Towards conversational assistants for health applications: using ChatGPT to generate conversations about heart failure

Anuja Tayal¹ Devika Salunke ² Barbara Di Eugenio¹ Paula G Allen-Meares ³ Eulalia P Abril ⁴ Olga Garcia-Bedoya³ Carolyn A Dickens³ Andrew D. Boyd²

¹Department of Computer Science ²Department of Biomedical and Health Information Sciences ³Department of Medicine ⁴Department of Communications

{atayal4,dsalun2,bdieugen,pameares,eulalia,ogarciab,cdickens,boyda}@uic.edu

Abstract

We explore the potential of ChatGPT (3.5-turbo and 4) to generate conversations focused on self-care strategies for African-American heart failure patients-a domain with limited specialized datasets. To simulate patient-health educator dialogues, we employed four prompting strategies: domain, African American Vernacular English (AAVE), Social Determinants of Health (SDOH), and SDOH-informed reasoning. Conversations were generated across key self-care domains-food, exercise, and fluid intake-with varying turn lengths (5, 10, 15) and incorporated patient-specific SDOH attributes such as age, gender, neighborhood, and socioeconomic status. Our findings show that effective prompt design is essential. While incorporating SDOH and reasoning improves dialogue quality, ChatGPT still lacks the empathy and engagement needed for meaningful healthcare communication.

1 Introduction

Heart failure (HF), or congestive heart failure, occurs when the heart cannot pump enough blood to meet the body's needs. Effective self-care-such as managing salt intake, staying hydrated, exercising, adhering to medications, and attending regular check-ups-is critical for managing the condition (Savarese and Lund, 2017). However, African Americans (AA) in the U.S. face disproportionately worse outcomes due to genetic factors, limited healthcare access, socioeconomic challenges, and lower health literacy (Nayak et al., 2020). Existing self-care materials often cater to a white, educated population, lacking cultural relevance for minority communities (Barrett et al., 2019). This gap contributes to poor adherence and worsened outcomes. Personalized education can improve self-care understanding and reduce readmissions (Di Eugenio et al., 2019).

This study is part of a broader project aimed at developing a culturally sensitive conversational agent to support AA heart failure patients in asking self-care related questions. A significant challenge is the lack of real-world patient-centered conversational data from underrepresented communities. To address this, we recruited three patient educators (PEs) to provide heart failure education to 18 AA and 2 Hispanic/Latino (H/L) patients (Reference withheld). Initial analysis revealed that educators dominated the conversations, with patients contributing less. The key topics discussed during these sessions included exercise, fluid intake, symptom management, sleep, weight management, familial aspects, and salt intake.

Unlike the recorded interactions, we wanted to generate conversational datasets that are initiated by patients and, more importantly, personalized based on the Social Determinants of Health (SDOH) features. With the advancement of Large Language Models (LLMs), we thought to examine different prompting strategies and evaluate whether they could be used for creating synthetic conversational datasets. Our study is a feasibility assessment aimed at exploring ChatGPT's ability to generate self-care conversations and its ability to adapt its responses based on varying prompts. The dataset is publicly available¹. In this paper, we look into 4 different prompting approaches that will supplement the real-world interactions to support the development of a patient-driven dialogue system.

- We started with generating simulated conversations based on different domains required for self-care of heart failure patients of food, exercise, and fluid intake.
- We introduced an additional prompt where the patients communicate using African American Vernacular English (AAVE) while the educator communicates in standard English.

¹https://anonymous.4open.science/r/HF-Dataset

- We prompted to integrate SDOH Features of the patients. We considered gender {male, female}, age {young, mid-age, old}, neighborhood {safe, unsafe} and socio-economic conditions {below poverty line, well to do}.
- We first prompted ChatGPT to generate reasoning given the SDOH features of the patient and then prompted ChatGPT again to generate conversations given the reasoning and SDOH features.

In summary, our main goal was to explore the potential of ChatGPT 3.5-turbo and GPT-4 (OpenAI et al., 2024) in generating simulated conversations when framed within the context of self-care for AA heart failure patients. Specifically, we focused on addressing the following key questions:

- Can ChatGPT generate relevant conversations for Heart Failure Self-Care?
- Can ChatGPT personalize conversations based on the Social Determinants of Health (SDOH) features of the patients?
- Can ChatGPT express empathy with the patients?
- Is having ChatGPT to generate reasoning before conversations more effective than directly generating the conversations?

2 Related Work

Health Education. Linguistic and cultural barriers can significantly impact patients' access to healthcare. As noted in (Handtke et al., 2019), language differences and varying health beliefs often prevent linguistically diverse patients from effectively engaging with healthcare services.

To overcome these challenges, approaches have been developed to improve patient education. The authors in (Mendu S, 2018) designed an interactive virtual patient educator to counsel Hispanic women about cervical cancer and human papillomavirus (HPV). Similarly, PaniniQA (Cai et al., 2023) helps patients understand discharge instructions through a question-answering system. One of the first and best well-known systems that provided information to patients, albeit as a summarizer, not as a dialogue system, is BabyTalk (Portet et al., 2009), which provided personalized summaries of neonatal intensive care data for their parents (and for healthcare providers as well). Additionally, natural language processing (NLP) is being leveraged to create diabetes self-care corpus (Cunha et al., 2024), demonstrating the potential of AI and language technologies to enhance patient communication and health management.

Prompting Recent advancements in LLMs have been driven by scaling up both model size and training data, resulting in improved performance and sample efficiency (Hoffmann et al., 2024; Brown et al., 2020). Researchers have explored various prompting techniques to enhance LLM capabilities, starting with few-shot prompting (Brown et al., 2020), followed by more advanced methods such as chain-of-thought prompting (Wei et al., 2022) and chain-of-thought with self-consistency (Wang et al., 2023). To address the remaining challenges, new approaches like tree-of-thought prompting have been introduced (Yao et al., 2023a), where each "thought" is a coherent language sequence representing an intermediate step toward problemsolving.

Reasoning is a crucial capability for complex problem-solving. A comprehensive overview of reasoning strategies in LLMs is provided in (Qiao et al., 2023), covering commonsense reasoning (Liu et al., 2022), mathematical reasoning (Wang et al., 2017), and symbolic reasoning (Khot et al., 2023). The ReACT framework (Yao et al., 2023b) further integrates reasoning with action in a unified task. This reasoning ability is especially critical in healthcare contexts, where accurate, informed decision-making is essential.

With the release of large-scale medical dialogue datasets, e.g., MedDialog (Zeng et al., 2020), MedDG (Xu et al., 2023), medical dialogue response generation attracts increasing attention. (Li et al., 2023) undertakes the task of enhancing and fine-tuning the LLaMa model with a dataset of approximately 100,000 patient-doctor dialogues. In (Guevara et al., 2024), the authors used LLM to extract SDOH features of housing, employment, transportation, parental status, relationship, and emotional support from the EHR data.

3 Methodology

3.1 Can ChatGPT generate relevant conversations for Heart Failure Self-Care?

By "relevant conversations," we refer to ChatGPT's ability to facilitate dynamic, two-way interactions between the patient and the health educator (HE), rather than limiting the conversation to a simple

question-and-answer format initiated solely by the patient. Furthermore, the conversation should not only provide answers to the patient's inquiries but also offer actionable advice (Walker and Whittaker, 1990), empowering the patient to manage their heart failure effectively. To measure the relevance of the conversations, we assessed the quality of two-way interactions, the balance of participation between speakers, and the appropriateness of the health educator's responses, using a combination of quantitative and qualitative metrics.

3.2 Can ChatGPT personalize conversations based on the SDOH features of the patients?

SDOH are defined by the World Health Organization as "the conditions in which people are born, grow, live, work, and age...shaped by the distribution of money, power, and resources at global, national, and local levels" (Marmot and Wilkinson, 2005). These factors significantly influence health outcomes by affecting access to and the quality of medical care, playing a major role in health disparities. We examined whether ChatGPT can adjust its dialogue generation based on individual patient characteristics, focusing on four key SDOH features: age, gender, neighborhood, and socioeconomic conditions.

3.3 Can ChatGPT express empathy with the patients?

Effective healthcare communication demands both factual accuracy and genuine concern for patients. We explored whether ChatGPT can recognize appropriate moments to express empathy during conversations.

3.4 Is having ChatGPT to generate reasoning before conversations more effective than directly generating the conversations?

Research, including (Yao et al., 2023b), has demonstrated that reasoning is not an innate capability of ChatGPT, and incorporating reasoning improves performance. We explored whether generating the SDOH-informed reasoning before generating the conversation is more effective.

3.5 Approaches to Generate Simulated Conversations

In the absence of a specialized dataset focused on self-care strategies for African-American heart failure patients, we employed four progressively refined prompting strategies to generate simulated conversations, but before that, let's look into some additional instructions given in the prompt.

In our initial prompts to ChatGPT, even though we specified it to be a health educator, the model still advised the patient to consult a doctor. To address this, we added a specific instruction to avoid phrases related to consulting a healthcare provider, as shown in Table 2. Furthermore, in our earlier attempts, there was no defined structure for the generated conversations. The lack of a standardized format made it difficult to analyze and compare the conversations effectively. We anticipated that specifying a consistent format for the dialogue would lead to clearer and more organized outputs from the model. To achieve this, we introduced a specific conversation structure, where each exchange between the participants follows a predefined format: [speaker][utterance]. This structure explicitly separates the speaker from their utterance.

Recognizing that heart failure patients face significant challenges managing their health, we emphasized the need for empathetic communication from patient educators. Since many patients have lower health literacy compared to their general literacy (Paasche-Orlow et al., 2005), we instructed the model to present medical information in simple terms. Additionally, to accommodate different conversational styles, we experimented with various dialogue lengths, as some patients might prefer shorter exchanges while others engage in longer conversations. To maintain clarity and avoid overwhelming the patient, we also prompted the model to limit each educator's turn to 20 words, using plain English throughout (Table 5). These adjustments were aimed at creating more realistic dialogues.

3.5.1 Approach 1- Generating Conversations According to Domain

Heart failure patients must manage various aspects of their health, including exercise, diet, water intake, medications, lifestyle adjustments, sleep, and overall self-care (Gupta et al., 2020). To explore how these areas could be addressed in patienthealth educator conversations, we prompted Chat-GPT to generate dialogues centered around different domains of heart failure care. By focusing on these domains, we aimed to generate conversations that could offer patients practical advice on how to manage these areas while allowing us to study the model's ability to generate relevant and domainspecific dialogue.

Heart failure patients are primarily advised to limit their salt intake rather than focusing on reducing calories or sugar (Gupta et al., 2020; Tayal et al., 2024). Additionally, they are encouraged to restrict their fluid intake, with no recommendation to increase water consumption. This contrasts with earlier advice given by ChatGPT, which suggested reducing sugar, unhealthy fats, and extra calories while also recommending an increase in water intake, which is wrong, as shown in Table 1 along with limiting salt and alcohol intake.

Speaker	Utterance
Patient:	Okay, but what kind of foods should I be eating or avoiding?
PE:	Great question! In general, you should aim to eat more fruits,
	vegetables, whole grains, and lean protein. These provide
	heart-beneficial nutrients. Limit salt, sugar, unhealthy fats,
	and alcohol intake as they can worsen heart conditions.
Patient:	Is it bad for me to eat fried chicken or pork ribs with my
	condition? I have been eating them all my life.
PE:	I understand that these foods are part of your cultural and
	personal food habits. However, these are typically high in
	saturated fats which can increase cholesterol levels. Try to
	limit it, or prepare them in healthier ways. Maybe bake the
	chicken instead of frying, and use herbs and spices for flavor
	instead of excessive salt or fat.
Patient:	How about beverages? Can I still drink things like sweet-
	natured tea or alcohol?
PE:	Sweet tea and alcohol can add extra calories and sugar to
	your diet, which can lead to weight gain and can strain your
	heart. Try drinking more water or unsweetened beverages,
	and limit alcohol intake.

Table 1: Excerpt of conversation where the patient is advised to limit calories and sugar, along with salt intake, and advised to drink more water instead of less.

3.5.2 Approach 2 - African American Vernacular English

One way to introduce cultural compatibility is through language. African American Vernacular English (AAVE) (Green, 2002), is a dialect of Standard American English (SAE) with defined syntactic-semantic, phonological and lexical features. Since African American patients may speak AAVE (it is important to note that not all AA's speak AAVE), we prompted ChatGPT so that the educator would speak in standard English while the patient communicated in AAVE (Table 2). However, instead of keeping the educator's speech in standard English, we noticed instances where the educator also used AAVE, as seen in Table 3.

This is problematic because non-AAVE speakers attempting to use AAVE with patients may come across as offensive and disrespectful. Educators should be aware of cultural boundaries and sensitive to the linguistic preferences of African American patients. While they should be prepared to respectfully engage if the patient uses AAVE, they

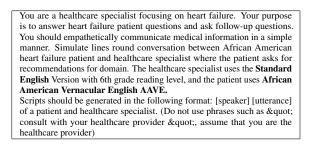


Table 2: Prompt for generating conversations where the patient converses in AAVE

should not initiate or adopt the dialect themselves. Maintaining cultural awareness is key to fostering respectful and effective communication.

Utterance
Got it, 1.5 to 2 liters. Does that include stuff like juice and
soup?
Yup, it sure does. Juice and soup count, too. Just remember
to spread 'em out during the day so you ain't guzzlin' too
much at once
What 'bout coffee and tea? I love my mornin' coffee.

Table 3: Excerpt of a conversation where both patient and educator are speaking AAVE

In Table 4, it is acceptable for the patient to ask about cultural foods like watermelon, okra, and herbal teas, as this aligns with their personal interests or cultural background. When patients bring up these topics, it allows for a natural and open conversation that respects their perspective. However, if the HE had initiated this discussion, it might be perceived as introducing bias, especially if the conversation were based on assumptions about the patient's background or identity. In such cases, the HE might unintentionally appear to be stereotyping or making generalizations, which could compromise the neutrality and professionalism expected in healthcare settings.

Speaker	Utterance
Patient:	Thank you for letting me know. I often enjoy foods like wa-
	termelon and okra, which I've heard have high water content.
	Do I need to count those in the 1.5 to 2 liters?
PE:	Yes, you're correct. Foods like watermelon and okra do con-
	tribute to your fluid intake. While you do need to consider
	them, the 1.5 to 2-liter guideline typically includes both liq-
	uids and foods with high water content.
Patient:	I enjoy herbal teas, but I've also heard about the effects of
	caffeine. Should I stick to caffeine-free options?
PE:	Herbal teas are a good choice, especially if you want to avoid
	caffeine. Some herbal teas can have health benefits too. Just
	be sure to read the labels and choose options that are free of
	caffeine and low in added sugars.

Table 4: Excerpt of a conversation on fluid-intake where patient discusses cultural foods like watermelon, okra, herbal teas

3.5.3 Approach 3 - Integrating SDOH Features

Given the importance of SDOH, it is critical that generated conversations for healthcare applications reflect the diverse experiences of individuals based on their unique circumstances. To achieve this, our approach selectively differentiates key features such as gender {male, female}, age {young, midage, old}, neighborhood {safe, unsafe}, and socioeconomic status {well-to-do, below poverty line} in simulated patient conversations (Table 5). Although the list of SDOH-related factors we selected is not exhaustive, we focused on these key areas-gender, age, neighborhood, and socioeconomic conditions-because they heavily influence healthcare access and outcomes. By tailoring these dialogues to reflect specific SDOH features, we can more accurately capture the nuanced ways in which these factors influence patient-educator interactions.

You are a healthcare educator focusing on heart failure. Your purpose is to answer heart failure patient questions based on patient description. You should empathetically communicate medical information in a simple manner. Simulate lines round conversation between African American heart failure patient and healthcare educator where the patient asks for recommendations for domain. Scripts should be generated in the following format: [speaker] [utterance] between patient and the healthcare educator. Each educator turn should not be longer than 20 words and should use simple english. (Do not use phrases such as " consult with your healthcare provider ", assume that you are the healthcare provider) **Patient Description:** gender: gender socio-economic condition: socio_economic neighborhood: neighborhood age: age

Table 5: Prompt for generating the conversation giventhe SDOH Features

For example, the way a young, well-to-do patient discusses self-care strategies might differ significantly from the conversation of an elderly patient living in a low-income neighborhood. By adjusting these features in our simulated conversations, we aim to capture the diverse realities that patients face when managing their health.

3.5.4 Approach 4 - Generating Reasoning as an Intermediate Step

Building on the idea that reasoning enhances the capabilities of LLMs (Wei et al., 2022; Yao et al., 2023b) and is essential for generating meaningful conversations, we introduced an intermediate step to first generate reasoning prior to generating the simulated conversation.

We approached conversation generation as a reasoning chain, using chaining (Wu et al., 2022) to divide the process into two phases. In the first phase,

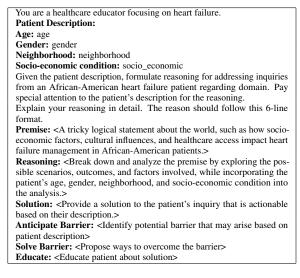


Table 6: Prompt for generating the reasoning given theSDOH Features

we prompted ChatGPT to analyze the patient's social determinants of health (SDOH) features to create logical reasoning. The reasoning process was segmented into six steps: (1) Premise, a tricky logical statement about how factors like socioeconomic status, cultural influences, and healthcare access affect heart failure management; (2) **Reasoning**, where the premise is analyzed with respect to the patient's SDOH features; (3) Solution, proposing an actionable plan; (4) Anticipate Barrier, identifying potential obstacles based on the patient's circumstances; (5) Solve Barrier, offering ways to overcome those obstacles; and (6) Educate, ensuring the educator not only addresses the patient's query but also provides further education.

You are a healthcare educator focusing on heart failure. Your purpose				
is to answer heart failure patient questions. You should empathetically				
communicate medical information in a simple manner.				
Patient Description:				
age: age				
gender: gender				
neighborhood: neighborhood				
socio-economic condition: socio_economic				
{reasoning}				
Given the patient description and reasoning, simulate lines round con-				
versation between African American heart failure patient and healthcare				
educator where the patient asks for recommendations for domain.				
Scripts should be generated in the following format: [speaker] [utterance]				
between the patient and the healthcare educator. Each educator's turn				
should not be longer than 20 words and should use simple English.				

Table 7: Prompt for generating the conversation giventhe reasoning and the SDOH Features

This segmented approach, shown in Table 6 and adapted from (Gupta et al., 2021), is designed for ChatGPT to focus on analyzing the patient's needs based on their SDOH features. For example, reasoning generated for a {gender: female, age: elderly, neighborhood: unsafe, socio-economic condition: below poverty line } in the exercise domain is shown in Table 8. It highlights appropriate reasoning, such as suggesting low-cost exercises at home and addressing the difficulty of finding a safe and affordable environment by proposing community centers or local parks as alternatives.

Anticipate Barrier: The patient may struggle to find a safe and affordable environment to exercise, leading to inconsistency in her physical activity routine.

Solve Barrier: Provide resources for community centers, local parks, or discounted gym memberships that offer safe and affordable exercise options. Encourage the patient to enlist the support of family members or friends to exercise together for added safety.

Educate: Educate the patient on the importance of regular physical activity in managing heart failure, the benefits of exercise in improving heart function and overall health, and the impact of socio-economic factors on health disparities. Emphasize the need to prioritize her health and wellbeing despite the challenges she may face.

Table 8: A reasoning generated for patient {gender: female, age: elderly, neighborhood: unsafe, socioeconomic condition: below poverty line } in the exercise domain

Speaker	Utterance
Patient:	What exercises can I do at home to help with my heart failure?
PE:	You can start with walking, using household items as weights,
	or following online workout videos.
Patient:	I'm worried about safety in my neighborhood.
PE:	Try walking in a safe area or look for community centers with
	affordable exercise options.
Patient:	I don't have much money for a gym membership.
PE:	Look for discounted gym memberships or consider exercising
	at local parks for free.

Table 9: Generated conversation with Prompt 7

In the second phase, we instructed the model to generate the conversation based on the generated reasoning. This ensured the dialogue aligned with the patient's SDOH features, resulting in more personalized and contextually appropriate conversations, as shown in Table 9. This two-step process improved the quality of the guidance offered by making it more relevant to the patient's specific needs, grounding the model's reasoning in factors like socio-economic conditions, cultural influences, and healthcare access.

4 Experiment and Evaluation

ChatGPT (versions 3.5-turbo and 4) was utilized to generate simulated conversations using four dis-

tinct approaches of Domain, AAVE, SDOH, and SDOH-informed reasoning. For each approach, conversations were created with varying numbers of conversation rounds {5, 10, 15} and across different domains {food, water, exercise}.

Additionally, in the SDOH and SDOH-informed reasoning approaches (Approaches 3 and 4), conversations were further varied by incorporating different SDOH features of gender {male, female}, age {young, mid-age, old}, neighborhood {safe, unsafe}, and socio-economic conditions {below the poverty line, well-to-do}. For the Domain and AAVE approaches (Approaches 1 and 2), conversations were also generated with varying temperature settings {0, 0.5, 0.7, 1.0}, which influenced the model's response variability.

In the Domain approach, additional topics like medication, sleep, and self-care were included alongside food, water, and exercise. In total, 144 conversations were generated for the Domain approach, 72 for AAVE, and 432 (2 (gender) x 3 (age) x 2 (neighborhood) x 2 (socio-economic conditions) x 3 (domain) x 3 (conversation length) x 2 (model)) for the SDOH and SDOH-informed reasoning approaches, resulting in a rich and diverse set of simulated dialogues for evaluation.

Systematic human evaluation of the generated conversations was conducted, incorporating both qualitative and quantitative evaluation. For the qualitative analysis, we distributed a questionnaire to 10 NLP PhD students specializing in NLP within healthcare, none of whom were involved in the research. Each participant was asked to review conversations and provide feedback based on targeted questions. The qualitative questionnaire can be found in Appendix B which is inspired by (Finch and Choi, 2020). All the questions were Likertbased questions (1-5, with 5 being the highest score and 1 being the lowest score), with some questions asking for clarification about specific instances. Seven students responded, with each reviewing three conversations per prompt, resulting in a total of 84 conversations being evaluated (4*21 conversations for each prompt). While even 84 conversations are a limited sample size, the key findings of our study remain consistent.

For the quantitative analysis, we assessed the instructions provided in the prompts, focusing on the number of conversation rounds and adherence to the correct format [*speaker*][*utterance*]. We calculated the percentage of conversations that followed the correct number of rounds (Round Adher-

Premise: Socio-economic factors, cultural influences, and healthcare access impact heart failure management in African-American patients, leading to disparities in disease outcomes.

Reasoning: Considering the patient's age, gender, living in an unsafe neighborhood, and being below the poverty line, it is crucial to address the barriers she may face in accessing safe and affordable exercise options. Lack of resources, fear of safety, and limited access to healthcare facilities may hinder her ability to engage in physical activity for heart failure management.

Solution: Encourage the patient to start with simple, low-cost exercises at home, such as walking in a safe area, using household items as weights, or following online workout videos. Emphasize the importance of consistency and starting slow to avoid injury.

ence Ratio), as well as the ratio of conversations that adhered to the required format (Format Adherence Ratio). The results, presented in Table 10, show that both models struggled to follow even simple instructions consistently.

4.1 Can ChatGPT generate relevant conversations for Heart Failure Self-Care?

To assess the relevance of the simulated conversations, we evaluated the quality of two-way interactions, the balance of participation between speakers, and the appropriateness of the health educator's responses using a combination of quantitative and qualitative metrics.

To assess the 2-way nature of the conversation, we used the metric - Follow-up Ratio, which is defined as the number of follow-up questions asked by the HE to that by the patient. The HE should ask follow-up questions—either to clarify the patient's condition or to gather more context—reflecting a more natural and dynamic dialogue (Walker and Whittaker, 1990). As shown in Table 10, HEs rarely asked follow-up questions unless explicitly prompted to do so. This was most evident in the AAVE approach (Approach 2), suggesting that ChatGPT is not aware of the 2-way nature of the conversations.

We examined whether the conversation was dominated by one speaker by calculating the ratio of words spoken by the health educator (HE) to those spoken by the patient. Table 10 shows that HEs consistently dominated the conversations. However, when the model was prompted to limit the responses to 20 words in approaches 3 and 4, the answers became overly brief, offering little explanation. One evaluator remarked that these responses felt vague and unsatisfying, with the lack of followup questions leaving the conversations incomplete and uninformative.

To assess the appropriateness of the HE responses, we asked evaluators to identify instances where the HE should have provided a different answer. Across all approaches, at least 20% of the conversations contained such instances. One evaluator highlighted the need for more specific guidance, pointing out that health educators often emphasized only positive examples (e.g., what to eat) while neglecting to mention critical details such as what to avoid. For instance, a response like "This includes water, juice, and other beverages" was criticized for being too vague, as certain beverages, such as coffee, can cause dehydration. In another conversation about fluid intake, a patient asked whether they should be concerned about drinking too much water. Instead of directly addressing that concern, the HE provided information about the dangers of drinking water too quickly, completely missing the underlying question. This kind of mismatch suggests a lack of contextual understanding in ChatGPT's responses.

4.2 Can ChatGPT personalize conversations based on the Social Determinants of Health (SDOH) features of the patients?

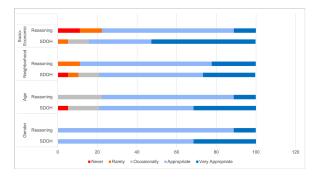


Figure 1: Comparison of Appropriateness of SDOH Features between Approaches 3 and 4.

To evaluate whether ChatGPT has the capacity to personalize the conversations based on the SDOH features, the evaluators were asked to qualitatively assess the generated conversations, specifically examining how well ChatGPT tailored the discussions to each of these SDOH features and whether the system appropriately adapted its responses based on the patient's unique context.

The results can be seen in Figure 1. These results indicate that ChatGPT has some capacity to personalize conversations based on SDOH features. However, the presence of lower ratings shows that there is still room for improvement in making conversations more consistently aligned with SDOH features.

4.3 Can ChatGPT express empathy with the patients?

Effective healthcare communication requires both factual accuracy and a genuine display of empathy toward patients (Rashkin et al., 2019). To explore ChatGPT's ability to express empathy, evaluators were asked to assess whether the health educator (HE) demonstrated concern for the patient during the conversation. Across all four approaches, the level of perceived empathy was relatively unchanged, with 25% of conversations re-

ceiving a Likert-scale rating of 3 or lower. One evaluator noted that the educator failed to inquire about the challenges or obstacles the patients might encounter when trying to implement the given advice. For instance, in a conversation with a patient living in an unsafe neighborhood, the educator's response not only lacked empathy but also offered a solution that showed little awareness of the patient's circumstances.

For example: "[Patient] Can you recommend exercises that are safe for me to do in my neighborhood?

[Healthcare Educator] "Walking or cycling on safe streets can be good options for you."

This response was criticized for being tone-deaf, as it ignored the patient's specific concern about the safety of their neighborhood. One evaluator described the responses as robotic, lacking emotional depth and genuine empathy. The model displayed empathy primarily in positive situations (e.g., "That's fantastic!") but failed to convey understanding in negative contexts (e.g., "That's unfortunate, I understand it's tough"). Furthermore, the educators often did not ask about the difficulties patients might face in following the advice, nor did they acknowledge the practical barriers involved. As a result, the conversations felt cold and impersonal, making the educators seem disengaged and uninterested in the patient's experiences.

4.4 Is having ChatGPT to generate reasoning before conversations more effective than directly generating the conversations?

When providing the conversations for evaluation, we ensured that the patient features remained consistent for Approaches 3 and 4. This consistency allowed us to make meaningful comparisons based on the SDOH features. Although the generated conversations varied, maintaining the same patient characteristics ensured that we could effectively assess and compare the quality and relevance of the conversations across these approaches and evaluate whether generating the reasoning before generating the conversation was more effective.

When comparing these results to Approach 3 results in Section 4.2, it is evident that the incorporation of reasoning significantly improved the appropriateness of the conversations. The majority of conversations in Approach 4 received higher ratings, demonstrating the model's enhanced ability to engage in nuanced, context-sensitive interactions.

Generating reasoning before the conversations

proved to be a meaningful enhancement. However, there remains room for further improvement.

5 Conclusion and Future Work

This study assessed the capabilities of ChatGPT (versions 3.5-turbo and 4) in generating simulated conversations related to self-care strategies for African-American heart failure patients. Simulated conversations were generated using four distinct prompts: Domain, African American Vernacular English (AAVE), Social Determinants of Health (SDOH), and SDOH-informed reasoning. Our findings highlight the critical role of prompt design, revealing that while ChatGPT can incorporate SDOH features and improve dialogue quality by generating reasoning prior to the conversation, further improvements are needed. Specifically, there is a clear need to refine the conversational style to make interactions feel more engaging and empathetic, an essential element in healthcare communication.

In the future, we aim to develop a task-oriented dialogue system tailored to the self-care needs of African-American heart failure patients, utilizing these simulated conversations. Key factors such as age, gender, neighborhood, and socio-economic conditions will be integrated into the to generate the educator's response.

6 Limitations and Ethics Statement

Our research focuses on exploring the dynamics of conversations generated by ChatGPT, utilizing simulated dialogues based on carefully designed prompts. The dataset is unique to each prompt, showcasing the adaptability of ChatGPT in generating context-specific conversations.

In the qualitative evaluation, we engaged a small group of participants to assess the conversations. While the sample size was limited, this initial user study provided valuable insights into how ChatGPT handles dialogue generation in this context.

References

- Matthew Barrett, Josiane Boyne, Julia Brandts, Hans-Peter Brunner-La Rocca, Lieven De Maesschalck, Kurt De Wit, Lana Dixon, Casper Eurlings, Donna Fitzsimons, Olga Golubnitschaja, et al. 2019. Artificial intelligence supported patient self-care in chronic heart failure: a paradigm shift from reactive to predictive, preventive and personalised care. *Epma Journal*, 10:445–464.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind

	GPT3.5-turbo				GPT4			
	Domain	AAVE	SDOH	Reasoning	Domain	AAVE	SDOH	Reasoning
Round Adherence Rate	0.02	0.083	0.83	0.26	0	0.04	0.64	0.35
Follow-up ratio	0.4	0.52	0.003	0.007	0.01	0.85	0.003	0.02
Ratio of words	2.8	1.5	1.4	1.32	3.4	2.68	1.83	1.8
Format Adherence	0	0.75	0.93	0.96	1.0	0	0	0.23
Rate								

Table 10: Quantitave Results table

Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.

- Pengshan Cai, Zonghai Yao, Fei Liu, Dakuo Wang, Meghan Reilly, Huixue Zhou, Lingxi Li, Yi Cao, Alok Kapoor, Adarsha Bajracharya, Dan Berlowitz, and Hong Yu. 2023. PaniniQA: Enhancing Patient Education Through Interactive Question Answering. *Transactions of the Association for Computational Linguistics*, 11:1518–1536.
- Rossana Cunha, Thiago Castro Ferreira, Adriana Pagano, and Fabio Alves. 2024. A persona-based corpus in the diabetes self-care domain - applying a human-centered approach to a low-resource context. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 1353–1369, Torino, Italia. ELRA and ICCL.
- B Di Eugenio, R Cameron, A Boyd, K Lopez, P Martyn-Nemeth, C Dickens, A Ardati, and D Chattopadhyay.
 2019. Designing self-care technologies for hf patients: a conceptual model. In *Conference on Human Factors in Computing Systems*, pages 12–16.
- Sarah E. Finch and Jinho D. Choi. 2020. Towards unified dialogue system evaluation: A comprehensive analysis of current evaluation protocols. In Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 236– 245, 1st virtual meeting. Association for Computational Linguistics.
- Lisa J Green. 2002. African American English: a linguistic introduction. Cambridge University Press.
- Marco Guevara, Shan Chen, Spencer Thomas, Tafadzwa L Chaunzwa, Idalid Franco, Benjamin H Kann, Shalini Moningi, Jack M Qian, Madeleine Goldstein, Susan Harper, et al. 2024. Large language models to identify social determinants of health in electronic health records. *NPJ digital medicine*, 7(1):6.

- Itika Gupta, Barbara Di Eugenio, Devika Salunke, Andrew Boyd, Paula Allen-Meares, Carolyn Dickens, and Olga Garcia. 2020. Heart failure education of African American and Hispanic/Latino patients: Data collection and analysis. In *Proceedings of the First Workshop on Natural Language Processing for Medical Conversations*, pages 41–46, Online. Association for Computational Linguistics.
- Itika Gupta, Barbara Di Eugenio, Brian D. Ziebart, Bing Liu, Ben S. Gerber, and Lisa K. Sharp. 2021. Summarizing behavioral change goals from SMS exchanges to support health coaches. In *Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 276–289, Singapore and Online. Association for Computational Linguistics.
- Oriana Handtke, Benjamin Schilgen, and Mike Mösko. 2019. Culturally competent healthcare – a scoping review of strategies implemented in healthcare organizations and a model of culturally competent healthcare provision. *PLOS ONE*, 14(7):1–24.
- Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Oriol Vinyals, Jack W. Rae, and Laurent Sifre. 2024. Training compute-optimal large language models. In *Proceedings of the 36th International Conference on Neural Information Processing Systems*, NIPS '22, Red Hook, NY, USA. Curran Associates Inc.
- Tushar Khot, Harsh Trivedi, Matthew Finlayson, Yao Fu, Kyle Richardson, Peter Clark, and Ashish Sabharwal. 2023. Decomposed prompting: A modular approach for solving complex tasks. In *The Eleventh International Conference on Learning Representations*.
- Yunxiang Li, Zihan Li, Kai Zhang, Ruilong Dan, Steve Jiang, and You Zhang. 2023. Chatdoctor: A medical chat model fine-tuned on a large language model meta-ai (llama) using medical domain knowledge. *Preprint*, arXiv:2303.14070.
- Jiacheng Liu, Alisa Liu, Ximing Lu, Sean Welleck, Peter West, Ronan Le Bras, Yejin Choi, and Hannaneh Hajishirzi. 2022. Generated knowledge prompting for commonsense reasoning. In *Proceedings of the* 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages

3154–3169, Dublin, Ireland. Association for Computational Linguistics.

- Michael Marmot and Richard Wilkinson. 2005. Social determinants of health. Oup Oxford.
- Gordon JR Mendu S, Boukhechba M. 2018. Design of a culturally-informed virtual human for educating hispanic women about cervical cancer.
- A Nayak, AJ Hicks, and AA Morris. 2020. Understanding the complexity of heart failure risk and treatment in black patients. *Circulation: Heart Failure*, 13(8):e007264.
- OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel

Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. Gpt-4 technical report. Preprint, arXiv:2303.08774.

- Michael K Paasche-Orlow, Ruth M Parker, Julie A Gazmararian, Lynn T Nielsen-Bohlman, and Rima R Rudd. 2005. The prevalence of limited health literacy. *Journal of general internal medicine*, 20(2):175–184.
- François Portet, Ehud Reiter, Albert Gatt, Jim Hunter, Somayajulu Sripada, Yvonne Freer, and Cindy Sykes. 2009. Automatic generation of textual summaries from neonatal intensive care data. *Artificial Intelligence*, 173(7-8):789–816.
- Shuofei Qiao, Yixin Ou, Ningyu Zhang, Xiang Chen, Yunzhi Yao, Shumin Deng, Chuanqi Tan, Fei Huang, and Huajun Chen. 2023. Reasoning with language model prompting: A survey. In *Proceedings of the* 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 5368–5393, Toronto, Canada. Association for Computational Linguistics.
- Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. 2019. Towards empathetic opendomain conversation models: A new benchmark and dataset. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*,

pages 5370–5381, Florence, Italy. Association for Computational Linguistics.

- Gianluigi Savarese and Lars H Lund. 2017. Global public health burden of heart failure. *Cardiac failure review*, 3(1):7.
- Anuja Tayal, Barbara Di Eugenio, Devika Salunke, Andrew D. Boyd, Carolyn A. Dickens, Eulalia P. Abril, Olga Garcia-Bedoya, and Paula G. Allen-Meares. 2024. A neuro-symbolic approach to monitoring salt content in food. In *Proceedings of the First Workshop on Patient-Oriented Language Processing (CL4Health)* @ *LREC-COLING 2024*, pages 93–103, Torino, Italia. ELRA and ICCL.
- Marilyn Walker and Steve Whittaker. 1990. Mixed initiative in dialogue: An investigation into discourse segmentation. In 28th Annual Meeting of the Association for Computational Linguistics, pages 70–78, Pittsburgh, Pennsylvania, USA. Association for Computational Linguistics.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2023. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations*.
- Yan Wang, Xiaojiang Liu, and Shuming Shi. 2017. Deep neural solver for math word problems. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 845–854, Copenhagen, Denmark. Association for Computational Linguistics.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35:24824–24837.
- Tongshuang Wu, Michael Terry, and Carrie Jun Cai. 2022. Ai chains: Transparent and controllable human-ai interaction by chaining large language model prompts. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, CHI '22, New York, NY, USA. Association for Computing Machinery.
- Kaishuai Xu, Wenjun Hou, Yi Cheng, Jian Wang, and Wenjie Li. 2023. Medical dialogue generation via dual flow modeling. In *Findings of the Association* for Computational Linguistics: ACL 2023, pages 6771–6784, Toronto, Canada. Association for Computational Linguistics.
- Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik R Narasimhan. 2023a. Tree of thoughts: Deliberate problem solving with large language models. In *Thirty-seventh Conference on Neural Information Processing Systems*.

- Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik R Narasimhan, and Yuan Cao. 2023b. React: Synergizing reasoning and acting in language models. In *The Eleventh International Conference on Learning Representations*.
- Guangtao Zeng, Wenmian Yang, Zeqian Ju, Yue Yang, Sicheng Wang, Ruisi Zhang, Meng Zhou, Jiaqi Zeng, Xiangyu Dong, Ruoyu Zhang, Hongchao Fang, Penghui Zhu, Shu Chen, and Pengtao Xie. 2020.
 MedDialog: Large-scale medical dialogue datasets. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 9241–9250, Online. Association for Computational Linguistics.

A Quantitative Analysis

For the quantitative analysis, we assessed the instructions provided in the prompts, focusing on the number of conversation rounds and adherence to the correct format [*speaker*][*utterance*]. We calculated the percentage of conversations that followed the correct number of rounds (Round Adherence Ratio), as well as the ratio of conversations that adhered to the required format (Format Adherence Ratio). The results, presented in Table 10, show that both the models struggled to consistently follow even simple instructions.

B Qualitative Questionnaire

• General Questionnaire

- Was the health educator able to answer the patient's questions?
- Was the advice given by the health educator actionable/ could easily be implemented by the patient?
- Did the HE show concern toward patients? (If likert scale <=2, Why not)
- Is there any question for which you think the health educator should give a different answer? (If likert scale <=2, Which instance)

• SDOH Questions

- How appropriate was the conversation for each individual feature

• Reasoning Questions

- Was the reasoning generated appropriate given the patient's sdoh features ?
- Was the response generated according to the reasoning generated?