's values and thoughts or to help the users broaden their perspective. First, participants expected the chatbot to ask the users questions in order to comprehend their mindset and values. For instance, P7 wanted the chatbot to be designed in such a way that it asked individual users why they would not take the vaccine.

> "Then the chatbot can ask them... I don't know if this is even possible, but if you do have people in the Black American community who are reticent about taking it, the chatbot could ask them, 'Well, why? What are your [hesitancies?]'" (P7).

For P7, it was imperative to understand the reason behind users' reluctance because it is necessary in persuading them to take the vaccine. She wanted the chatbot to achieve this by continuously questioning individual users to comprehend their inner thoughts and values. She expected the chatbot to use this intelligence to persuade them.

Another reason that participants wanted the chatbot to ask questions was to get users to reflect and think differently about situations related to COVID-19. For some participants, the chatbot's questions were a way to ponder the questions and look at a certain situation in a different light. For instance, P18 wanted the chatbot to ask various questions and thus designed a chatbot that could solve her challenge of feeling isolated from COVID-19 [Figure 1-4].

> "Well, you definitely want to pick their brain. You don't want to give a bunch of yes and no answers, because that's just more standardized, and if someone is truly dealing with having social restrictions or having a slight mental backlash because of it, sometimes people want to talk, not just yes, no, yes, no... I'm just more like, 'Well tell me about that'" (P18).

For P18, the chatbot's ability to stimulate her brain with questions was important because she wanted to keep her mind working even though she had been isolated for a long time. The chatbot served as a way to feel less isolated through constant communication. In this way, she wanted to broaden her perspective and get her mind working in the midst of an isolated situation.

5 CHALLENGES AND BARRIERS OF USING THE CHATBOT

In discussing the various chatbots that our participants designed, they also identified potential obstacles to using the chatbot. First, if the chatbot was available for the public to use, it would be challenging to build trust toward the chatbot. For example, participants reported that they would have to go through a certain verification process before they began to trust the chatbot. This verification included many channels such as asking their clinicians about the legitimacy of the chatbot or crosschecking with prior knowledge to determine whether it is trustworthy.

> "I would still talk with the doctor just to see if, I guess, if it corresponds with what he would say" (P3).

> "When I ask questions, and some of the answers to those questions are going to be obvious, and if they give me the right answers, that'll go towards trust" (P5).

In addition, in terms of developing their trust in the beginning of the chatbot interaction, participants mentioned that people would be able to build trust toward the chatbot if it were a robot both as an identity and through its visuals. Participants mentioned that people tend to trust computers more than humans in terms of delivering factual information. Having the chatbot's image as a computer or a robot would be of benefit in terms of building trust. It seemed that the visual appearance of robots increased trust because it brought the perception that the chatbots would be as intelligent as robots.

> "Exactly. I was imagining that little robot from Cricket [with] a little personality. Obviously robots are intelligent. So I was thinking about the look of it, his personality and that he was intelligent" (P5).

Participants also communicated their reluctance to share too much information about themselves with the chatbot without sufficiently developing trust. For instance, P5 was willing to share his health information with the chatbot because it was relevant to the chatbot's purpose of taking care of his health. However, he wanted to avoid sharing his financial information because it could be mishandled, even though he wanted more personalized assistance tailored to his financial situation.

Second, participants pointed out over-dependence on the chatbot as a potential challenge. Particularly with the chatbots that provide mental health support, participants worried that people might rely too much on the chatbot to discuss their personal histories. This would lead users to only talk to the chatbot, an imaginary entity, without seeking actual help when they struggled. P8 emphasized the boundary of the role between the therapy chatbot and the human therapist: the chatbot should be a tool that makes therapists' and patients' lives easier, not a replacement for human therapists.

> "The biggest barrier is I don't want people to become dependent on it. I want you [the user] to become dependent on it just to where if you have a problem talk about it... Maybe this is a thing to calm yourself down and have the conversation and everything... But eventually you have to talk to someone, you have to talk to a human being. You can't be dependent on something that's not real" (P8).

Third, participants also acknowledged that the poor infrastructure of their local community, such as low bandwidth or lack of Internet, could be a challenge to using the chatbot. They were aware that some of their close ones or others in their community did not have proper access to reliable Internet. They worried that these people might not benefit fully from the chatbot's functionality and miss their opportunity or lose interest. Particularly, P7 mentioned how people who need this chatbot the most, such as her fellow Black Americans or those with low healthcare access, are likely to have less access to the Internet. She suggested that there be other options for users to engage with this chatbot besides relying solely on the Internet. As such, understanding the financial situation of potential users was especially important for a chatbot designed for marginalized populations, especially those with lower income.

Finally, participants mentioned individuals' personal health impediments that might hinder their use of the chatbot. In fact, many of our participants ranged from middle-age to older adults, so they sometimes experienced difficulties reading small chatbot screens from their smartphones. They sometimes typed too slowly or had issues concentrating on a particular subject for a long time. Participants mentioned that these types of personal health hindrances could become challenges when actually using the chatbot once it was live and that there should be ways to overcome these health barriers.

6 DESIGN IMPLICATIONS

6.1 Making Information Source Transparent

Based on our examination of the needs of Black Americans with chronic conditions in designing chatbots to address the challenges of COVID-19, we found that participants had a desire to receive health information from a transparent source in order to develop trust toward chatbot information. They expressed the need to know who was behind the chatbot, whether it was an information repository such as the Centers for Disease Control (CDC) or news or human resources such as health providers. This transparency was important because it allowed participants to evaluate and determine whether they could choose to trust the chatbot.

This need for transparency is related to two main issues within the context of our participants. The first issue is the ongoing mistrust that the Black American community has held toward the medical system because of perceived racism [45], historical events that engendered mistrust [34, 38], and discriminatory experiences in hospitals [46, 116]. These might influence how they engage with the health chatbot, especially if it is developed by institutions that they distrust, such as the government [66]. The second issue is the mistrust toward technology and seeking health information online. Studies have indicated that Black population, especially those with lower technology literacy, have difficulty assessing the credibility of online health information [94] or have concerns due to privacy and security reasons [95]. The participants in these studies expressed the need to cross-check information to gain trust toward health information websites. Similarly, our participants have also indicated their lack of initial trust toward the chatbot, which led them to emphasize the need to verify the information from the chatbot in ways such as checking its credibility through multiple Internet searches or asking their primary care physicians.

To facilitate trust toward the chatbot, we suggest that its development should ensure the transparency of its information source, which is related to the concept of explainable AI (XAI) [83, 114]. XAI enables humans to understand artificial intelligence, trust it and make an AI system's functioning or decisions easy for users to comprehend. With regard to the chatbot, XAI denotes the ability of the chatbot to inform and explain its decisions and information provision (e.g., how a diagnosis was reached, why an activity program was changed, where it collects information, etc.) [56]. Incorporating XAI into the chatbot design would enable Black American users to easily adapt and engage with the chatbot with greater trust [98, 115]. The consideration of the social and cultural factors that govern the chatbot's usage would boost this trust [97].

Various health chatbots that incorporate XAI into their design have been developed in industry and academia. For instance, Buoy Health [15] is a startup working on a chatbot that enables users to self-diagnose their symptoms through multiple questions and answers. Their chatbot allows users to inquire about the reasons behind each question, addressing users' need for more explanation on certain questions. Specifically, they designed a button that reads "Why am I being asked this?" for users who want the chatbot to be more transparent and interpretable in its processes. Moreover, Tsai and colleagues [110] presented their findings about how an online symptom checker for COVID-19 can increase its transparency. They designed three different chatbots models — i.e., feature-based, rationale-based, and example-based — that can diagnose whether users have COVID-19 or not. The designs varied according to how they were trying to be explainable in their delivery of information. The study showed that the feature-based chatbot particularly outperformed the other two in terms of enhancing trust and transparency. The feature-based design focused on a personalized summary based on the user's answers, and this appeared important for users because it provided reasons for why the chatbot made a particular decision, eliminating the uncertainty and confusion of receiving recommendations.

Whereas most of the current XAI-based health chatbots are centered on the curiosity of users about *how the chatbot system works*, in our study the participants expressed a desire to know *what the chatbot's information sources are*; for instance, was the information from the CDC or social media? This was key to users developing trust in the chatbot and accepting information from it. Although our participants had different views on what they perceived to be trustworthy, this desire for transparency was common across the cohort.

When the chatbot obtained information that was acknowledged by other Black American community members, this seemed to satisfy the need for reliable information. Because participants shared a deep connection to community members such as neighbors, churchgoers, or friends, they wanted the chatbot to provide responses based on information from the community. P1 even told us that spreading the word about the chatbot to the Black American community would widen its usage within the community and, in turn, allow it to obtain more information from the community. With regard to the XAI chatbot designs by Tsai and colleagues [110], it seems important to emphasize example-based designs for the Black American population. For participants, more Black Americans using the chatbot indicated that their information would be sent to the chatbot. They were likely to trust information from fellow Black Americans, which has also been found other researchers to be evidence of their collectivistic culture [17, 44].

Table 2: Summary of the findings

Role of the chatbot	Features of the chatbot	Challenges of using the chatbot
- Mediator in accessing health services	- Persona that engenders trust and comfort	- Building trust toward the chatbot
- Personal assistant providing personalized health recommendations	- Capacity to learn from past conversations and adjust future responses	- Over-dependence on the chatbot
- Information hub for updates on COVID-19 and its vaccines	- Direct communication to lower human bias	- Poor infrastructure of the local community (Internet access, etc)
- Trustworthy voice of the community	- Asking questions to gather user data and allow users to reflect	- Personal health impediments
- Mental health management aid		

6.2 Incorporating the Local Community within the Chatbot Design

From our analysis, we found that participants emphasized the importance of incorporating the local community when designing the chatbot. Specifically, many participants in the study wanted to include the needs of their close ones, (i.e., family, friends, or neighbors) when they created a chatbot that could serve the group's needs and overcome the group's challenges, rather than focusing on their own experience. This was interesting because participants immediately thought of how the chatbots could benefit the community as a whole, not only themselves.

Multiple examples from our study illustrate this point. When asked to design their chatbot, participants drew on experiences from not only themselves but from other members of the community to support their needs. This was because their needs and struggles aligned with those of the community, and they wanted the chatbot to address these as a whole. For example, participants wanted the chatbot to solve the problems shared by the members of their local communities, such as financial struggles or lack of COVID-19 protocol information. This reflects and extends the history of community-based efforts to overcome challenges and improve the lives of Black communities regarding health and education [48, 81]. Moreover, participants discussed the long-held mistrust toward the health system and the government shared within their local communities. This impacted their attitude toward the COVID-19 deaths within the community and the COVID-19 vaccines. They wanted to speak out about their frustrating experience of how their close ones were denied treatment, or to persuade the community about the importance and safety of the vaccine. They wanted the chatbot to act as a bridge, carrying the voices of their local community regarding their difficulties but at the same time attempting to mitigate their historical mistrust.

In the prior literature on technology design for the Black community, Parker and colleagues used community-based design [80] to conduct studies that examined how technology could be embedded in community-based health intervention programs, or how community-based participatory research could be used to develop technological tools for providing diabetes medication information [51]. These efforts demonstrated that this type of community-based approach works effectively for Black Americans and addresses disparities they faced. The strong participation of the faith communities in churches [21, 40] and the collectivistic culture [17, 44] were suggested as reasons for the effectiveness of such community-based intervention approaches.

Although most of the existing chatbot designs have focused on an individual, not the group or community [19, 33, 74], there have been a few chatbot designs based on such community-based approach. For instance, Kim and colleagues examined the possibility of chatbots serving as moderators or facilitators within a group [62] although it had less emphasis on the participant groups' cultural or shared values. O'Leary and colleagues conducted a more recent study where Black participants created virtual agents that could tailor to the cultural needs of the population both individually and collectively as a community such as the use of spiritual language or biblical content [75]. Moreover, Rankin and Henderson [85] demonstrated that Black youth wanted to provide a persona of Black women to conversational agents. This suggested the youth's desire of embodying the culturally shared idea of Black women's power and positive influence within the conversational agents. In this study, we added to this set of literature by highlighting how Black Americans tried to incorporate the shared culture and community values when designing the chatbots for their health. They wanted the chatbot to help remedy community-wide issues by providing financially viable health options, delivering health information to those with less health literacy and access to medical professionals, or reducing medical mistrust and persuading community members of the safety of the vaccines. This community-based design is all the more important because past literature has noted how insufficient tailoring to the community has generated criticism and ineffectiveness [41, 42]. Therefore, chatbot design should keep in mind that the chatbot should serve not only individuals, but the community as a whole. Understanding the community's needs should enable the chatbot to engage with the individual even more effectively because it comprehends their cultural values.

From this, we derived a design implication for the chatbot that can address the emphasis on the local community. The chatbot should maintain a database of the users' struggles, not only individually but as a community-wide effort. This database should be the source from which the chatbot draws solutions to match the needs of struggling users. As the needs of one local community can be vastly different from those of another one, devising solutions that satisfy the needs of a specific group is important. For instance, there might be a particular community that is more prone to mistrust of the vaccines. In this case, the chatbot must keep records of the reasons why this community lacks trust and endeavor to provide persuasive answers for the specific group.

Focusing too much on the individual can make the chatbot lose sight of the whole community's needs. As important as personalization is, chatbot design for the Black American communities should keep in mind that focusing on the group will allow better engagement from the individual.

6.3 Designing Chatbots while Considering the Socioeconomic Factors of the Population

Our analysis also highlights the importance of considering the socioeconomic context when designing a chatbot for the Black American community. Here, we do not intend for our analysis to be monolithic, but rather to focus on the aspects that participants wanted for the chatbot design in terms of inclusivity. Understanding the socioeconomic context was specifically pertinent to how participants designed their chatbots to support lower-income households, or how they expressed concerns about them. Three examples that support this could be derived from our findings. First, participants designed chatbots that provide health options aimed at lower-income households. They were aware of the difficulties their communities faced and wanted the chatbot to gear its recommendations based on this context. Also, participants discussed the potential obstacles for those who did not have access to high-speed Internet. They were mindful of the fact that chatbot usage requires a certain degree of Internet bandwidth. They expressed the concern that people without high-speed Internet would not be able to access the useful information from the chatbot because of their financial hardship and lack of bandwidth. Finally, participants wanted to access mental health therapies through the chatbot because they wished for mental health aid that was always accessible at a low cost. Because they had experienced long wait times for medical services and had had difficulty getting mental care, they viewed the chatbot as a potential replacement for such services.

In HCI and CHI communities, there have been ongoing research efforts intended to design health technology for marginalized populations while moving the design away from the mainstream and reflecting upon the role of technology. These works strive to incorporate the diversity of the users' context with the aim of reducing disparities that exist, such as health literacy disparities [8, 20, 59] or income gap [43, 78]. Artificial intelligence technology design is also starting to consider the context of marginalized populations because demographic disparities can be magnified when the input data used to feed the AI algorithm do not take into account for their context [28, 104].

One example of how AI algorithms result in ineffectiveness concerns image recognition technology. In one study, when an AI algorithm was programmed to recognize images of household objects (e.g., soap, toothpaste, spices), it did not work for objects in lower-income households as well as it worked for those in higher-income households [24]. Because lower-income households might not have the items typically owned by higher-income populations, the AI algorithm has difficulty recognizing images of the objects from those households. This exemplifies how the same technology cannot be used to derive equally positive results when targeted toward different populations with different contexts. Since the chatbots are also driven by AI algorithms, what the algorithms should learn is of great importance.

Despite such efforts to consider the context of marginalized populations in the HCI community, relatively few chatbots have been developed for marginalized populations. A common pattern that exists among the chatbots is that they seek to reduce the information gap between low-income and high-income communities. For instance, Yadav and colleagues [118] designed and evaluated a chatbot that educates women in impoverished parts of India about breastfeeding. To create the chatbot in a holistic way, they drew attention to situated-knowledge (e.g., complementary food for mothers, mothers' perception of breastfeeding) while also accounting for the sociocultural and socioeconomic factors of the users. Moreover, Bickmore and colleagues [6] designed a virtual agent that delivers hospital discharge plans to patients with inadequate health literacy. They discovered that the agent has the potential to deliver health information in an acceptable and usable manner to those with lower health literacy.

Similarly, we offer three chatbot designs drawn from our participants' insights in order to minimize the information gap and ensure accessible healthcare. First, participants wanted the chatbot to provide health options that are accessible by low-income households. However, it is important to note that participants were only willing to disclose their financial information after trust was sufficiently developed with the chatbot. Therefore, the chatbot must first inquire about the users' surrounding situations and try to create a rapport with them. The chatbot should then attempt to understand their financial circumstances and provide recommendations based on financially viable choices.

Second, participants expressed the potential challenge of users lacking access to the high-speed Internet that makes utilizing the healthcare chatbot possible. In this case, the chatbot must be able to download necessary information and knowledge so that it can also provide it offline. Users could download such information in areas where Wi-Fi connections are free, such as public libraries or coffee shops. When a need arises, the chatbot should be able to provide answers without connecting to the Internet because it has already downloaded the necessary information.

Third, the chatbot should be designed to allow participants to express their emotions comfortably. Because mental health resources or therapists are costly and difficult to access by the Black American community, the chatbot could act as a receptacle into which participants can pour their emotions without financial concerns. Indeed, many participants showed their desire to vent their feelings to the chatbot without monetary or emotional burdens. In this process, the chatbot should be designed to ask questions that could broaden users' perspectives. Asking questions about why users have felt that way or suggesting other ways to view certain situations would enable the chatbot to provide mental health access that is otherwise difficult to attain by Black American users.

7 LIMITATIONS AND CONCLUSION

A few limitations exist within our study. First of all, most of our participants were Black American women in the Midwest region, so we are unable to generalize to all Black Americans in the United States. However, our focus in this study was to gather preliminary data about what Black Americans with chronic conditions would deem as necessary and useful in developing chatbots to serve their needs. Therefore, the findings from this study can serve as an initial set of data upon which future researchers can build. Additionally, we did not control for the income and education levels of the participants, so the results might have differed had Black Americans with other education or income levels been included. Along a similar line, we collected data from participants with access to a laptop or a desktop with a webcam, which ended up excluding many potential Black Americans without the device. We therefore hope to conduct future studies that sample participants who only have access to smartphones to investigate the needs of such populations. This might lead to gathering more data about younger adults with lower income or education levels [120].

In this paper, we examined the expectations of Black Americans with chronic conditions in designing chatbots that could help them overcome the challenges of COVID-19. We discovered that participants wanted four different roles from the chatbot: mediator in accessing health services, personal assistant, information hub for COVID-19 and the vaccine, and mental health aid. We also identified three features that participants wanted: a chatbot persona that increases trust, a chatbot with learning capabilities, and a direct chatbot communication style that asks questions. We also presented obstacles that users might face in interacting with the chatbot. We believe that our work contributes to the HCI domain by suggesting design implications for a marginalized community and providing a user-centric way for them to better serve such communities' needs through AI chatbots.

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