The Impact of Healthcare Chatbots' Communication Style on User Eye Gaze Behavior

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ABSTRACT

Healthcare chatbots play a vital role in improving patient engagement and education. This study examines how chatbot communication style—conversational versus informative—impacts user eye gaze behavior and knowledge acquisition. Using a 2x1 factorial design with 21 participants, we analyzed fixation duration, saccadic amplitude, and improvement scores. Results showed that the informative style led to longer fixation durations and higher improvement scores. Scan path analysis revealed sequential fixation in the informative condition and revisits to prior responses in the conversational condition. These findings inform chatbot design to optimize engagement and learning outcomes.

KEYWORDS

Eye gaze behavior, health informatics, human-AI interaction, knowl-edge acquisition

1 INTRODUCTION

In recent years, chatbots have emerged as vital tools across various industries and their use is projected to rapidly grow due to advancements in artificial intelligence (AI) ([21]). These AI-driven agents are increasingly becoming essential to facilitate interactions between users and digital systems ([13]). Among the sectors benefiting from this technology is healthcare, where chatbots play a crucial part in improving patient engagement, providing preliminary diagnoses, and offering mental health support ([22]).

Healthcare chatbots are particularly valuable since they offer scalability and accessibility, addressing the growing demand for cost-effective healthcare services. By assisting patients with several tasks such as symptom checking, medication reminders, and appointment scheduling ([15]), these systems are helping alleviate some of the pressure put on healthcare providers ([22]). However, the design and communication of sensitive health information through AI-driven chatbots pose significant challenges. Unlike traditional face-to-face communication between people, where tone, body language, and trust can be built, chatbots must rely solely on a digital interface to relay critical information, which can lead to issues in clarity, trust, and user compliance ([14]).

Several studies have attempted to address these challenges. For example, psychological frameworks such as Cognitive Load Theory have been applied to minimize user frustration by simplifying interactions and reducing mental effort required of users ([20]). Similarly, research in human-computer interaction (HCI) has explored how different design elements like natural language processing (NLP) and adaptive interfaces can enhance user experience and trust in chatbot recommendations ([16]). Despite these advancements, more research is required to optimize healthcare chatbot design to fully meet the complex needs of both patients and providers ([6]). To bridge this gap, this study investigates the relationship between chatbot interface design and user engagement through the use of eye-tracking technology. The objective of this study is to provide design implications for the development of interactive and effective educational healthcare chatbots, while also establishing a methodological frameworks to inform future research in this area.

2 BACKGROUND

The purpose of this study is underscored by findings from diverse fields such as psychology, human-computer interaction (HCI), and eye tracking, highlighting the necessity of integrating theories and principles from these interconnected domains to enhance the design and functionality of AI healthcare chatbots. The following section will present a literature review of key findings that contextualize and illuminate the significance and primary objectives of this research.

2.1 Media Richness Theory

Media Richness Theory (MRT) was developed by Daft, Lengel, and Trevino [3–5], and it posits that the efficiency of communication is influenced by the suitability of the medium and the nature of the communication task. The theory defines media richness as an objective property characterized by the ability to facilitate shared understanding within a given time frame, as rich (i.e., lean) communication enables this understanding more effectively. The objectivity of richness of the media can be evaluated based on four criteria: (1) capacity for immediate feedback, allowing for quick consensus; (2) ability to transmit multiple cues, including verbal and non-verbal signals; (3) use of natural language, which conveys broader concepts compared to numerical data; and (4) personal focus, which allows for emotional expression and tailoring to the receiver's needs ([3, 5]).

Research by Rohit et al. [17] applied MRT to human-AI interaction studies, demonstrating nuanced effects of "voicebots" versus chatbots, as well as the roles of product categories and localization levels on user engagement in online retail. It highlights that while voicebots enhance cognitive and affective engagement, particularly with experiential products, chatbots excel in cognitive tasks but slightly lag in emotional connection ([17]). The findings emphasize the strategic importance of tailoring virtual assistant interfaces to align with specific engagement goals and product characteristics to optimize user interactions. While the findings of Rohit et al. [17] can apply to MRT's (2) criteria (i.e., ability to transmit multiple cues, including verbal and non-verbal signals), research that integrates other aspects of MRT within the field of human-AI interaction—such as the varying communication styles of text-based chatbots, which relate to criteria (3) and (4)— remains nascent.

2.2 Importance of Improving MRT

By establishing a framework to evaluate human-AI interactions with chatbots, we can explore other aspects of established theories that can enhance Media Richness Theory (MRT) and improve the overall communication effectiveness of chatbots. One such theory is Social Presence Theory (SPT), which posits that the degree of presence individuals feel during communication significantly influences their engagement and interaction quality ([19]). Specifically, SPT emphasizes that media conveying emotional warmth and fostering interpersonal connections lead to deeper engagement ([19]), and this has been applied in the field of HCI, with one study demonstrating that matching the synthesized voice personality to user personality positively affects feelings of social presence, particularly among extroverted users ([11]). This study's findings indicated that users experience a stronger sense of social presence when the personality of the synthesized voice aligns with the personality of the textual content.

Past studies have even applied it to the field of human-AI interaction, revealing that text-based chatbots with human-like characteristics significantly enhance customer trust, purchase intention, word-of-mouth, and overall satisfaction during interactions ([9]). Notably, social presence emerged as a key mediating factor in these relationships, underscoring its critical role in fostering effective customer-chatbot engagements, regardless of the shopping context or the sensitivity of the information disclosed ([9]). Such findings are significant because they can be used to inform the design of chatbots that can effectively convey information to users. Moreover, according to SPT, a higher sense of social presence enhances user engagement, potentially influencing eye gaze patterns. Users may maintain eye contact longer with interfaces that feel more engaging, which could result in extended gaze durations on a chatbot's varied responses, potentially varying based on the communication style employed.

2.3 Connecting Eye Gaze to MRT and SPT

Past research employing eye-tracking methods has shown that chatbots with more anthropomorphic features foster greater user engagement, with one study reporting higher fixation counts and prolonged gaze durations on interfaces exhibiting these characteristics ([7]). This finding suggests that when chatbots exhibit higher levels of social presence through anthropomorphic design, users not only feel more engaged but also direct their visual focus more intensely on the chatbots, aligning with the principles of Media Richness Theory (MRT). Additionally, in a study examining how a chatbot impacts the use and effectiveness of electronic health record patient portals, participants in the text-based chatbot condition spent the least amount of time searching for information, while video conditions resulted in significantly longer search times ([23]).

The presentation format also influenced total fixations and fixation duration, with fewer fixations and shorter durations in text conditions compared to video ([23]). Eye gaze fixations can be understood through the lens of Engagement Theory ([8, 18]), which emphasizes the role of interactive and collaborative environment to foster deep user engagement for learning and interacting with chatbots. According to this framework, users are more likely to immerse themselves in chatbot content when the engagement is rich and interactive ([8, 18]). SPT supports this notion by suggesting that environments promoting social presence enhance user immersion. This may manifest in prolonged eye gaze on relevant information, as users allocate their visual attention more intensively during interactions with virtual assistants in highly engaging contexts.

2.4 Designing Effective Human-AI Educational Interactions

When designing chatbots, particularly for educational purposes (i.e., healthcare chatbots), designing them so that they maintain users' attention is essential to increase the chatbot's overall effectiveness. While past research has demonstrated that eye gaze has been used in chatbot research ([7, 23]), there is still limited understanding of how to design these interactions to enhance varying outcome measures of user experience (e.g., usability, trust, effectiveness, social presence). As chatbots become more prevalent in daily life, it will be increasingly important to investigate how gaze behavior varies with different information presentation styles. Future research could offer valuable insights by applying Flow Theory, or "optimal experience theory," to improve human-chatbot interactions in educational contexts . Flow Theory emphasizes that improving user engagement-through clear goals, appropriate challenges, and minimizing distractions-can help users achieve a state of flow, where they are fully immersed and deeply focused ([2]).

In chatbot interactions, enhancing engagement by creating an interactive and immersive environment can foster this flow state ([2]), leading to better user experience and more meaningful interactions. By integrating principles from Media Richness Theory, Social Presence Theory, and Flow Theory, chatbot design can significantly enhance user engagement, ultimately improving its effectiveness. Combining these theoretical foundations to examine user eye gaze behavior in healthcare chatbots represents a novel approach, which can be leveraged to create more interactive and personalized experiences. This, in turn, can sustain user attention, foster immersion, and ultimately improve learning outcomes in educational chatbot contexts.

3 METHODOLOGY

3.1 Apparatus

The study utilized the Gazepoint GP3 eye tracker which sampled the position of participant's eyes at 60 Hz. Calibration was done at the beginning of each session by having participants follow a moving dot to ensure accuracy. During the experiment, the eye tracker recorded participants' eye gaze behavior while they interacted with the chatbot, capturing detailed data on how long and where participants focused their attention during the experiment. The experiment was conducted using a simulated healthcare patient portal (shown in Figure 1). Within this portal, participants were continuously tracked to analyze how long and where they focused during the interaction.

3.2 Subjects

Participants were recruited from Clemson University to examine the effects of chatbot communication style on user interaction and The Impact of Healthcare Chatbots' Communication Style on User Eye Gaze Behavior



Figure 1: Simulated healthcare patient portal.

knowledge acquisition. Participants were randomly assigned to one of the two communication style conditions (conversational or informative) to balance the distribution of participants across both groups.

3.3 Experimental Design

A 2x1 factorial between-subjects design was employed to examine the impact of chatbot communication style-conversational versus informative-on eye gaze behavior and knowledge acquisition about blood pressure and hypertension. The study utilized two distinct communication styles to explore differences in user engagement and learning outcomes. In the conversational style, the chatbot simulated human-like interactions through interactive and dynamic dialogue, fostering a more personalized and engaging experience. It engaged participants by asking follow-up questions and prompting clarification, replicating a dynamic conversation. The conversational style was intended to encourage participants to reflect on the information they received and reinforce their understanding. This approach allowed for further exploration and created opportunities for personalized engagement. The informative communication style was designed to deliver comprehensive information without further prompts for engagement or follow-up questions. The chatbot in this condition provided clear, structured answers without additional interaction, ensuring that participants received the necessary information without exploratory dialogue. Figure 2 displays the conversational chatbot while Figure 3 demonstrates the informative chatbot.Both communication styles were implemented using pre-prepared PowerPoint presentations, allowing participants to experience a simulated chatbot interaction. This approach provided consistency in the content delivered to participants while maintaining distinct communication styles. It also allowed for precise control over the structure of the chatbot's responses, ensuring that the only variable manipulated was the communication style. Each chatbot response was designed to ensure that participants received an equivalent amount of information, with the only difference being the style in which it was delivered.

3.4 Stimulus

In this study, participants were tasked with interacting with a chatbot on a healthcare mock-up patient portal designed to answer questions about high blood pressure. A 2x1 factorial between-subjects design was used to investigate the effects of chatbot communication style (conversational vs. informative) on eye gaze behavior and knowledge acquisition related to blood pressure and hypertension. The chatbot interactions were simulated using pre-designed PowerPoint slides rather than a live chatbot system. This setup ensured consistency across participants and allowed for a structured comparison between the two communication styles without requiring real-time responses.



Figure 2: Example stimuli of the informative communication style.

(MedMind Healthcare Chatbot Human-Al Healthcare	C C C C C C C C C C C C C C C C C C C				
		Linda Walker				
or	MedMind Healthcare Chatbot	What causes high blood pressure?				
The exact cause of high blood pressure is unknown. Several factors may play a role. These factors include race, family history, and weight. A few other possible factors include tobacco use, being physically inactiv satir intake, alcohol use as well as some chronic illnesses.						
nn ke	Choose from the following factors associated with hypertension to discuss further in depth: Age Race Family History Weight Tobacco Consumption Physical Inactivity Sodium Consumption Potassium Consumption					
or		Linda Walker				
	MedMind Healthcare Chatbot	Family History				
51	Family history: High blood pressure can be genetic. In other words, it is passed down from parents or grandparents to kid. It tends to be in families who also have other hereditary diseases that include high blood pressure. One example of such a possible genetic disease is diabetes.					
	If you want to continue our conversation discussing factors related to high following: Age Race Family History Weight Tobacco Consumption Physical II Potassium Consumption	blood pressure, choose from the nactivity Sodium Consumption				
		Linda Walker				
		Race				
yc /e						

Figure 3: Example stimuli of the conversational communication style.

3.5 Procedures

Participants completed a demographic survey to collect background information, including age, gender, and educational background.

Participants then completed a multiple-choice test on blood pressure topics to establish their baseline knowledge. Following the pre-test, participants were introduced to the scenario in which they were tasked with assisting a fictional character named Linda Walker with a healthcare mock-up patient portal. This was to ensure that the chatbot was perceived as an educational tool rather than a source of personal medical advice and to minimize the potential for participants to feel they were receiving personalized medical information. This scenario was designed to minimize ethical concerns by ensuring that participants understood the chatbot was not providing personal medical advice, but rather general information for Linda Walker. Participants then interacted with the chatbot via a PowerPoint interface that simulated a typical chatbot interaction. The eye gaze behavior of participants was tracked using the Gazepoint GP3 eye tracker, a standalone device that records eye movements while allowing for interaction with the computer display. After a calibration process to ensure accuracy, the eye tracker recorded participants' gaze patterns throughout the chatbot interaction, focusing on how they engaged with the information presented. Following their interaction with the chatbot, participants completed a post-test to evaluate the effectiveness of the chatbot and then filled out a post-experience questionnaire to capture their experience with the chatbot, evaluating ease of interaction and learning style.

3.6 Statistical Analysis of Eye Gaze Behavior

To examine differences in eye gaze behavior between participants in the conversational and informative conditions, a mixed-effects linear regression model was employed. Eye gaze behavior was measured using fixation duration and saccadic amplitude. Due to the presence of between-subject variability, participant ID was treated as a random effect. Fixed effects included the communication condition (conversational vs. informative) and the type of visual element (e.g., AOIs) participants interacted with. All statistical analyses were performed in R (version 4.4.1) using the Imer package (v1.1-35.4) to build the models. We built three linear mixed-effects regression models to examine the effects of chatbot communication style on saccade amplitude, fixation duration, and improvement score as a function of communication style and eye-gaze behavior.

4 **RESULTS**

4.1 Descriptive Analysis

We collected data from 21 participants: 10 in the conversational condition and 11 in the informative condition. The mean age was 23.35 years (SD=2.78). The sample included 10 females and 11 males. Most participants were undergraduates (n=16), while three were graduate students, and two were not currently enrolled. Regarding chatbot usage, 5 participants reported daily use, 7 used chatbots weekly, and 9 seldom or never used them.

Figure 4 illustrates scan paths for a representative participant in each condition. Participants in the informative condition demonstrated localized fixations, while those in the conversational condition exhibited broader transitions across AOIs. The qualitative analysis of the AOI fixation graphs is represented in this sample, as participants in the conversational condition revisited previous chatbot responses, exhibiting more dynamic eye movements. In contrast, participants in the informative condition, while targeting multiple AOIs within a single chatbot response, primarily exhibited sequential fixations, lacking the interactive eye movement patterns observed in the conversational condition.



(a) Informative condition.

(b) Conversational condition.

Figure 4: Scan paths for a representative participant in each condition.

Figures 5 and 6 illustrate the impact of chatbot communication style on fixation duration, saccade amplitude, and improvement score. Participants in the informative condition exhibited longer fixation durations (Figure 5a), while those in the conversational condition demonstrated greater saccadic amplitudes (Figure 5b). The informative condition resulted in higher improvement scores compared to the conversational condition (Figure 6). The Impact of Healthcare Chatbots' Communication Style on User Eye Gaze Behavior



Figure 5: Fixation duration (a) and saccade amplitude (b) by chatbot communication style.



Figure 6: Improvement scores by chatbot communication style.

4.2 Mixed Linear Regression Model Results

The linear mixed-effects models revealed distinct effects of chatbot communication style on saccade amplitude, fixation duration, and improvement scores. Saccade amplitude showed no significant difference between the conversational and informative conditions (Table 1). However, fixation duration was significantly longer in the informative condition compared to the conversational condition ($\beta = 0.10$, p < .001; Table 2).

Additionally, we measured improvement improvement scores by a mixed linear regression model, where we used explanatory variables of the chatbot communication style and the mean fixation duration per slide (MFDS) for each participant. The improvement scores had a statistically significant main effect in the communication style, as they were significantly higher in the informative condition ($\beta = 3.05$, p < .001; Table 3). However, there was no statistically significant main effect of MFDS or interaction between chatbot communication style and MFDS.

Table 1: Assessing Saccade Amplitude by CommunicationStyle

Term	β	SE	t	р
(Intercept)	4.70	0.00	2179.98	<.001*
Condition (Informative)	0.00	0.00	-1.47	0.14

 Table 2: Assessing Fixation Duration by Communication

 Style

Term	β	SE	t	р
(Intercept)	-2.68	0.00	-1061.97	<.001*
Condition (Informative)	0.10	0.00	30.08	<.001*

Table 3: Assessing Improvement Score by Chatbot Communication Style and MFDS

Term	β	SE	t	р
(Intercept)	4.43	0.02	454.1	<.001*
Condition (Informative)	3.05	0.01	241.2	<.001*
MFDS	<.001	<.001	0.001	0.999
Interaction (Cond. * MFDS)	<.001	<.001	-0.001	0.999

5 DISCUSSION

This study examined how a chatbot's communication style impacts its effectiveness in a simulated healthcare scenario. We assessed user eye-gaze behavior in a simulated healthcare chatbot interaction where users engaged in an information-seeking task about blood pressure and hypertension topics. By comparing conversational and informative communication styles, our results indicate that different chatbot approaches affect user eye gaze behavior and learning outcomes in healthcare information-seeking contexts.

Participants interacting with the informative chatbot style exhibited longer fixation durations and achieved higher improvement scores compared to those in the conversational style. Longer fixations suggest that participants found the informative chatbot more engaging or cognitively demanding, leading to deeper processing of the material. This indicates that the direct nature of the informative style may have been more effective in focusing user attention and enhancing knowledge retention. Previous research has shown that the ability to flexibly maintain and update working memory is strongly related to fixation duration behavior [12]. The information presentation design of the informative chatbot condition may have included unique features that enhanced users' ability to focus their attention and update their working memory. Future research should investigate which specific design features of user interfaces in human-AI interactions can effectively sustain user interest and attention.

In contrast, participants in the conversational condition demonstrated broader transitions across different Areas of Interest (AOIs), often revisiting previous chatbot responses. This behavior suggests a more exploratory learning approach, where participants re-engage with prior information. While this style created a more interactive experience, it resulted in less sustained focus on individual content areas. Furthermore, no significant differences were observed in saccade amplitude between the two communication styles, indicating that while fixation patterns and learning outcomes varied, rapid eye movements remained consistent. These findings suggest that while the conversational style may encourage dynamic and interactive exploration of content, the informative style is more effective for supporting focused learning and improving knowledge outcomes in healthcare chatbot interactions.

This work builds on Koscelny and Nevens (2024) who found that informative chatbots were perceived as content-heavy, while conversational chatbots encouraged exploratory engagement with greater interaction freedom and understandability [10]. However, the results of this eye-tracking study indicate that such engagement may lack the structured focus necessary for efficiently absorbing complex information. In this study, we used the same information for the healthcare chatbot (blood pressure and hypertension) but introduced a significant change to the conversational channel. While the earlier study employed a narrow conversational channel, the current study expanded it to better reflect modern large language model (LLM) applications and to facilitate eye-tracking measures across a wider screen. This modification in interface design may have directly influenced the findings, as a larger conversational channel could enable healthcare chatbots in patient portals to more effectively present and process information. These results suggest that interface structure plays a critical role in user experience and learning. Specifically, for healthcare chatbots, a wider conversational channel may be necessary to balance user engagement and comprehension. Given the technical nature of health information, future chatbot designers should prioritize understanding users' needs and interaction styles to create conversational agents that effectively balance engagement and clarity [1].

Referring back to Media Richness Theory (MRT), understanding users' needs and interaction styles enables designers to enhance chatbot effectiveness while expanding the theory's scope. By integrating user-centered design principles, healthcare chatbots can be optimized to sustain user attention and engagement, dynamically adapting communication styles and interface structures to diverse user contexts [5]. Additionally, insights from Social Presence Theory and Flow Theory provide a foundation for creating chatbots that foster immersion, personalization, and richer user experiences across educational and informational settings [2, 9].

5.1 Limitations and Future Research

A limitation of this study is that the majority of participants were university students, which may limit the generalizability of the findings to broader populations. The learning behaviors of students might differ from those of other groups, such as working professionals. For example, students might engage with digital learning tools more frequently and could exhibit higher comfort levels with technology-driven interactions. As a result, the effectiveness of different chatbot communication styles may vary when applied to populations with different educational backgrounds or professional experiences. The study also focused on the specific context of a healthcare mock patient portal. While the findings offer insights into how chatbot communication styles can impact learning and engagement in this setting, the results may not directly translate to other contexts. Future work should consider other contexts for chatbots, such as financial services or customer support. Additionally, the experiment utilized pre-prepared PowerPoint presentations with preconstructed chatbot interactions to simulate a patient portal experience. While this approach is effective for maintaining experimental control, it lacks the dynamic features of real-time chatbot interactions. Real-time chatbots can adjust their communication style based on user behavior and provide more personalized feedback, potentially influencing user engagement, trust, and learning outcomes.

Future work should explore the potential of multimodal chatbot interactions (e.g., text-to-audio, text-to-video, audio-to-audio) to enhance human-AI interaction. Multimodal designs could provide users with more intuitive and engaging experiences, allowing for diverse preferences and interaction styles. There is an opportunity for future research in human factors to develop dynamic statistical models that gauge, measure, and monitor these interactions in continuously. Such models could adapt chatbot responses based on user behavior, engagement levels, and contextual needs, ensuring a personalized and safe user-interaction experience.

6 CONCLUSION

This study investigates the impact of chatbot communication styles on user eye-gaze behavior engagement for an information-seeking task in healthcare contexts. Informative chatbots were more effective in maintaining focus and improving knowledge retention, while conversational chatbots encouraged interactive exploration but may have lacked structured attention, as evidenced in the significantly lower blood pressure and hypertension improvement scores. These findings demonstrate the importance of tailoring chatbot designs to user needs, leveraging theories such as Media Richness Theory and Social Presence Theory to enhance engagement and usability. Future research should expand to diverse user groups and assess multimodal interactions to optimize human-AI interactions across broader contexts.

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