

Evaluating User Experiences with an AI Chatbot for Health-Related Social Needs: A Cross-Sectional Mixed Methods Study

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Abstract

Background: Health-related social needs (HRSNs), such as food security and housing, significantly impact health outcomes and wellbeing. Although screening tools are widely adopted to identify the needs, sustainable linkage to resources remains challenging. Conversational agents (chatbots) offer potential solutions for tailored and personalized feedback, real-time navigation, yet their usability and trustworthiness among populations with high needs require further exploration.

Methods: We conducted a mixed-methods study to evaluate user experiences with the DAPHNE© chatbot, which is designed to identify unmet HRSNs and provide personalized resource recommendations. Quantitative and qualitative data were collected from 128 adults having child(ren). Online study design combined scenario/ task-based chatbot use and free form, to guide the engagement. Study measures included usability, task load, satisfaction, and trust. Qualitative analysis involved user feedback and user-chatbot conversation transcripts. We used regression analyses to explore associations between demographic characteristics, self-reported unmet HRSNs and user experience outcomes (usability, satisfaction, task load and trust).

Results: Most participants were female (68%), aged 30-49 years (71%), and White (44%) or Black/African American (36%) and Hispanic/Latino (27%), relied on Medicaid/Medicare (83%), and cared for a child with special needs (78%). Participants reported high usability (SUS= 84.7, SD=12.4), low task load (NASA-TLX= 6.8, SD=2.8), strong satisfaction (NPS= 8.0, SD=2.4), and high trust (Mean= 4.1, SD=0.8). Nearly all participants (98%) reported unmet HRSNs, notably food insecurity (76%) and financial limitations (75%). Free-form conversation sessions averaged 3 min and ~20 turns, with greater amount use of assistive buttons than typing. Dialogues centered on financial, housing, and nutrition needs, and 94% of participants reported that the tool helpful finding resources, while requesting design features like saved histories, voice interaction, and richer local resource details. Regression models revealed limited but informative associations. Usability and trust were broadly consistent across most demographic groups, though participants with higher education and lower income showed modest decrements in usability. Several HRSNs, including transportation and utility disruptions, were associated with higher trust and satisfaction, suggesting the assistant may hold particular value for users facing structural barriers.

Discussion: The DAPHNE chatbot demonstrates potential as a useful tool for addressing HRSNs, with

strong usability and trust among diverse populations. Future designs should focus on longitudinal impact assessments and effectiveness to enhance accessibility and address practical implementation challenges.

Keywords: Chatbot, Health-related social needs, User Experience, Usability, Trust, Digital health, Mixed-methods

Introduction

Health-related social needs (HRSNs), such as housing, transportation, food security, access to healthcare, and financial stability, account for over half of modifiable health outcomes and are closely associated with elevated morbidity, increased healthcare utilization, and premature mortality.^{1,2} These needs cluster along entrenched lines of income, race, and geography, amplifying inequities in health outcomes.^{3,4} Children are particularly vulnerable: persistent material deprivation impairs physical, emotional, and cognitive development and predicts poorer adult health trajectories.³⁻⁶ Routine HRSN screening is recommended across pediatric and adult healthcare settings, prompting widespread adoption of brief screeners in primary care, emergency departments, and inpatient wards.⁶ However, screening alone is insufficient; sustainably linking families to community resources remains a critical challenge.^{7,8}

In many clinics, a positive screening yields only brief provider guidance and a printed “resource sheet,” leaving patients and caregivers to navigate a fragmented constellation of supports. Staffing constraints, language discordance, and shifting eligibility requirements often derail this passive model -fewer than half of referred patients ultimately receive services.^{9,10} Electronic health record-embedded screeners and patient portals improve data capture but, without integration with a dynamic referral system, rely on static directories and manual matching, increasing the risk of sharing outdated information and missed connections.¹¹⁻¹³ Conversational agents (chatbots) can bridge the gap in understanding needs and navigating resources, by coupling natural-language processing with adaptive dialogue to deliver tailored guidance at scale.^{14,15} Looking at the literature of chatbot use in healthcare, systematic reviews and pilot studies focusing on health-information seeking, preventive screening, medication adherence, and chronic-disease self-management consistently report high perceived usability and promising clinical impact.¹⁶⁻²⁰

Our prior iterative design and evaluation study of a semi-functional HRSN chatbot, demonstrated perceived utility for resource linkage but also highlighted concerns regarding accuracy, resource sharing, and user trust.¹⁷ Collectively, these findings motivate further investigation of chatbots as scalable tools for personalized HRSN screening and real-time resource navigation in socioeconomically disadvantaged communities. Therefore, the current study builds upon our earlier work with improved and fully functional DAPHNE (Dialog-based Assistant Platform for Healthcare and Needs Ecosystem) chatbot,¹⁷ and presents an empirical investigation of its capacity to identify HRSNs and deliver real-time, personalized resource recommendations. Specifically, we assessed user experience through multidimensional measures of usability, satisfaction, task load, and trust, while examining how sociodemographic factors and identified HRSNs moderate these outcomes. By elucidating how individuals with unmet HRSNs perceive and engage with distinct chatbot features, our findings aim to inform design principles and implementation strategies for equitably scaling digital social care interventions across diverse clinical and community settings.

Methods

Study Design

We conducted a cross-sectional, mixed-methods study to evaluate DAPHNE chatbot. We employed a convergent parallel design,²¹ wherein quantitative and qualitative data were collected simultaneously, analyzed separately, and then merged to compare findings and draw comprehensive inferences.

DAPHNE Chatbot

The chatbot was designed to understand reported HRSNs via natural language and deliver personalized recommendations based on users' disclosed zip codes and self-reported HRSNs. Interactions with the chatbot followed a semi-structured conversational approach, enabling users to freely inquire about and explore community resources tailored to individual and contextual factors. After provided recommendations, upon user input to complete the session, the chatbot requested feedback on both resource and conversational quality to be used to improve its services.

Amazon Web Services (AWS) was used for dialogue flow design and early experiments with large language models, testing and validation. Then, DAPHNE was hosted on a chatbot prototyping platform (Voiceflow.com), enabling access via a secure web link. The user interface supported interaction via free-text responses and button-based navigation. The conversation logic was flexible to accommodate follow-up questions and provide further elaboration on previously suggested resources. Figure 1 provides an outline of DAPHNE chatbot and its ecosystem. The chatbot was hosted as a web app, and adaptive to use via web browser on desktop or mobile device.

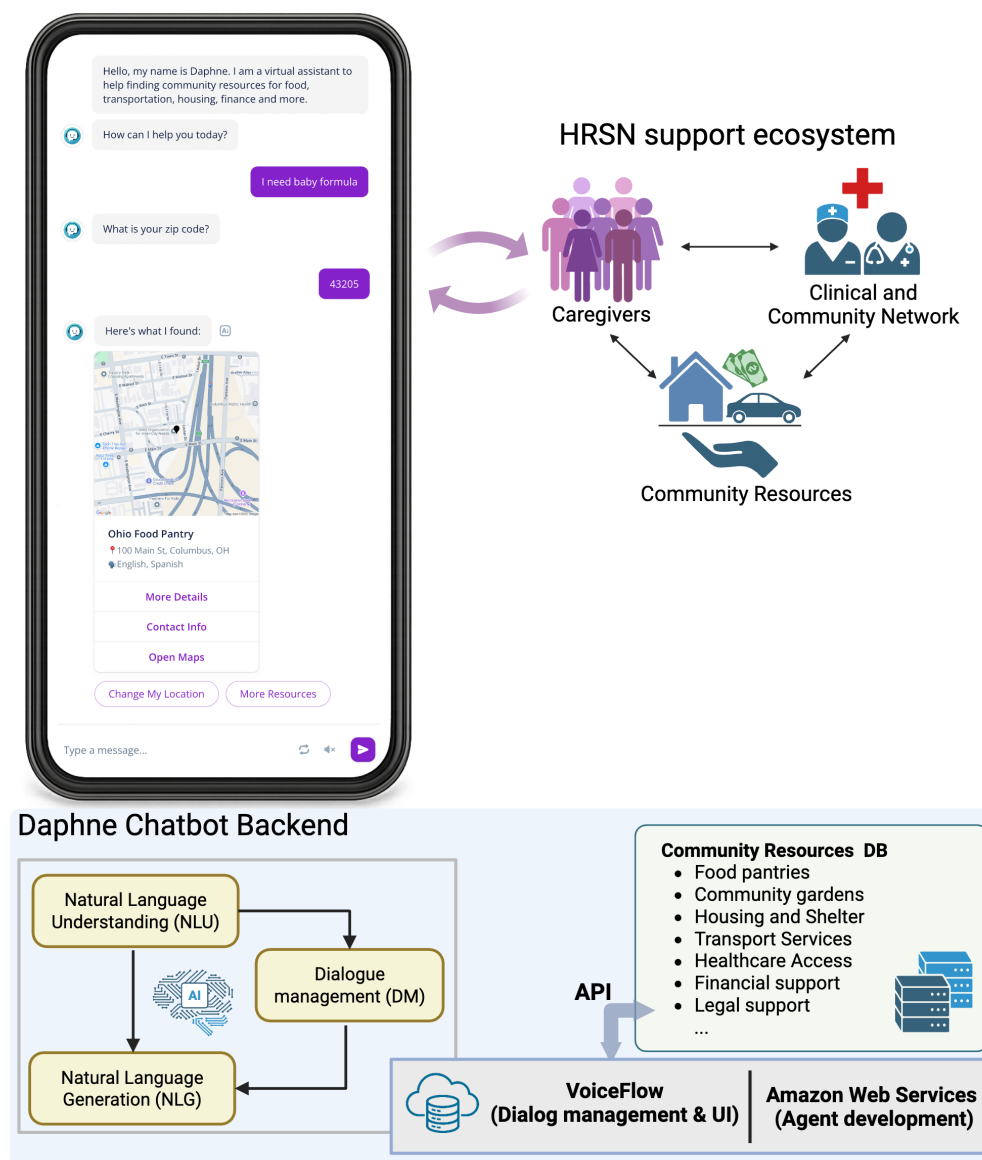


Figure 1. Overview of the DAPHNE chatbot. This system uses NLU and API for its functionality and to augment existing HRSN support

Given the mixed nature of user interactions (button and free-text), a hybrid approach was used by integrating rule-based dialogue management with natural language understanding (NLU) models. This approach enabled the chatbot to accurately interpret and categorize user intents, ensuring structured conversational flows by identifying and responding appropriately to HRSN requests. To manage user inputs, large language models (GPT-3.5 Turbo and Claude 3.5 Haiku)^{22,23} were employed for NLU and NLG tasks, further supporting clarification messages and empathetic response generation. Additionally, for non-categorized user entries and information that was unavailable through the application programming interface (API), we used a scripted fallback mechanism to indicate when an input was not understood. Resource recommendations were generated through natural language generation (NLG) limited to and only contingent upon data retrieved via API requests from social care and resource platform (Findhelp.org). This approach

ensured that the chatbot did not autonomously generate responses without direct reliance on API-provided information. This structured retrieval and generation approach was based on the established Retrieval Augmented Generation (RAG) framework,^{24,25} ensuring the accuracy and personalization of recommendations aligned with user-stated attributes and contexts.

Recruitment and procedure

Participants were recruited through an online research platform (Prolific.com) following a purposeful sampling approach. Recruitment and study participation occurred between January 1st and March 30th, 2025. Inclusion criteria required participants to be caregivers aged 19 years or older, residing in the United States, cared for at least one dependent child, and reporting an annual household <\$40,000 (amount selected by income equal to or below the U.S. national average with one dependent or more). Participants were excluded from the study if they declined consent, opted out at any step of the study, or failed attention-check tasks embedded within chatbot interactions. Informed consent was obtained electronically, and participants completed study participation via a HIPAA-compliant online survey platform (REDCap).²⁶ Participants were compensated for their time.

Participants received their instructions and completed quantitative and qualitative measures on REDCap before and after engaging with the chatbot. Engagement with the chatbot was guided through four scenarios with attention checks. Prior to the data collection, a pilot group of participants (N=8) were recruited to test for understandability and clarity of survey questions, scenarios and chatbot conversations. In response to their feedback, we revised the study instructions in the survey, added clarifications to HRSN-related questions, and refined scenario content to improve understandability. The data from pilot participants were not included in the analysis.

Scenarios

The study team designed four scenarios, informed by our finding from our earlier investigation.¹⁷ The goal is to simulate real-world cases and to demonstrate the chatbot's capabilities. Scenarios helped to have a standard evaluation mechanism on how participants engaged with and responded to suggested recommendations (details in Supplementary Appendix 1). The first scenario required participants to address nutritional needs by entering a zip code to identify a relevant nutrition assistance program and then obtain details about its operating hours. In the second scenario, participants explored healthcare-related resources in a new zip code and requested information regarding the new program's cost of service. The third scenario involved participants seeking housing support resources in a nearby city, focusing specifically on determining service coverage and obtaining relevant contact information. Following the completion of these structured scenarios, the last scenario instructed participants to freely engage and explore the chatbot's capabilities in line with their personal interests or social needs.

The scenario topics were selected purposefully to reflect high-priority HRSNs, food insecurity, healthcare access, and housing instability, that align with CMS screening requirements and commonly targeted domains in Medicaid and health system initiatives.²⁷ Each scenario tested a distinct chatbot function (e.g., location-based search, cost inquiry, service coverage), allowing structured evaluation of key features. The final open-ended task enabled observation of natural user behavior, offering a balanced assessment of performance and real-world engagement.

Data Collection

Quantitative data collection included demographic characteristics, HRSNs, and user experience. The HRSNs assessed in the survey comprised food insecurity, housing instability, transportation barriers, financial strain, social isolation, and health literacy deficits. Items for measuring HRSNs were adapted from established screening instruments utilized by the U.S. Census Bureau,²⁸ advocacy organizations,^{29–31} healthcare systems,^{32,33} research institutes,^{34–38} and community health centers. User experience was assessed using four standardized instruments: the NASA Task Load Index (NASA-TLX), System Usability Scale (SUS), Net Promoter Score (NPS), and a Trust scale (adapted from Jian et al.).

Qualitative data were collected via open-ended responses within REDCap. Specifically, participants provided narrative responses on describing a positive experience, a negative experience, and suggested improvements for the chatbot. In addition, transcripts of participant-chatbot interactions were recorded. Figure 2 outlines the overall study design and procedures.

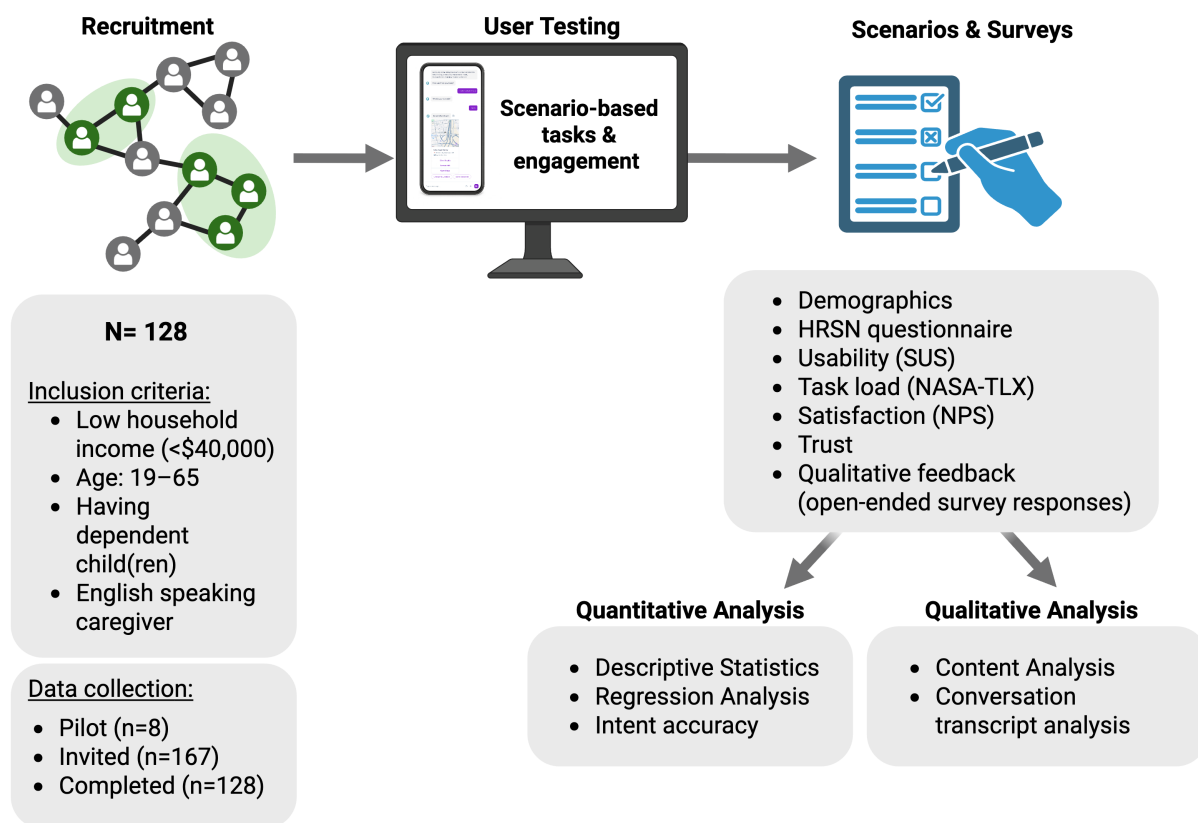


Figure 2. Study design, procedure and data collection

Data Analysis

We reported descriptives of demographics and HRSN responses. As exploratory measures, the association between these outcomes and individual covariates, selected a priori, were estimated separately using univariable regression models. Chatbot usability, satisfaction, and task load

were modeled via linear regression, whereas chatbot trustworthiness was modeled using an ordinal logistic regression. All statistical analyses were conducted using a statistical software, R (v4.5.0).³⁹

Qualitative data were two-fold: (1) Free-text feedback over the survey and (2) chatbot conversation transcripts. Free-text feedback was analyzed for sentiment and intensity to highlight positive, negative, and neutral interactions with the chatbot. Sentiment was rated by the study team (AH, DJ) on a Likert scale from 1 (Negative) to 5 (Positive) indicating the level of satisfaction in the user's language. Intensity similarly coded by the study team on a Likert scale from 1 (Low) to 5 (High) indicating the level of emotional content in user's language (see Supplementary Appendix 2). Furthermore, we conducted a thematic analysis, developing an initial codebook through an inductive review of 10% of the transcripts (DJ, AH). Codes were refined iteratively after each transcript was reviewed. After the final transcript, codes were reviewed once more to define our themes. Organization of transcription data was processed through Python,⁴⁰ and coding of the dataset was done through Microsoft Excel. Interrater reliability was assessed using Cohen's Kappa.⁴¹ Any disputes were resolved by a senior team member (ES).

Chatbot conversation transcripts were coded and manually analyzed by research team members (DJ, AH) using a structured rubric to categorize patterns in resource-seeking behaviors for each free-form conversational turn. The defined rubric notes when users mention (1) a specific resource, (2) the purpose for the resource, (3) their personal background, (4) multiple needs, and (5) thoughts on finding a resource (see Supplementary Appendix 3). Each behavior was a binary measure where present strategies were labeled as 1 and absent strategies were labeled as 0. A *specific resource* included a title or descriptor to explain their need (for example, "allergen-free food"). A *purpose for the resource* included mentions on who or why the resource is necessary ("for my friend"). The *personal background* meant for contextual details about their circumstances ("I just moved"). *Multiple needs as a resource-seeking* behavior including at least two distinct needs that would require different types of assistance (such as across multiple HRSNs). Finally, we had the category for participants expressed *their thoughts on finding a resource* with implicit or explicit intent of exploring community resources.

As an ad hoc analysis, to validate the chatbot's (NLU) ability to recognize HRSNs from the user's free-form entry, study team calculated user "intents" as a percentage of accuracy. For each message that requires a fallback mechanism from the chatbot to correctly identify the topic of interest, the intent is approximated out of the possible services available in the API. We automatically tagged each occurrence in the chatbot's infrastructure while exporting transcription data.

Results

We recruited 167 participants to the study, and 128 participants (76.6%) completed all activities and were included in the analysis.

Demographics

Participants were geographically distributed across diverse urban and rural settings throughout the United States (Table 1). The sample (N=128) was predominantly White (44%) and

Black/African American (36%), with 27% identifying as Hispanic or Latino. Most participants identified as female (68%), were between 30 and 49 years old (71%), and primarily spoke only English (78%). Although 22% were bilingual, the most spoken second language was Spanish (64% of bilingual participants). Participants typically had varied educational backgrounds, with the majority having completed some college or an associate/bachelor's degree (69%). Most were employed (60%), primarily at mid-to-senior career stages (81% of employed participants), and reported an annual household income between \$20,000 and \$39,999 (73%). A significant majority relied on Medicaid or Medicare insurance (83%). Participants were commonly married or in an unmarried partnership (54%), while about one-third (34%) reported never being married. Nearly all participants actively cared for at least one dependent child (97%), or one/ two children (78%), most frequently aged between 6 and 12 years old (37%). Most participants (78%) reported having at least one dependent child with special healthcare or developmental needs. Participants also reported prior experience with chatbots (95%), including voice assistants like Siri and Alexa.

Table 1. Demographics of included participants

Category	N=128	%
<i>Race</i>		
White	56	44%
Black / African American	46	36%
Native American / American Indian	5	4%
Mixed (selected 2 or more)	15	12%
Unknown / Prefer not to answer	6	4%
<i>Ethnicity</i>		
Hispanic or Latino	34	27%
Non-Hispanic or Latino	94	73%
<i>Sex</i>		
Female	87	68%
Male	41	32%
<i>Age Groups of Participants</i>		
18-29	25	20%
30-39	53	41%
40-49	39	30%
50-66	11	9%
<i>Bilingual</i>		
No	100	78%
Yes	28	22%
Spanish	18	
German	1	
French	1	
Prefer not to answer	8	
<i>English Fluency (of Bilinguals)</i>		
Fluent	26	
Good	1	

Limited	1	
None	0	
<i>Education</i>		
Highschool (Diploma, GED)	27	21%
Some college, no degree	41	32%
Associate degree (AA, AS)	22	17%
Bachelors (BA, BS, BBA, AB)	26	20%
Masters (MA, MS, MEng, MEd, MBA)	9	7%
Doctoral Degree (PhD, PsyD, EdD)	2	2%
None of the above	1	1%
<i>Household Income</i>		
Less than \$10,000	19	14%
\$10,000–\$15,999	3	2%
\$16,000–\$19,999	12	9%
\$20,000–\$29,999	40	31%
\$30,000–\$39,999	54	42%
<i>Employment Status</i>		
Currently Employed	77	60%
Early (0-2 years)	15	
Mid (3-6 years)	26	
Senior (7+ years)	36	
Seeking Employment	51	40%
1 month or less	1	
2-6 months	4	
7 months to a year	4	
Longer than a year	42	
<i>Health Insurance</i>		
Medicare / Medicaid	107	83%
Other Insurance Plan	5	4%
Uninsured	16	13%
<i>Marital Status</i>		
Married	47	37%
Divorced	10	8%
Widowed	1	1%
Separated	4	3%
Never married	44	34%
A member of an unmarried couple	22	17%
<i>Child Dependents</i>		
None	4	3%
1-2	100	78%
3-4	22	17%
5 or more	2	2%
<i>Special Need Dependents</i>		

Yes	100	78%
No	22	17%
Prefer not to answer	2	2%
Don't have child dependents	4	3%
<i>Age Groups of Dependents*</i>		
0-2 years old	26	
3-5 years old	36	
6-12 years old	61	
13-17 years old	44	
Prefer not to answer	0	
<i>Chatbot Use Experiences</i>		
Don't Use Chatbots	7	5%
Yes	121	95%
< 2 times per week	38	
2-6 times per week	44	
> 7 times per week	39	

* Not mutually exclusive, as participants could report more than one dependent

Health-related Social Needs

Nearly all participants who engaged with the chatbot reported at least one unmet HRSN (98%). In Table 2, we provided combined scores (binary; y/n) of HRSNs grouped by short-term needs, long-term needs, and time-independent needs (full responses are available in Supplementary Appendix 4). The most frequently reported short-term (within the past 30 days) needs included food insecurity (75%), financial limitations (75%), and transportation barriers (57%). Food insecurity (71%) was also the most frequently reported long-term (within the past 12 months) need, followed by transportation barriers (48%) and financial limitations (38%). Additionally, while relatively few participants reported recent physical isolation from social activities (11%), a substantial number reported persistent feelings of social isolation (65%) without a specified time frame. Smaller proportions indicated difficulties related to overall literacy (reading and comprehension; 10%) and medical literacy confidence managing health-related issues (9%).

Table 2. Frequencies of user-reported health-related social needs

HRSNs	N= 128	%
<i>Short Term (30d need)</i>		
Housing	59	46%
Food	97	75%
Transport	73	57%
Finance	96	75%
Isolation	14	11%
<i>Long Term (12m need)</i>		
Housing	36	28%
Food	91	71%
Transport	62	48%
Finance	49	38%

Time-Independent

Isolation	83	65%
Literacy (overall)	13	10%
Literacy (medical)	12	9%
No HRSNs disclosed	2	2%

User Experience

As given in Table 3, participants rated the chatbot as being highly usable (mean = 84.7, SD = 12.4), trust (mean = 4.1, SD = 0.8), and satisfactory (mean = 8.0, SD = 2.4). The chatbot was rated around the lowest third of the task load index (mean = 6.8, SD = 2.8).

Table 3. Descriptive results on user experience categories

Characteristic	Task load	Satisfaction	Trust	Usability
Mean (SD)	6.8 (2.8)	8.0 (2.4)	4.1 (0.8)	84.7 (12.4)
Median (Q1, Q3)	6.3 (4.3, 8.8)	9.0 (7.0, 10.0)	4.0 (4.0, 5.0)	88.0 (78.0, 95.0)
Min, Max	1.8, 13.3	0.0, 10.0	2.0, 5.0	46.0, 100.0

Exploratory analysis

Demographics Factors and User Experience

We examined the association between demographic factors and user experience metrics using category-wise regression models. For each demographic category, regression coefficients were interpreted relative to a reference variable (RV), which is displayed as the first category in Figure 3. Demographic variables included both binary (e.g., Insurance: Yes/No) and categorical predictors with multiple response levels (e.g., Marital Status). For multi-level categorical predictors, we highlight response options with statistically significant coefficients (i.e., 95% confidence intervals that do not cross the null value defined by the RV). Where appropriate, we also present binarized contrasts (e.g., Married vs. all other marital statuses). Additionally, we observed monotonic trends across ordinal variables such as income and education.

No significant associations were observed between usability ratings and demographic variables. However, we observed directional trends, such as increasing usability ratings with higher education levels and income brackets, though these were not statistically significant. Trust ratings were significantly higher among senior adults compared to young adults (OR = 2.47; 95% CI: 0.18, 59.5), and among participants with children compared to those without (OR = 4.01; 95% CI: 0.70, 22.9). Perceived burden (Task Load) was significantly lower among participants who were Divorced ($\beta = -2.7$; 95% CI: $-4.6, -0.85$), Never Married ($\beta = -1.3$; 95% CI: $-2.4, -0.14$), and Unmarried ($\beta = -1.4$; 95% CI: $-2.8, 0.00$), relative to those who were Married. When aggregated, all non-married statuses were associated with significantly lower Task Load scores ($\beta = -1.5$; 95% CI: $-2.5, -0.46$). Satisfaction ratings were significantly higher among middle-aged participants compared to young adults ($\beta = 0.99$; 95% CI: 0.14, 1.8).

Additional trends included increasing ratings across all metrics with higher income levels (RV: Less than \$10,000), and a general increase in both usability and task load with higher education (RV: High School). See Figure 3 for forest plots and Supplementary Appendix 4, Table 2 for regression results.

Figure 3.a. Usability

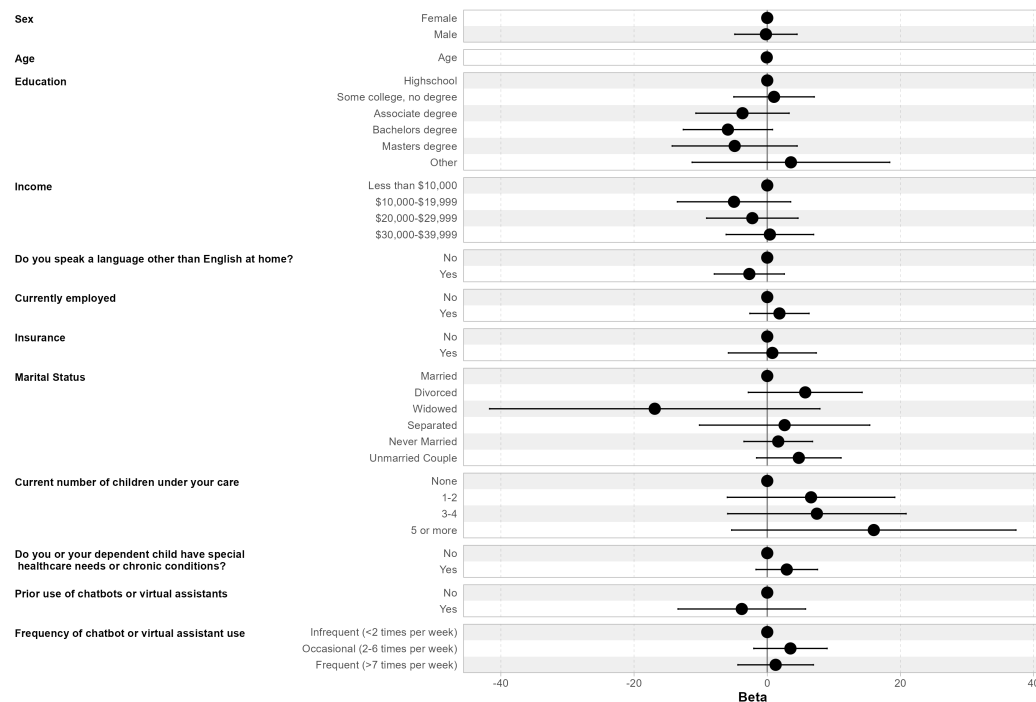


Figure 3.b. Trust

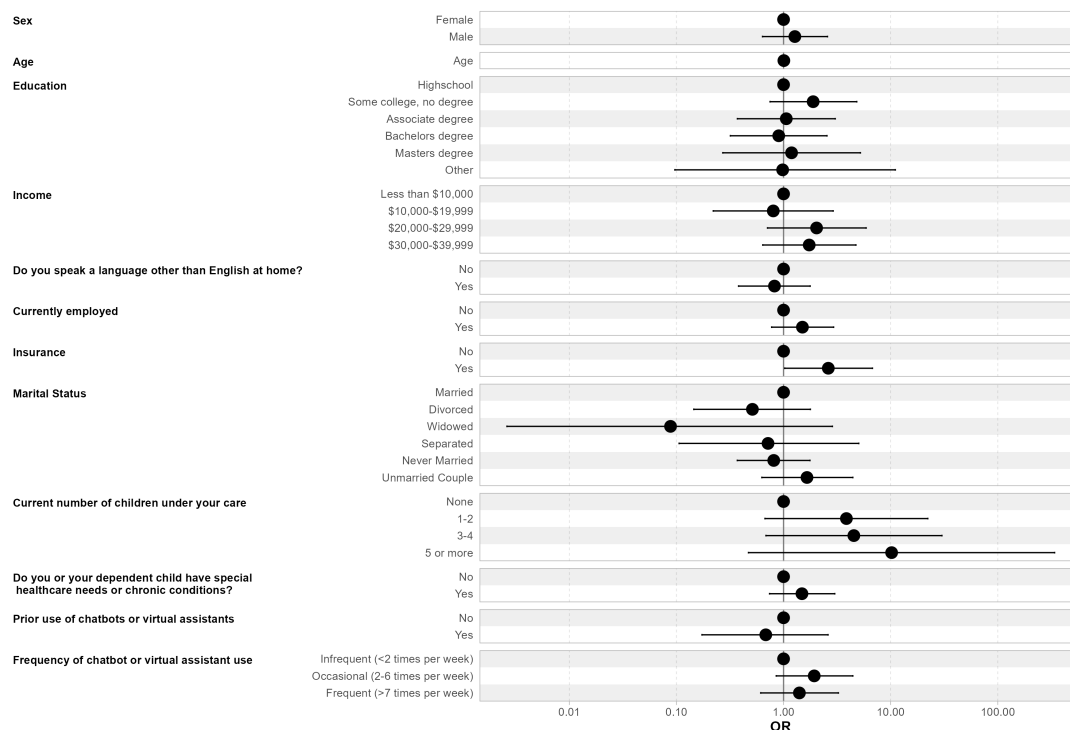


Figure 3.c. Task load

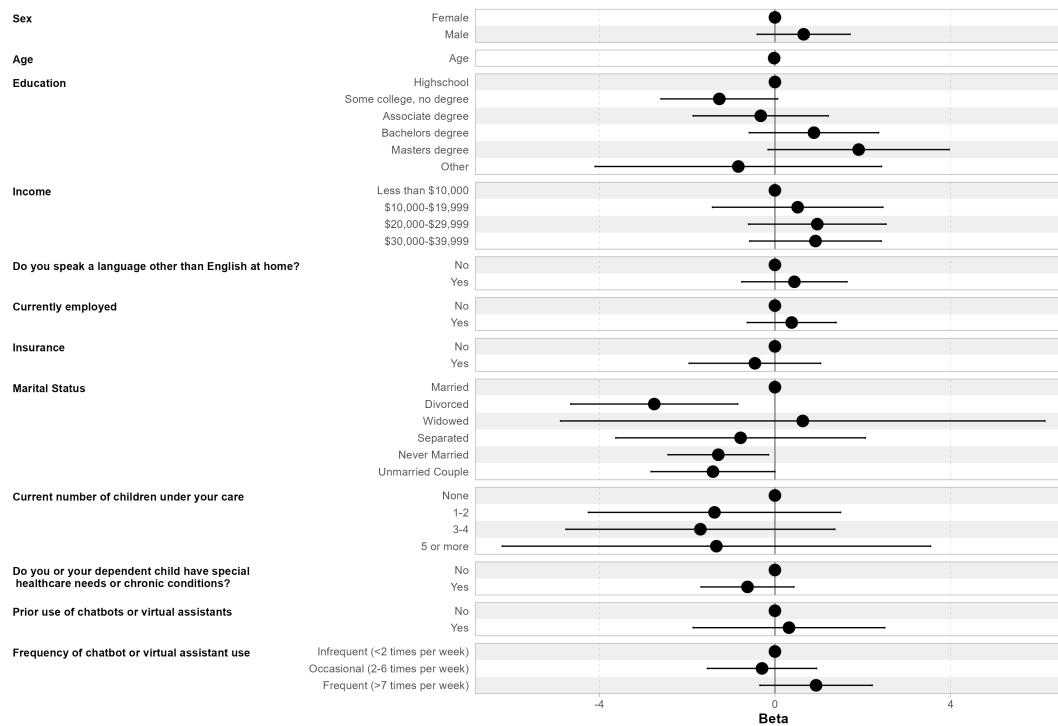


Figure 3.d. Satisfaction

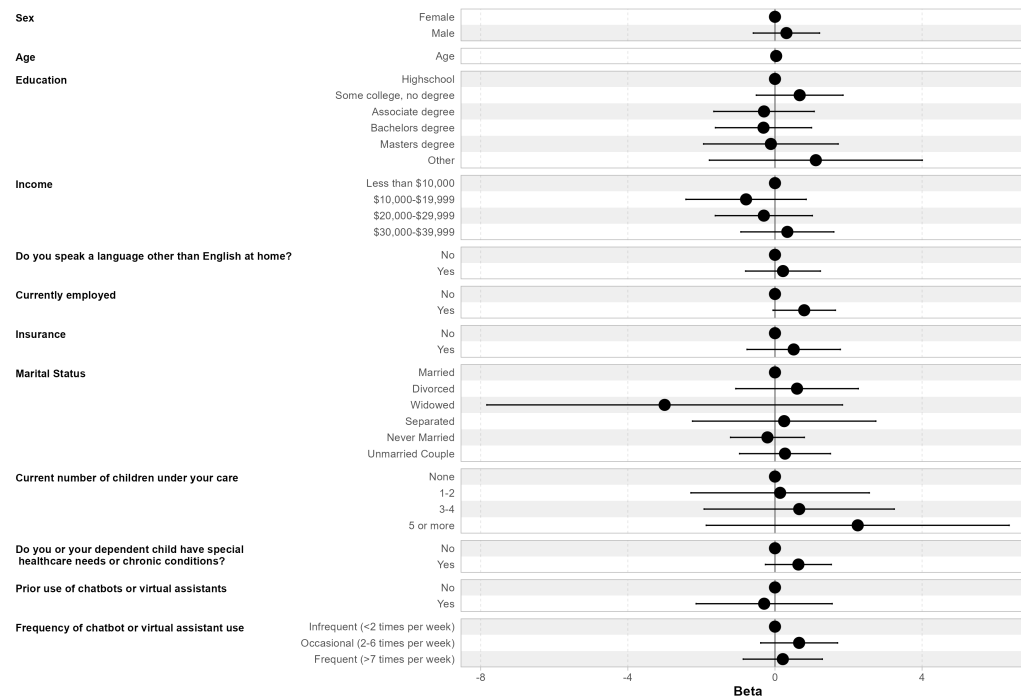


Figure 3. Regression analysis forest plot for demographics and user experience

Health Related Social Needs and User Experience

We examined associations between HRSNs and user experience metrics (see Figure 4 for forest plots; full regression results available in Supplementary Appendix 4, Table 3). No statistically significant associations were observed between HRSNs and usability. Participants who reported that transportation issues prevented them from attending medical appointments had significantly higher trust ratings compared to those without such barriers (OR = 3.21; 95% CI: 1.03, 10.7). Users who reported being "very often worried about food" reported significantly lower task load scores than those who were never worried ($\beta = -1.8$; 95% CI: $-3.6, -0.11$). Participants who reported any type of transportation-related access issue (compared to those without any difficulty traveling) had significantly higher satisfaction scores ($\beta = 0.89$; 95% CI: 0.06, 1.7).

Several additional trends emerged that did not reach statistical significance but may warrant future exploration. Reports of insufficient food quantity (relative to the reference group reporting enough of the food they wanted to eat) were associated with lower usability, higher trust and satisfaction, and lower task load. Reports of utility shutoff followed a stepped pattern, with increasing levels of disruption (No $\rightarrow$ Yes $\rightarrow$ Already shut off) associated with higher trust, task load, and satisfaction. Increasing difficulty in meeting basic needs (RV: "Not hard at all") was associated with increased usability and satisfaction, and decreased task load. Lastly, increased social isolation (fewer than five social interactions per week, relative to the RV) appeared to be associated with higher satisfaction.

Figure 4.a. Usability

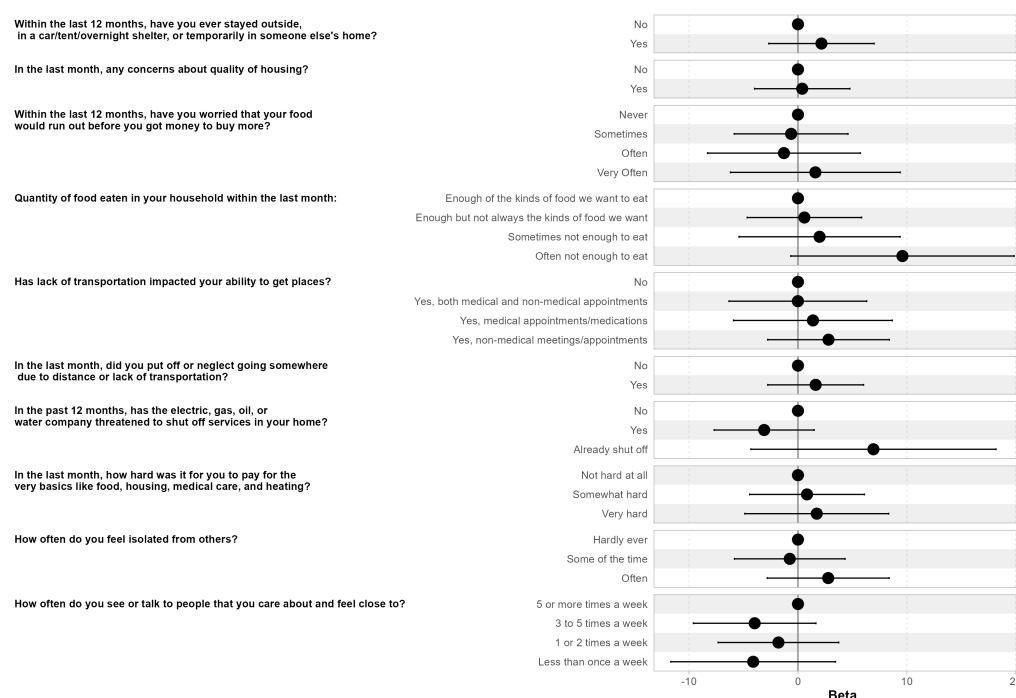


Figure 4.b. Trust

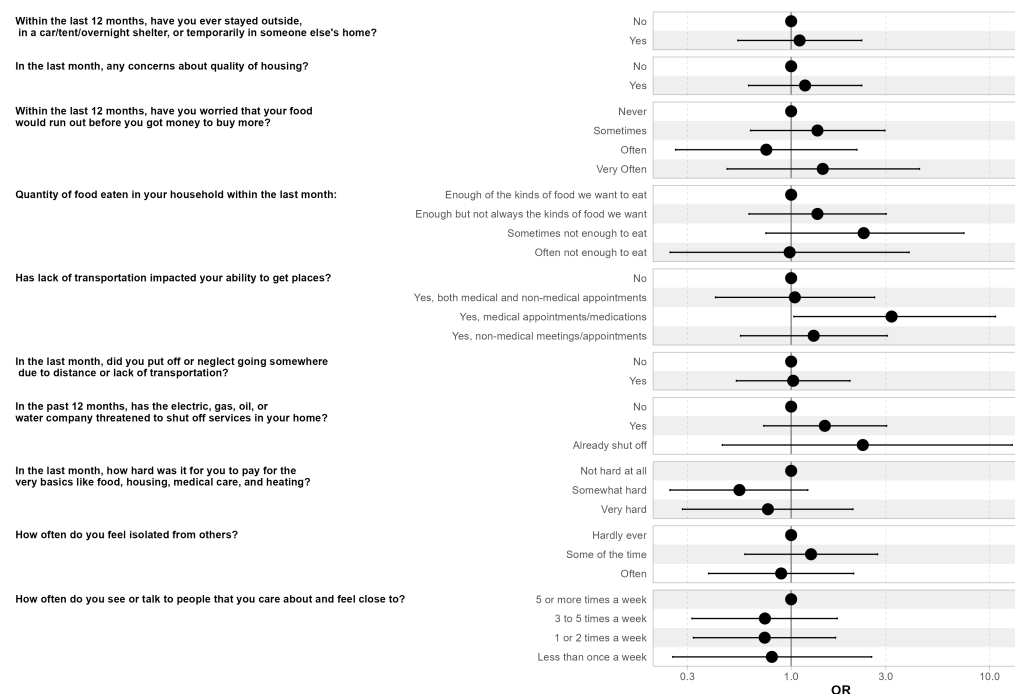


Figure 4.c. Task Load

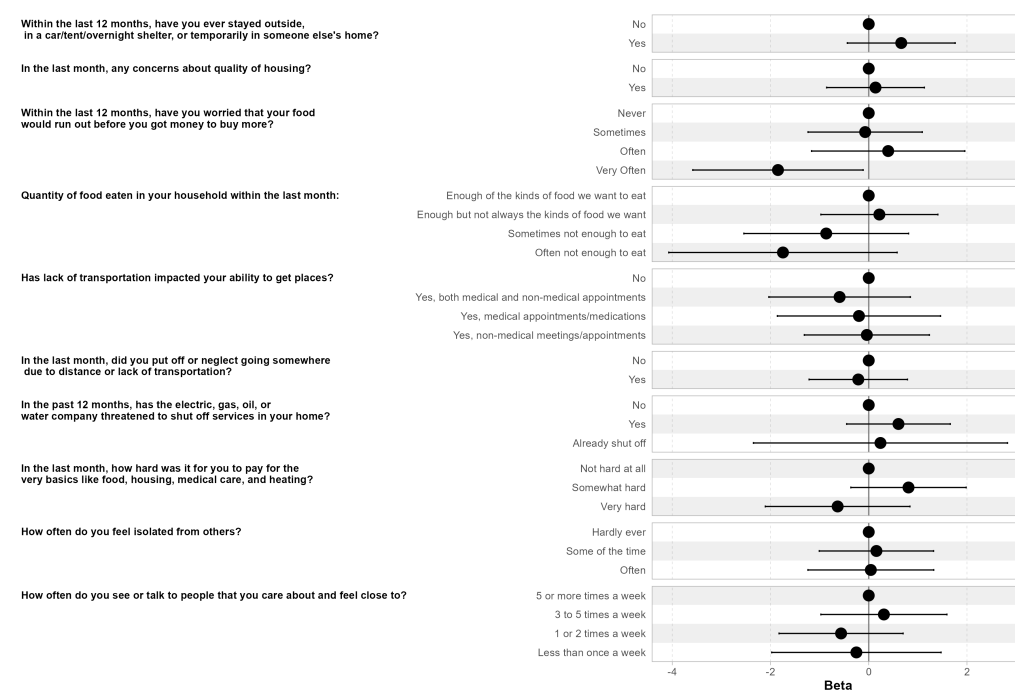


Figure 4.d. Satisfaction

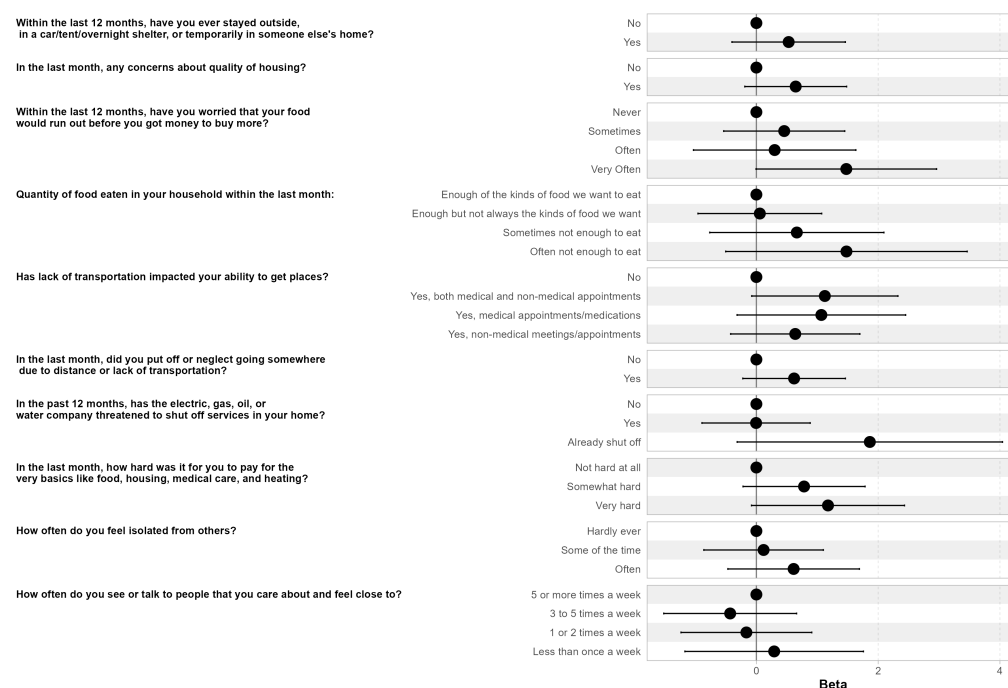


Figure 4. Regression analysis forest plot for HRSN and user experience

Conversational analytics

To better understand user interactions and preferences, we analyzed chatbot conversation transcripts, examining message characteristics, interaction types, content specificity, and conversation topics. Since the interactions for scenarios 1-3 are scripted, our analysis in this section is only focused on conversational data during the free engagement (last scenario). Participants generated total of 204 chatbot transcripts through their engagements, where each user held between 1 to 4 unique conversations ($M = 1.46$, $SD = 0.76$).

Participants interacted with the chatbot for approximately 3 minutes per session ($M = 3$ min 8 sec, $SD = 4$ min 59 sec), averaging 20 conversational turns (range: 3 to 49). Individual user messages averaged 3 words (17 characters), ranging from brief inputs (1 word, 3 characters) to longer statements (up to 43 words, 214 characters). Participants strongly preferred using assistive buttons ($N = 2,749$ button presses) rather than free-text entries ($N = 1,151$), with the 'Coverage' button most frequently used prior to session completion (see Table 1 in Supplementary Appendix 5).

Further qualitative examination of free-text entries provided deeper insights into how users communicated their resource needs. Using a structured rubric (Supplementary Appendix 3), two raters (AH and DIJ) assessed message specificity and user behaviors, achieving strong interrater reliability ($\kappa = 0.721$). Users typically indicated specific community resources or facilities by name ($M = 0.37$, $SD = 0.48$), while a minority of the initiated interactions unrelated to social or resource needs ($M = 0.91$, $SD = 0.28$) (see Table 2 in Supplementary Appendix 5).

Keyword frequency analysis further illustrated user priorities (see Table 3 in Supplementary Appendix 5), highlighting terms closely aligned with resource needs such as 'program(s),' (16%) 'shelter,' (12%) and 'food' (8%). Conversation topics similarly reflected key user concerns, predominantly focusing on financial issues (18%), housing (17%), and nutritional (16%) needs. Users also raised diverse unique topics beyond predefined HRSN categories, underscoring the chatbot's capacity to address a broad range of community-related issues (see Table 4 in Supplementary Appendix 5). Including fallbacks in the conversation, chatbot successfully identified the user's intent 1511 out of 1523 messages (99.21%).

User Preferences

Participant free-text comments (open-ended responses to a positive experience, a negative experience, and suggested improvements for the chatbot) were analyzed and categorized into two components: the content and relevance of chatbot responses, and how information was presented and experienced during the interaction (see Supplementary Appendix 6). In their free-text feedback, participants discussed preferences for direct links, eligibility or scheduling information, and location-based customization. They also described the interface as intuitive and appreciated the chatbot's speed. Furthermore, participants also desired voice-based interaction, more relevant local options, and improved mechanisms to refine their search early in the conversation. Sentiment analysis of the comments indicated generally positive feedback ($M = 3.41$, $SD = 0.97$), and intensity analysis showed moderate emotional expressiveness ($M = 3.02$, $SD = 0.46$). While many comments reflected satisfaction with ease of use and responsiveness, others noted limitations in personalization, specificity, and verbal communication capabilities.

After completion of the last scenario, nearly all participants (94%) reported the DAPHNE chatbot helpful in identifying relevant community resources (94%). Post testing, they also reported preferred chatbot app enhancements (for future improvements beyond conversational capabilities). Participants expressed interest in several additional features, notably the inclusion of a "History and Favorites" (19%), the ability to create personal profiles (17%), password protection for enhanced security (15%), daily tips and personalized updates (15%), multilingual support (12%), integration with personal medical records (11%), and phone notifications (10%). A small proportion of users also suggested incorporating encouraging messaging, varied chatbot personalities, and additional technical guidance (see Supplementary Table 7).

Discussion

The present mixed-methods evaluation sought to investigate user experience towards an AI-enabled chatbot (DAPHNE) that helps to identify unmet HRSNs and share real-time, community-based resource recommendations for the low socio-economic status cohort. We extended our prior research,¹⁷ and using a convergent parallel design, we integrated quantitative assessments of usability, task load, satisfaction, and trust with qualitative analyses of conversational transcripts and free-text feedback. In doing so, we offer one of the first empirical demonstrations that a rules-guided, LLM-supported chatbot can deliver just-in-time HRSN guidance with high acceptability (in terms of usability, satisfaction and trust) and minimal cognitive burden.

Demographic composition and reported HRSNs

The study sample was largely representative of the racially and ethnically diverse, low-income, caregiver population targeted by current U.S. screening recommendations. Nearly all participants reported at least one unmet HRSN, with food insecurity and financial strain predominating in the short term. The co-occurrence of multiple needs, including transportation barriers and chronic social isolation, underscores the layered vulnerabilities confronting these families and highlights the importance of integrated referral mechanisms rather than siloed interventions.^{42,43} Although online recruitment may select for digitally literate participants, the high prevalence of Medicaid coverage and bilingual status suggests that DAPHNE assessed by the cohort who are often underserved by traditional resource-navigation models.^{44,45}

User experiences

Across standardized instruments, the chatbot demonstrated high usability, low task load, elevated satisfaction, and substantial perceived trustworthiness -metrics that surpass typical digital health benchmarks and are notable given the complexity of HRSN navigation.^{45,46} Conversational-analytics reinforce these quantitative ratings: users interacted through succinct, goal-oriented exchanges via text or button options, the dialogue manager mapped intents with high fidelity, and fallback LLM prompts were rarely invoked, all of which enabled transparent dialogue and align with the low task load observed.^{47,48}

Qualitative feedback adds nuance, indicating that while participants appreciated the interface's intuitiveness and speed, they sought richer informational specificity, such as detailed eligibility criteria, hyperlinked referrals, and finer geospatial granularity. Users also expressed interest in multimodal enhancements, including voice input, personalized dashboards, secure logins, and proactive notifications. Sentiment analysis confirmed a generally positive affect yet only moderate emotional engagement, suggesting room for more empathic and context-aware dialogue.⁴⁹⁻⁵¹ Together, these behavioral and attitudinal data suggest not merely high perceived ease of use scores but an emerging expectation for deeper personalization and multimodal interaction that can convert brief screening encounters into sustained, longitudinal support.⁴⁹

Relationship between Demographics, HRSN and User experience

Demographic and HRSN covariates revealed limited but informative associations with user experience outcomes. Usability and trust were broadly consistent across sex, age, and insurance status, suggesting wide acceptability across populations that are often underserved in digital health contexts. One of the clearest demographic patterns emerged in task load: non-married participants, including those who were divorced, never married, or unmarried, reported significantly lower burden compared to their married peers. This may reflect fewer caregiving responsibilities or greater autonomy in navigating health tools. Additionally, participants with higher education levels trended toward lower usability and higher burden, possibly due to elevated expectations or more critical evaluation of digital systems. While income and social contact showed only directional associations (namely, lower usability among participants with

lower income, and higher satisfaction among those with limited social interaction). These trends align with prior literature on digital exclusion among structurally marginalized groups.^{44,52,53}

Several HRSNs were more directly associated with user experience. Participants reporting transportation limitations or utility shutoffs reported higher trust and satisfaction, suggesting that users facing access barriers may derive greater perceived benefit from digital support tools. Similarly, users who were very often worried about food reported lower task load, which may reflect the chatbot's cognitive accessibility or affective value during times of stress. Notably, social isolation was associated with higher satisfaction, hinting at a potential role for conversational agents in supplementing social support. These findings challenge assumptions that unmet needs necessarily impair engagement; instead, they suggest that such tools may hold unique relevance for structurally marginalized users.⁵⁴

Implications

The screening for HRSNs in clinical settings is a crucial first step, they often do not translate into successful resource connections for patients out of the clinic.^{33,55} Therefore, these results are encouraging. DAPHNE functioned not as a passive screener but as an active bridge to tailored referrals, directly addressing the long-standing “screen-to-referral” gap documented.^{56,57} From design perspective, our findings imply that an effective social-care chatbot for low-SES cohorts should foreground quick, low-load button prompts while preserving free-text (and future voice) channels that capture nuanced circumstances. Equity-focused co-design involving community stakeholders and ongoing equity audits, tracking intent-recognition errors and unmet requests, will be critical to prevent digital access biases and safeguard equitable linkage to resources.^{58,59} Moreover, given that technology alone cannot resolve structural barriers, provider-technology collaboration, user education, and positioning chatbots as social-care navigators may further ensure culturally relevant and context-sensitive support, aligning closely with contemporary health-equity frameworks.⁶⁰

Looking ahead, our study indicates the potential for AI-enabled chatbots to support policy mandates for HRSNs screening and resource linkage. Given current CMS requirements for hospitals to screen and report social drivers of health and Medicaid initiatives incentivizing systematic HRSN assessment,⁶¹ AI-enabled chatbots could substantially ease implementation burdens.⁶² However, the USPSTF has so far found insufficient evidence to recommend universal screening for certain social risks (such as food insecurity) due to uncertain impact on health outcomes.⁶³ This evidence gap highlights that simply implementing screening mandates is not enough, effective solutions are needed to actually address the identified needs. Our findings contribute to an emerging evidence base by illustrating that an AI-enabled chatbot, as a navigator, can achieve high engagement and potentially assist in resource connection. If such tools can be proven to improve outcomes (for example, reducing unmet needs or downstream health care utilization), they could substantially strengthen the case for routine social risk screening and intervention as a covered, reimbursable preventive service.⁶⁴

Strengths and Limitations

Key strengths of this study include the mixed-methods, convergent design and deployment of the chatbot in a realistic context with real-time resource data. Collecting quantitative (survey) and qualitative (interaction logs and interviews) data allowed us to triangulate findings, enhancing the validity of our conclusions.⁶⁵ The use of an actual resource referral API (as opposed to a static or hypothetical list) increases the validity of our usability results and demonstrates technical feasibility for real-world integration. We also prioritized user-centered development with an equity lens, recruiting a diverse sample of low-income participants and incorporating their feedback into design refinements.

Nonetheless, several limitations warrant discussion. First, outcomes were measured via self-report instruments and short-term task performance in English language only; we did not directly measure long-term impacts on resource uptake or health outcomes including multiple languages. Participants' subjective ratings of trust and satisfaction may have been influenced by social desirability or novelty effects. Second, the study lacked a comparator group, without a control condition (e.g. usual care or an alternative navigation method), we cannot definitively attribute benefits to the chatbot or assess its relative effectiveness. Future studies should consider randomized trials or quasi-experimental designs to compare chatbot-assisted social care navigation against standard practice. Third, our sample size and setting limit generalizability. All participants had at least some internet access and consented to engage with a digital tool; thus, our findings may not extend to those with severe digital literacy barriers or distrust of technology.^{66,67} This digital divide bias means additional strategies are needed to reach and support the most marginalized groups who might not engage with a chatbot.⁶⁸ Finally, while our RAG-based approach was intended to ensure accuracy, we did not formally evaluate the accuracy of chatbot responses or recommendations. There remains a risk of hallucinations or errors when large language models are involved.⁶⁹ Although no serious issues were reported in our study, establishing rigorous content validation and oversight (such as human review of a subset of chatbot outputs or user-friendly feedback mechanisms) will be important as the system scales.

Conclusions

In conclusion, our study demonstrates the promise of an AI-enabled chatbot, DAPHNE, to efficiently identify HRSNs and connect families with community resources in an acceptable and user-friendly manner. It contributes to the growing literature on digital social care practices and integration by providing empirical evidence that a chatbot can engage vulnerable populations with high usability and trust. To fully realize this potential, future work must rigorously evaluate effectiveness, ensure equity in design and deployment, and address practical implementation challenges. With continued refinement and evidence generation, AI-driven chatbots could become a valuable adjunct in the ongoing efforts to integrate social care into healthcare.

Data Sharing

Due to the sensitive nature of participants' conversations with the chatbot, we are unable to share individual-level transcripts and historical records of interactions.

Ethics

This study received approval to conduct human-subjects research (STUDY00004369) from the Internal Review Board (FWA000002860) at Nationwide Children's Hospital.

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Declaration of Interests

All authors claim no conflicts of interest with the research study.

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