
Research and Applications

Information needs and perceptions of chatbots for hypertension medication self-management: a mixed methods study

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ABSTRACT

Objective: Chatbots have potential to deliver interactive self-management interventions but have rarely been studied in the context of hypertension or medication adherence. The objective of this study was to better understand patient information needs and perceptions of chatbots to support hypertension medication self-management.

Materials and Methods: Mixed methods were used to assess self-management needs and preferences for using chatbots. We purposively sampled adults with hypertension who were prescribed at least one medication. Participants completed questionnaires on sociodemographics, health literacy, self-efficacy, and technology use. Semi-structured interviews were conducted, audio-recorded, and transcribed verbatim. Quantitative data were analyzed using descriptive statistics, and qualitative data were analyzed using applied thematic analysis.

Results: Thematic saturation was met after interviewing 15 participants. Analysis revealed curiosity toward chatbots, and most perceived them as humanlike. The majority were interested in using a chatbot to help manage medications, refills, communicate with care teams, and for accountability toward self-care tasks. Despite general enthusiasm, there were concerns with chatbots providing too much information, making demands for lifestyle changes, invading privacy, and usability issues with deployment on smartphones. Those with overall positive perceptions toward chatbots were younger and taking fewer medications.

Discussion: Chatbot-related informational needs were consistent with existing self-management research, and many felt chatbots would be valuable if customizable and compatible with patient portals, pharmacies, or health apps.

Conclusion: Although most were not familiar with chatbots, patients were interested in interacting with them, but this varied. This research informs future design and functionalities of conversational interfaces to support hypertension self-management.

Key words: hypertension, self-management, conversational agent, chatbot, mobile health

BACKGROUND AND SIGNIFICANCE

Nearly half (46%) of U.S. adults have hypertension,¹ making it the most common chronic disease and a leading risk factor for heart disease.^{1,2} While there are multidimensional health system and patient-related factors associated with inadequate blood pressure control, a main contributor is poor self-management related to diet, exercise, sleep, and medication management.³ Medication self-management is defined as the extent to which a medication is taken as prescribed, including the appropriate dose, frequency, spacing, and safe use over time.⁴ Although approximately 75% of U.S. adults take hypertension medications, only half have blood pressures that are adequately controlled.⁵ Hypertension is typically asymptomatic, and patients may not perceive immediate benefits from taking medications or adhering to strategies that promote lifestyle changes.⁶ Digital health approaches to improve hypertension medication self-management have been investigated using mobile applications (apps), short message services (SMS), and devices that connect to apps, such as Bluetooth pill boxes.⁷⁻⁹ Prior research has demonstrated improvements in medication self-management primarily through informational, behavioral, and motivational approaches, such as education, tracking, reminders, and social support.⁷⁻¹² However, many digital health approaches often fall short due to suboptimal adherence toward the technologies and limited patient engagement.^{9, 13} This may be due, in part, to limited personalization of digital solutions or lack of user motivation to interact with the intervention.¹³⁻¹⁵

Emerging digital health technologies, such as conversational agents, have the potential to communicate with patients and serve as effective self-management tools for chronic conditions.¹⁶⁻²² Conversational agents, also known as chatbots, are systems that can communicate in natural language through text or voice.²³ Chatbots have unique characteristics that make them highly suitable for delivering self-management interventions. For example, chatbots can mirror a therapeutic process, such as cognitive behavioral therapy or brief motivational interviewing.¹⁹ The first well-established chatbot, ELIZA, was developed in 1966 and mimicked a Rogerian psychotherapist.²⁴ ELIZA detected keywords and then used a series of decomposition and reassembly rules to respond to users with open-ended messages. ELIZA and other text-based systems have also been used to engage users in sensitive or stigmatized topics such as mental health concerns.^{25, 26} Affective chatbots, which show empathy, can also help alleviate negative symptoms or emotions.^{27, 28} These social and relational characteristics of chatbots may be valuable to actively engage users in self-management tasks.

Related work

Within the last 20 years, an increasing body of evidence has demonstrated the potential for health-related conversational agents.²² Recent improvements in computing power and artificial intelligence (AI) have spurred a number of more sophisticated dialogue systems with natural language processing capabilities.^{16, 17, 20} Although the evidence is limited, prior reviews of health-related conversational agents have demonstrated high acceptability and positive health outcomes, such as diet, physical activity, symptoms, and treatment adherence.^{21, 22, 29-31} To date, the field has primarily focused on mental health conditions and most studies lack a comprehensive understanding of patients' needs.^{21, 22, 29-31} Patients may also require varying levels of support depending on sociodemographic character-

istics, health status, and cultural factors, and these needs largely remain implicit and unaddressed in the existing body of research.^{29, 30} These are important considerations for designing conversational agents because they impact one's ability to self-manage health and use technologies.

Very few studies have assessed the use or perceptions toward conversational agents for hypertension self-management.^{32, 33} Persell et al evaluated the effectiveness of a home blood pressure monitor plus text-based chatbot, which provided encouragement for blood pressure tracking, medication adherence check-ins, and coaching for barriers to adherence.³² Although no differences were found between intervention vs control groups for mean blood pressure or medication adherence at six months, self-confidence in controlling blood pressure was significantly higher in the chatbot intervention group.³² Migneault et al assessed the use of a culturally adapted voice-based system, which provided coaching on medication adherence, physical activity, and diet in patients with hypertension. There were no differences in medication adherence or blood pressure (intervention vs control) over the one-year study period, but there were improvements in diet quality and energy expenditure.³³ These early findings suggest the optimal design, features, and preferences of conversational agents for hypertension self-management are not well known, and a deeper understanding of information needs and perceptions are necessary to inform design improvements to facilitate blood pressure control. Our study seeks to address these gaps and assess patients' needs across health-related and sociodemographic characteristics.

OBJECTIVE

The objective of this study was to better understand information needs and perceptions toward using a chatbot to support hypertension medication self-management as the initial phase of the user-centered design process toward developing a chatbot prototype. We also examine other aspects of self-management skills as they relate to hypertension and how these might be supported through the use of a chatbot.

METHODS

Study design

We used a convergent mixed methods design,³⁴ which combined qualitative and quantitative data collected from in-depth semi-structured interviews and self-administered questionnaires. The qualitative description research was conducted in accordance with the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist.³⁵ Because several sociodemographic characteristics are associated with access and use of technology (eg age, education),^{36, 37} a mixed methods approach was used to generate a more comprehensive understanding of perceptions across sociodemographics to optimize the future design of the chatbot. This study was reviewed and exempted by the University of North Carolina at Chapel Hill Office of Human Research Ethics Institutional Review Board.

Study setting and participants

Participants were adults (18+) who self-reported having a diagnosis of hypertension, took at least one hypertension medication, spoke English, took their medications without assistance, could attend an in-person interview, and owned a smartphone or tablet. Purposive

sampling was used to select 15 adults based on age, race, gender, education, and number of medications. The sample size of 15 individuals was chosen because prior research has shown thematic saturation generally occurs within the first 12 interviews.³⁸ From this sample, interviews were conducted until data saturation was reached, which was defined as when no new themes emerged from the data.³⁹

Recruitment

Participants were recruited using websites, e-mail list-servs, and flyers posted in clinics, hospital waiting areas, and community locations in Chapel Hill, North Carolina and the surrounding areas. Recruitment materials contained a link to an electronic screening questionnaire to assess eligibility. Then participants were sampled to vary representation among clinical and sociodemographic characteristics. The aim was to have at least: five adults who were 65+ years, five of minority race, five males, five with education less than college, and five who were taking at least three medications.

Interview guide and questionnaire development

The interview guide was developed by our study team and contained questions related to medication management and hypertension self-management as managing medications is often influenced by multiple factors (eg blood pressure control, social support, patient-provider communication).⁴⁰ The interview guide was informed by constructs from the Information–Motivation–Behavioral Skills Model⁴¹ and the Unified Theory of Acceptance and Use of Technology (UTAUT).⁴² For example, questions related to information needs included “What types of information or resources would be helpful for you to keep track of taking your medications?” Questions related to the UTAUT included “How do you think a chatbot could help you take or refill your medications?” Follow-up questions to probe on these topics were asked as needed to generate additional insights (see [Supplementary Material S1](#)).

The study questionnaire contained questions about sociodemographics, medical history (conditions and medications), and experience with using technology. We also used several validated questionnaires on the topics of health literacy,⁴³ medication self-efficacy,⁴⁴ and barriers to medication adherence.⁴⁵ The 3-item Brief Health Literacy Screener by Chew et al was administered to assess health literacy⁴³. Total scores range from 3 to 15, and any response >3 for any question indicates inadequate health literacy.⁴⁶ The Patient-Reported Outcomes Measurement Information System (PROMIS) Self-efficacy for Managing Medications and Treatments Short Form 8a (2016) was used to assess confidence in managing medication schedules and treatments.⁴⁴ This instrument was scored using the PROMIS HealthMeasures Scoring Service, where raw scores were converted into T-scores with a mean of 50 (SD = 10) with higher scores representing greater self-efficacy. The Adherence Starts with Knowledge 12 (ASK-12) by Matza et al assessed barriers to medication and treatment adherence in domains of inconvenience or forgetfulness, treatment beliefs, and behaviors.⁴⁵ Total scores for this instrument range from 12 to 60 with higher scores representing greater barriers to adherence. Prior approval was obtained for the use of 3-item health literacy measure and ASK-12.^{43, 45}

Procedures

One female researcher (A.G.), who has been trained in qualitative methods and interviewing, conducted the in-person, semi-structured interviews using the interview guide. The interview guide and study

questionnaire were initially pilot tested with several members of the study team. There were no established interviewer–participant relationships in the study sample, and the interviewer had no conflicts of interest.

The interviews were conducted face-to-face in a private office with only the participant and interviewer. First, participants were consented and completed the study questionnaire, which took place prior to the interview. Next, participants were asked about their current self-management behaviors and information needs to manage their blood pressure and to support their medication regimens. Since many may not have had any exposure to chatbots, participants were introduced to chatbots through a description and short video. The interviewer described a chatbot as “a system that can communicate with people; it is often called a virtual assistant or virtual coach even though it is not an actual person.” The video showed a commercially available text-based health chatbot, “Florence,” that focused broadly on health and wellness such as receiving health information or locating a doctor.^{47, 48} The video does not specify any particular condition or focus on hypertension. This video was selected to illustrate how someone would interact with a general health-related chatbot on a smartphone through text messaging. After watching the video, participants were asked about their perceptions toward using a chatbot to manage their blood pressure and medications. Perceived barriers and facilitators for using a chatbot were also elicited. Each interview lasted approximately 60 minutes, and participants were provided with a \$25 gift card. Interviews were audio-recorded, and the interviewer took brief notes during and after the interview. All 15 participants completed the interview and no one dropped out. There was no additional follow-up with participants.

Analysis

Audio files from interviews were transcribed verbatim and imported into NVivo qualitative data analysis software.⁴⁹ Participant narratives within the transcriptions were then analyzed using an iterative applied thematic analysis.⁵⁰ First, a codebook of structural codes was developed based on the initial topics from the interview guide prior to analysis. Two independent reviewers (A.G. and Z.X.) applied these structural codes to segment participant narratives by topic. Discrepancies in coding were adjudicated by a third reviewer (S.M.) when necessary. Transcripts were initially double-coded until Cohen’s kappa⁵¹ of 0.8 was reached, which was after three transcripts. After double-coding, the rest of the transcripts were equally distributed and single-coded by the reviewers, and discussion occurred after each batch of 2–3 transcripts. Next, each reviewer inductively identified and applied thematic content codes in each structural coding report with each report containing a topical area across all participant narratives (eg perceptions, barriers, facilitators, etc.). Structural coding reports were also initially double-coded and Cohen’s kappa was assessed again as above, which was achieved after coding three reports. The remaining reports were then equally distributed and single-coded among reviewers (A.G. and Z.X.), and reviewers discussed whether new or additional content codes should be added after each report. Lastly, reviewers met to organize the content codes thematically to describe the major themes, subthemes, and illustrative quotes within the themes. Quantitative data collected from the study questionnaire were summarized using descriptive statistics. Sociodemographic data were also integrated with the perceptions and perceived usage themes to better understand attitudes toward using a chatbot.

RESULTS

Sample characteristics

Thematic saturation was met after interviewing 15 participants. The average age of participants was 59 years, 8 (53%) were female, 10 (66%) were White, and 9 (60%) had at least a college education (Table 1). Nine individuals (60%) had hypertension for at least 5 years, and nine (60%) were “very or completely confident” their blood pressure was under control. On average, participants had three comorbidities and were taking six prescription medications (ie medications for hypertension plus those for other conditions). The majority (87%) had adequate health literacy, had scores above the U.S. population average for medication self-efficacy (52.3), and felt that the greatest barrier to adherence was behavior (ie “not had a medication with you when it was time to take it”). Only 20% of participants reported using a chatbot before, which were focused on financial, cable TV/Internet support, or to control home appliances. None reported using a chatbot for health-related purposes.

Information needs for a hypertension medication self-management chatbot

Qualitative analysis identified four key domains (medications, refills, communication with the care team, and healthy lifestyles), which comprised 10 themes for information and support needs for hypertension medication self-management (see Table 2). Medication information needs included: having a list of current and past medications, the ability to set medication reminders, and information about the medications and side effects. For managing refills, participants were interested in reminders to order or pick-up medications and the ability to view the number of refills left, date of next available refill, and expiration date. Some wanted a chatbot to integrate with their pharmacy to automatically order refills. Most desired to communicate with their care team by sharing their health data (eg, blood pressure, weight, physical activity) and to be able to schedule appointments. For healthy lifestyles, the majority were interested in tracking health-related metrics and receiving encouragement based on these data from the chatbot. Several described how a chatbot could provide feedback on results after a clinic visit, and many felt it would be necessary to integrate the chatbot with existing apps, specifically MyChart patient portal and Fitbit. Several expressed the need for accountability to keep their blood pressure under control.

Perceptions and perceived use of a chatbot

Perceptions for using chatbots were categorized into three key themes: similarities to existing apps, curiosity about chatbots, and chatbots being humanlike (see Table 3). The majority of participants compared chatbots with smartphone apps they currently use to track or manage their health such as MyChart, Fitbit, Apple Health, and health insurance apps. Many were curious to know if a hypertension medication self-management chatbot already existed, and those who expressed curiosity were slightly younger on average than those who did not (56 vs 63 years). However, some older adults conveyed interest in using new technologies specifically because they were “older” and wanted to keep up with emerging technologies. Most of the participants who were curious about using a chatbot were taking fewer medications on average compared with those who did not (4 vs 7 medications). Many who were taking several medications felt they had already established a routine and would not be likely to rely on a chatbot for a reminder. Several also felt chatbots seemed humanlike and compared them with talking with a friend or health coach. Those who perceived them as humanlike were younger on average

Table 1. Sample characteristics

Characteristics	n (%)
Age (mean = 59, SD = 11) (years)	
45–54	6 (40)
55–64	4 (27)
65+	5 (33)
Gender	
Female	8 (53)
Male	7 (47)
Race	
White or Caucasian	10 (66)
Black or African American	4 (27)
Other	1 (7)
Ethnicity	
Not Latino/Latina	14 (93)
Latino/Latina	1 (7)
Education	
Less than college	6 (40)
College graduate or more	9 (60)
Household income	
\$20 000–\$34 999	2 (13)
\$35 000–\$49 999	4 (27)
\$50 000–\$74 999	5 (33)
≥\$75 000	4 (27)
Comorbidities, mean (SD)	3 (1)
Number of years with hypertension	
<1	1 (7)
1–2	3 (20)
3–5	2 (13)
≥5	9 (60)
Confidence blood pressure is under control	
Somewhat confident	6 (40)
Very confident	5 (33)
Completely confident	4 (27)
Number of prescription medications (mean = 6, SD = 4)	
1–3	6 (40)
4–6	4 (27)
7+	5 (33)
Internet use	
Once a day	1 (7)
More than once a day	14 (93)
Device use	
Smartphone	15 (100)
Tablet	10 (66)
Computer	13 (87)
Ever used a chatbot	
Yes	3 (20)
No/Do not Know	12 (80)
Health literacy level ⁽³⁸⁾	
Adequate	13 (87)
Inadequate	2 (13)
Medication self-efficacy ⁽³⁹⁾ , mean (SE)	52.3 (4.0)
Barriers to adherence ⁽⁴⁰⁾ , mean (SD)	
Behaviors	8.0 (3.9)
Treatment beliefs	7.7 (2.0)
Inconvenience/forgetfulness	6.1 (2.8)
Total score	21.8 (6.1)

(51 vs 64 years) and taking fewer medications (3 vs 6 medications) compared with those who did not. Based on this analysis, perceptions of chatbots may vary based on age and number of prescribed medications taken.

Preferred frequency of use of a chatbot was grouped into three categories based on analysis: daily, weekly to monthly, and rarely to

Table 2. Self-management needs and desired features of a chatbot for hypertension medication self-management

Themes for user needs	Representative selected quotes
Medications	
List of current and past medications	<p>“I can never remember the name [of the medication]... I wonder if that [chatbot] may be able to hold a history on your medications.” (P7)</p> <p>“It would be lovely to load in my medications because I have an extensive list.” (P8)</p>
Reminders	<p>“If it could prompt me only on days where there’s a high probability that I forgot [to take the medications], like weekends and holidays. . .” (P9)</p> <p>“I might only need my reminder once every three or four days to make sure that I’m where I need to be with my medications. . .” (P5)</p>
Information about medications and side effects	<p>“I’ll use various websites, sometimes WebMD or Mayo Clinic, to see what they’re giving me and what side effects I can look for. . . I always ask how it interacts with my other medicine, and if I’m allowed to adjust the times according to what works best for me.” (P2)</p>
Refills	
Reminders to order and pick-up medications	<p>“If that system worked the way you really wanted, you would put in your medication, milligrams, frequency, and how often it refills. Then, it’ll prompt you and say, ‘It’s time to refill your medicine.’” (P6)</p> <p>“When [the chatbot] says, ‘Okay, it’s time for a refill,’ [I’d say] ‘Can you request the refill without me going through the extra steps?’” (P3)</p>
Number of refills left and dates of next refill and expiration	<p>“It might be useful to see the refill date so I would know without having to count how many I have left.” (P11)</p> <p>“It’d be nice for my health professionals to help keep up when the prescriptions expire because I run into that a lot. . . Send a reminder or set it up so that it lets me know, ‘You have one month of it left.’” (P8)</p>
Communication with care team	
Sharing health information	<p>“It’d be really cool if there was some way when I take my blood pressure I could get it into my medical records. . . If the chatbot was something where I could put in my readings, when I go to my doctor, [I could] bring it in or go through it with the nurse during our quarterly call.” (P4)</p> <p>“I got one doctor that’s my primary doctor, and I’ve got two more doctors which are my cancer doctors. They ask me about each other. That right there’d be able to help me communicate; get them on the same level.” (P7)</p>
Appointment scheduling and reminders	<p>“It would be helpful if the chatbot could remind me a month before, ‘You need to schedule your appointment.’ Or, ‘It’s time for your physical.’” (P10)</p> <p>“I would much rather schedule my appointments through [the chatbot] than having to call. I don’t like calling because they want me to repeat my entire life story and give all my information to a person I don’t know.” (P14)</p>
Healthy lifestyles	
Health tracking and compatibility with apps	<p>“A lot of times my weight and blood pressure are tracked through my MyChart app. . . If all of that can be fed into the chatbot, it would be a better tracker because it would have a more rounded view.” (P8)</p> <p>“MyFitnessPal has weight. Fitbit can do weight. . . An application like this probably should tie into both. I’d be interested in letting them connect.” (P9)</p>
Feedback and encouragement	<p>“Apple has the Health app, and it tracks everything. . . it actually reads from MyChart app now. It collects but, it doesn’t communicate. At best, it tells you [that] you have new information in your chart. . . [The chatbot is] a place where you can actually have almost a dialogue.” (P12)</p> <p>“If there was some type of way [the chatbot] was able to check what my blood pressure was at the time it’s elevated, then it would [say], ‘It’s time to take a break. Maybe you should go for a walk.’” (P10)</p>
Accountability	<p>“I think it would be great because it’s telling you, ‘Do it’ . . . With MyFitnessPal, I’m just looking to see how many steps I did. With that one, it’s going to probably prompt you for more things.” (P6)</p> <p>“It can probably track my last time taking my weight. . . It’s on you at all times, so that’s what I like about that.” (P7)</p>

Table 3. Perceptions and perceived frequency of use of a chatbot

	Representative selected quotes
Themes for perceptions	
Similarities to existing apps	“I go through MyChart now to do most of [the appointment scheduling], and I guess that’s kind of like a chatbot.” (P1)
Curiosity about chatbots	“It reminded me of the United Health app. That’s pretty neat.” (P6) “Is this being used at all, or are we totally in testing mode for this thing? . . .It’s pretty fascinating stuff.” (P5) “I like that—do they have it already? . . .I don’t want to miss it, and not be able to have something like that.” (P7)
Humanlike	“It was like you were just texting a friend, so it looked friendly and inviting.” (P3) “You would think really that you were talking to a person in a lot of ways.” (P14)
Themes for perceived frequency of use	
Daily	“I would probably use it on a daily basis, almost. It’s right there on the phone. . .I’d love to try it.” (P7)
Weekly to monthly	“I wouldn’t mind [using it] every day. I have a lot of apps that I interact with every day.” (P15) “It would be useful if I could decide how much stuff I’m getting. . .For the health tips, maybe once or twice a week. . .” (P11) “Every few weeks would be fine unless I really had some follow-up stuff to do or if I was having a problem” (P10)
Rarely to never	“I probably wouldn’t use it. . .I would find it unnecessary because I think I have under control what I can control.” (P13) “I’m sure there are folks who take advantage of things like that. Maybe at some point I would, but right now, no. . .If things start getting too hectic, [I need to] slow down. . .” (P2)

never (see Table 3). Several described how the amount of interaction would depend on utility of information provided. Similar to aforementioned patient perceptions, those taking fewer medications were interested in more frequent interactions, especially for non-medication purposes such as blood pressure tracking. Many who were diagnosed with hypertension within the past five years did not feel very confident that their blood pressure was adequately controlled. Several of these participants described being open to approaches that might help, such as using a chatbot. Overall, perceived frequency of interaction differed across characteristics including number of medications, time since diagnosis, and the level of confidence that blood pressure was under control.

Barriers and facilitators of using a chatbot

Four main themes were identified for barriers and three themes were identified for facilitators of using a chatbot to help manage medication regimens and blood pressure (see Table 4). Barriers included smartphone usability issues, fears that the chatbot would provide excessive or unhelpful information, make demands, or invade one’s privacy. Several participants were concerned that a smartphone screen would be too small or that keeping track of their phone regularly to use the chatbot would be difficult. Although some felt their blood pressure and medication routine were already under control, a few mentioned non-blood pressure use cases, such as cancer self-management or monitoring a family member’s health. Several stated they specifically did not want a chatbot to tell them what to eat or to lose weight. In regards to privacy issues, some participants referenced Amazon Alexa and Google Assistant and were worried about a chatbot listening to their conversations or sharing their information with other companies.

Key facilitators for using a chatbot for medication self-management included customizability, convenience, and being unobtrusive. Nearly all wanted to personalize the chatbot, especially the frequency of reminders and tips. Among those who reported us-

ing a chatbot before, all of them discussed the importance of tailoring the amount and type of information to make the interactions useful. Most liked the convenience of a chatbot being accessible on their phone or having all of their health information in one location. However, many also did not want the chatbot to interrupt day-to-day activities.

DISCUSSION

Chatbot-related needs for medication self-management in patients with hypertension were consistent with needs identified in prior research on medication adherence and self-management.⁷⁻¹² Our research extends these perspectives by providing additional understanding and nuance around leveraging chatbots specifically for hypertension self-management as the user experience is different for this technology compared with mobile apps and text messaging interventions. Overall, participants had generally positive attitudes toward medication self-management interventions delivered via chatbots. While most had not previously used chatbots, almost all perceived the conversational nature to be potentially helpful for various self-management tasks such as tracking medications, refills, blood pressures, or communicating with care team members. Many believed chatbots would be valuable if tailored and compatible with patient portals, pharmacy apps, or health tracking apps. However, participants expressed several concerns with chatbots providing too much information, messages about lifestyle modifications being demanding, invading their privacy, and usability issues with interacting with chatbots on smartphone screens which are typically smaller than tablets or personal computers.

Our study revealed several design recommendations and implications for hypertension medication self-management conversational interfaces and user experiences. Patient perspectives varied across health-related and sociodemographic characteristics. Patients who were younger and taking fewer medications seemed more curious and interested in using a chatbot for hypertension self-management.

Table 4. Barriers and facilitators of a chatbot for hypertension medication self-management

	Representative selected quotes
Themes for barriers	
Cell phone issues	“I can go to MyChart, but I normally do that on the big computer. It’s just kind of aggravating on my smartphone. I don’t know how that [chatbot] might be.” (P7)
Too much information or not useful information	“It just felt like it was annoying, had too much information, and I didn’t want look at it cause it’s too many things to go through. . .” (P11) “To open the computer or iPad to get additional health information would be unnecessary because I’m pretty conscientious with my medicine.” (P13)
Making demands	“It’s either going to be a good conversation with the chatbot or it could get a little lippy if I put some weight on, in which we would reduce the chatbot usage to once a week.” (P4) “Telling me, ‘Don’t eat that burrito. There’s too much salt.’ . . . I don’t want to go to my iPhone to ask if I can eat my burrito.” (P1)
Invasion of privacy	“I’m not going see a message on my TV that [says] ‘Did you take your medicine?’ or Alexa’s not going to tell me, ‘You better check your phone.’ I get creeped out when technology is intrusive.” (P10) “I have one of those Google speakers at home. I unplug it when I’m home because sometimes I’ve had a conversation and it picks it up. The next thing you know I’m getting advertisements. . . as long as it wasn’t intrusive like that.” (P14)
Themes for facilitators	
Customizability	“If you could check some boxes of things you like and don’t want. . . You could check: I want tips daily, weekly, monthly, no tips, or I want reminders every day for checking my blood pressure.” (P11) “I imagine she will pop up on my phone and say ‘Take your meds,’ ‘It’s time for a refill,’ or ‘You don’t have refills left’ . . . There should be some flexibility in scheduling it like there is with your calendar.” (P8)
Convenience	“I think it’d be helpful with managing my health. . . It’d be nice to have it all in one place on my phone to use it whenever needed.” (P10) “It’s more like a health coach instead of me waiting for somebody to call me. . . I miss the call, call back, and then I have to go through many things to get to the person. I think that would be a little bit more helpful because I’m not trying to run someone down.” (P6)
Unobtrusiveness	“I prefer things to be as minimal and as automatic as possible. . . That’d be great if it’s streamlined and invisible.” (P1) “I would be interested in some kind of way of recording stuff as long as it wasn’t so time-consuming.” (P9)

These findings are in accordance with the Unified Theory of Acceptance and Use of Technology, which demonstrates that age is a moderator of one’s acceptance and behavioral intention to use a technology.⁴² Some older adults described limited use of their smartphone given the small screen or inability to keep track of it, which suggests the need to explore interfaces for these populations that better fit their needs (ie multimodal or voice-based). A few older adults desired to use new technologies, such as Amazon Alexa, and reported that younger relatives taught them how to use it. Providing technical assistance for older adults has demonstrated improvements in health technology adoption,⁵² and should be considered in the design and implementation of systems targeted toward older populations.

Similar to prior research, the ability for individuals to personalize nearly all aspects of the chatbot was important to patients, including content, frequency of receipt information and reminders, tone of language, and type of feedback.⁵³ Several participants in our study discussed the type of feedback and conversation they would have with the chatbot, which differed across participants. Some preferred to have a more active coaching style based on their established routines, self-efficacy, confidence, or duration of hypertension, while others felt it might be too intrusive. Since hypertension requires continual self-management, effective conversational agents must be able to store extensive information about user preferences and routines, and potentially evolve conversations based on

goals, self-efficacy, and health status. Several participants personified the chatbot and described it as “friendly” or “like talking with a friend.” Human-sentiment norms are present in human-agent interactions, and people have a natural propensity for interacting with computers as if they were people.^{54, 55} For example, people perceive computers as more likeable when flattered or humored by them.⁵⁵ This suggests that conversational agents should not only provide tailored self-management content, but also employ appropriate relational social dialogues.²⁷

To maximize utility, it is important to consider whether tethering chatbots to other applications to integrate health information from portals, pharmacies, or other health apps may improve the user experience or self-care tasks. For example, chatbots could provide enhanced interactions by contextualizing data, such as number of daily steps taken from a physical activity tracker or a lab result from the patient portal, into actionable lifestyle changes to improve hypertension control. A survey of physicians found overall positive perceptions toward chatbots being able to support and motivate patients,⁵⁶ though barriers and facilitators of integration within clinical settings has not been well-studied to date. Safety and the quality of information provided in chatbots should also be assessed before deployment.^{57, 58} Incorporating linguistic data from chatbots, mapping these data to existing terminologies, and interoperability within other technologies are also needed if chatbots are integrated into clinical workflows. As with incorporating any type of patient-

generated health data into care settings,^{59, 60} the relevancy and interpretability of health professionals should also be assessed.

Limitations

The study sample was limited to adults with a smartphone or tablet from a single geographic location in the Southeast, so these findings may not reflect the perceptions among all adults with hypertension. Moreover, those who agreed to participate may have had stronger inclinations toward using new technologies and may not be representative of all patient perspectives. As purposeful sampling is a non-probabilistic sampling method used in qualitative studies, we were unable to control for the potential influence of confounding variables or differences in perceptions based on individual sociodemographic characteristics. Three participants (20%) reported prior experience with a chatbot which might affect their perceptions and perceived use. Although all participants watched a video of the same example of a chatbot, those with no prior experience may have found it more challenging to envision interactions with a chatbot. The study sample also comprised a relatively older population, had high levels of adequate health literacy, and above average medication self-efficacy in comparison with the U.S. adult population, which may somewhat limit generalizability.

CONCLUSION

Given the growing burden and national focus on hypertension control in the U.S., novel self-management and medication adherence tools may help improve blood pressure control, which could be impactful both for patients and health systems.^{61, 62} Although most participants (80%) had never used a chatbot, the majority showed interest in using a chatbot to help track their medications, refills, blood pressures, or communicate with their care team. Our findings contribute to a better understanding of user needs and perceptions toward using a chatbot for hypertension self-management across individual characteristics, such as age, number of medications taken, duration of diagnosis, and level of confidence about blood pressures being under control. Being mindful of innate user differences and preferences would help facilitate the design and development of user-centered, personalized chatbot interventions. While the use of chatbots for self-management is still an emerging research area, chatbots have the potential to not only provide evidence-based resources, but to also actively engage patients through longitudinal conversations about their health information and goals. This research can inform the future design and functionalities of conversational interventions to support hypertension medication self-management. Additional investigation is needed to assess the usability, optimal timing and type of support, appropriate dialogues and interactions, effectiveness, and the privacy implications of chatbots.

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AUTHOR CONTRIBUTIONS

AG and AC were responsible for overall study concept and design. All authors contributed to the study design, interview guide, and questionnaire development. AG was primarily responsible for data collection. Qualitative analysis was conducted by AG, ZX, and SM. Quantitative analysis was conducted by AG. AG was responsible for the initial draft of the manuscript. All authors reviewed, edited, and approved the final version.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

CONFLICT OF INTEREST

None declared.

DATA AVAILABILITY STATEMENT

The data underlying this article will be shared upon reasonable request to the corresponding author.

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