

What Dialogue Content Leads to a Trust Relationship and Behavior Change? Dialogue and Questionnaire Analysis

Tae Sato
NTT Social Informatics Laboratories
Yokosuka, Japan
tae.sato@ntt.com

Taiga Sano
NTT Social Informatics Laboratories
Yokosuka, Japan
taiga.sano@ntt.com

Eiji Kumakawa
NTT Social Informatics Laboratories
Yokosuka, Japan
eiji.kumakawa@ntt.com

Kaori Fujimura
NTT Social Informatics Laboratories
Yokosuka, Kanagawa, Japan
kaori.fujimura@ntt.com

Naomi Yamashita
Social Informatics
Kyoto University
Kyoto, Japan
NTT Social Informatics Laboratories
Yokosuka, Japan
naomiy@acm.org

Abstract

Recently, there has been increasing research on designing chatbots for behavior change. While trust between individuals and their supporters is recognized as a crucial factor in fostering behavior change, it remains unclear what types of dialogue contribute to building such trust. In this study, we investigated health guidance interviews to address two key questions: 1. What kind of trust relationship facilitates behavior change? and 2. What type of dialogue contributes to fostering that trust? Our findings indicate that individuals were more motivated to pursue behavioral goals when they perceived the interviewer as having integrity. Furthermore, an analysis of interviewer speech using four dialogue categories revealed that perceptions of integrity were stronger when interviewers spent more time on “Providing Tailored Insights” rather than “Building a Trust Relationship.” These insights contribute to designing chatbots that effectively support behavior change by fostering trust through dialogue strategies.

CCS Concepts

• Human-centered computing → Empirical studies in HCI.

Keywords

trust relationship, behavior change, dialogue, chatbot

ACM Reference Format:

Tae Sato, Taiga Sano, Eiji Kumakawa, Kaori Fujimura, and Naomi Yamashita. 2025. What Dialogue Content Leads to a Trust Relationship and Behavior Change? Dialogue and Questionnaire Analysis. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '25)*, April 26–May 01, 2025, Yokohama, Japan. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3706599.3720143>

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

CHI EA '25, Yokohama, Japan

© 2025 Copyright held by the owner/author(s).

ACM ISBN 979-8-4007-1395-8/25/04

<https://doi.org/10.1145/3706599.3720143>

1 BACKGROUND AND RESEARCH QUESTIONS

Addressing behavioral risk factors for chronic diseases, such as physical inactivity and unhealthy diets high in salt, sugar, and fat, and promoting healthy behaviors are important for preventing of various chronic diseases [2, 12, 25]. However, chronic diseases often have no symptoms even in high-risk states, making them painless and difficult to motivate individuals. A common and effective approach has been for healthcare professionals and other specialist staff to closely engage with individuals to provide behavior change support communication [19]. On the other hand, due to the global increase in the prevalence of chronic diseases [22] and the need to respond to other health issues (such as sudden outbreaks of infectious diseases), specialist staff must perform many tasks in addition to providing preventive support. Consequently, support from specialist staff alone has its limitations.

In recent years, the use of chatbots has been widely researched as a means to motivate individuals and support behavior change (promote behavior modification) when human resources are insufficient [1, 6, 18, 21]. For example, chatbots are being integrated into health coaching systems aimed at improving health behaviors by monitoring patients, notifying them of appropriate activities, and educating users with relevant knowledge. Chatbots not only have the advantage of being able to collect user's data and provide valuable information 24 hours a day, 365 days a year through question-and-answer interactions and reminders [4, 13], even when human staff are unavailable, but also possess anthropomorphism. It is said that people tend to perceive chatbots as social entities because of their anthropomorphism, even when they recognize they are interacting with a computer [14, 15]. In chatbots perceived as social entities, the ability to build relationships is seen as a key component. There is a report that when trust is built in the relationship, behavior change is strengthened when trust in chatbots is increased [5]. A trust relationship is said to be the glue that allows things to move forward [16], and it plays an important role in behavior change support.

Recent research has increasingly emphasized building relationships with chatbots, particularly focusing on establishing trust

relationships [5, 8, 11, 23, 24]. However, many of these studies evaluate trust relationships under the unified concept of “trust”, making it unclear which specific aspects of trust relationships contribute to behavior change. Moreover, in research aimed at designing chatbots that enhance trust relationships, much of the focus has been on communication style and appearance. Therefore, this study investigated the following questions in context of health guidance interview between specialist health guidance staff to provide behavior change support (i.e., interviewer) and interviewee:

- What aspects of a trust relationship are related to behavior change?
- What type of dialogue is related to fostering a trust relationship that supports behavior change?

We conducted a survey of health guidance interviews and recorded the dialogues during the interviews, labeling the content of the interviewer’s speech. We surveyed the interviewees immediately after the interview to determine their motivation for behavior change and level of trust relationship with the interviewer. By analyzing the dialogue content labels and questionnaire responses, we clarified the above research questions.

In prior research, Chen et al. reported that when chatbots have a friendly style (characterized by empathy, warmth, and patient-centered language), it generates trust in the chatbot and strengthens treatment adherence [5]. To enhance the effectiveness of this research, we thought that the dialogue should be designed from a bird’s-eye view of what kind of content the chatbot (which replaces the interviewer) should speak and that knowledge about entire dialogues would need to be obtained. According to [10], effective interviewers encourage behavior change by “building a trust relationship with interviewees,” “assessing their life information,” “providing tailored insights,” and collaboratively “setting goals.” Therefore, it is important to understand which contents of dialogue build different kinds of trust relationships and enhance motivation. This study aims to examine how these four dialogue components contribute to trust relationships that shape motivation for behavior change. The findings of this research will contribute to designing chatbot dialogue that takes into account the building of a trust relationship with the user and supports the user’s motivation to continue their healthy actions.

2 METHOD

2.1 Participants and procedures for health guidance interviews

In surveying health guidance sessions, we used the snowball sampling method to invite four experienced professionals (three public health nurses and one registered dietitian with experience in providing Specific Health Guidance in Japan [10]) from different organizations to participate as interviewers. The participants in the role of the interviewees were recruited through a research company. The criteria for interviewees were individuals who had had mild or no abnormalities in their health check-up within the previous year, based on Specific Health Guidance standards (blood pressure, lipids, and blood glucose) [10]. Interviewees who had previously undergone Specific Health Guidance were excluded from this survey to prevent potential influences on survey results. A total of

26 interviewees (22 males, 4 females, average age = 45) attended. The interviewers and interviewees were provided with explanations about the purpose of this study, the data to be collected, the compensation, and the voluntary nature of participation, and their consent was obtained. After the experiment, compensation was provided to the interviewers and interviewees. The interviewees were asked to fill in a questionnaire about their trust relationship with the interviewer and their motivation immediately after the interview. The items measured by the questionnaire are listed in Section 2.2.

2.2 Measure

The interviewees were surveyed about their trust in the interviewer and about whether they had changed their motivation after the interview. To measure the trust felt towards the interviewer, a trust relationship scale was used which assesses trust on three aspects: competence, benevolence, and integrity [3]. The ten questions were modified to fit this survey’s context based on the original questions (i.e., the assessment of trust in interviewers in health guidance interviews). Four questions were about competence: “1. This interviewer has the expertise to understand my needs and preferences,” “2. This interviewer has the ability to understand my needs and preferences,” “3. This interviewer has good knowledge about health,” “4. This interviewer considers my needs and important attributes of health.” Three questions were about benevolence: “5. This interviewer puts my interests first,” “6. This interviewer keeps my interests in mind,” “7. This interviewer wants to understand my needs and preferences.” Three questions were about integrity: “8. This interviewer provides unbiased recommendations,” “9. This interviewer is honest,” and “10. I consider this interviewer to possess integrity.” A 5-point Likert scale (ranging from “1 - Not at all applicable” to “5 - Very applicable”) was used. To measure whether there was any behavior change, interviewees were asked to respond on a 5-point Likert scale (ranging from “1 - Strongly Disagree” to “5 - Strongly Agree”) whether they felt motivated to work towards the goals they had set.

2.3 Analysis

2.3.1 Dialogue Analysis. The recorded data were transcribed for each interview, with the speaker (interviewer or interviewee) noted. In the transcription, each speaker’s turn was defined as one turn, and the content labels were annotated for each turn of the interviewer’s utterances. The content labels were based on the dialogue content explained in the Specific Health Guidance Guidelines of the Japanese Ministry of Health, Labour and Welfare [10], and were divided into four types: “A: Building a trust relationship with the interviewee,” “B: Assessment (interviewee’s information gathering and judgment),” “C: Providing tailored insights,” and “D: Goal setting.” We did not annotate simple responses, back-channeling, or utterances that were only fillers that did not correspond to these content labels. Label A was assigned to utterances that included greetings, self-introductions, acceptance of or empathy towards the interviewee’s statements. Label B was assigned to utterances that confirmed the participant’s understanding and motivation or gathered information about their lifestyle. Label C was assigned to utterances that communicated the need for behavior change, suggested possible actions, and highlighted the benefits. Label D

was assigned to utterances that involved concretizing numerical goals and encouraging self-determination.

In the annotation process, we used both the Specific Health Guidance Guidelines and working guidelines that provides specific explanations for parts of the Specific Health Guidance Guidelines where annotation judgments may differ, developed through discussions between annotators and researchers. Two annotators conducted a trial annotation of one interview, referring to the guidelines, and after checking the results and reaching a consensus, they annotated all 26 interviews together. For utterances with different content labels, a decision was made through discussion. We counted the occurrence of each content label in each interview, and the occurrence rate was calculated by setting the total number of content labels that occurred in each interview to 100%.

3.2.2 Statistical Analysis. To determine “What aspects of a trust relationship are related to behavior change?” and “What type of dialogue is related to fostering a trust relationship that supports behavior change?”, we used Spearman’s rank correlation coefficient as a correlation analysis. Additionally, to determine characteristics of utterance rates of the four dialogue content levels, Pearson’s product-moment correlation coefficients were calculated. We then conducted path analysis to determine the overall relationship between dialogue content, trust, and behavior change.

3 RESULTS

3.1 Correlation between trust relationship and behavior change

The correlations between the trust that the interviewees felt towards the interviewer and their behavior change were as follows (Table 1). There was a weak positive correlation ($r=0.384$, $p<0.1$) between “This interviewer puts my interests first” and “I will work towards the goals I have set”(behavior change). There was also a weak positive correlation ($r=0.375$, $p<0.1$) between “I consider this interviewer to possess integrity” and “I will work towards the goals I have set”(behavior change). There was no significant difference in other trust relationships and behavior change (“I will work towards the goals I have set”), and the correlation coefficients ranged from 0.012 to 0.301.

3.2 Correlation between dialogue content and trust relationship

3.2.1 Distribution and characteristics of the dialogue content labels. The percentages of the four dialogue content labels in each interview were as follows: “Building a trust relationship with the interviewee” was AVG=21.2%, SD=6.8%, min=8.9%, max=35.9%; “Assessment (interviewee’s information gathering and judgment)” was AVG=42.0%, SD=10.3%, min=17.6%, max=65.0%, “Providing tailored insights” was AVG=17.8%, SD=8.0%, min=4.0%, max=34.3%, and “Goal setting” was AVG=19%, SD=9.0%, min=2.0%, max=38.5%.

Dialogue sentences labeled as “Building a trust relationship with the interviewee” included phrases such as “Thank you for your time today. I appreciate it,” “I am the public health nurse in charge today,” and “Oh, that’s amazing. Awesome. I see.” Dialogue sentences labeled as “Assessment (interviewee’s information gathering and

judgment)” included phrases such as “Do you usually eat something before you play baseball?”, “After looking at your check-up results, is there anything you felt or thought you might want to do?”, and “Do you feel like your daily routine has changed?” Dialogue sentences labeled as “Providing tailored insights” included phrases such as “This is just for your information, but have you ever heard of a walking method called interval walking?”, “After 8 PM, your body tends to store more fat due to its natural mechanisms,” “(After explaining exercise to interviewee concerned about their weight and triglyceride levels) To be honest, I think it would be better to start by establishing a regular daily routine. Once your lifestyle rhythm is in order, you might be able to lose weight naturally, without having to force yourself,” and “Your iron levels are a bit low, so once you get enough iron, you’ll feel more energized.” Dialogue sentences labeled as “Goal setting” included phrases such as “How about setting some goals and making a plan until your next health check-up?”, “Have fun choosing non-alcoholic drinks and stuff like that,” and “How much do you think you can increase your exercise?”

The correlations between the four occurrence rates of the dialogue content labels within each interview were as follows. There was a strong negative correlation ($r= -0.615$, $p<0.01$) between “Building a trust relationship with the interviewee” and “Providing tailored insights.” This shows that when utterances of “Building a trust relationship with the interviewee” were frequent in the interview, utterances of “Providing tailored insights” were infrequent. Likewise, a moderate negative correlation ($r= -0.428$, $p<0.05$) between “Building a trust relationship with the interviewee” and “Goal setting”, a strong negative correlation between “Assessment (interviewee’s information gathering and judgment)” and “Providing tailored insights” ($r= -0.521$, $p<0.01$), and a strong negative correlation between “Assessment (interviewee’s information gathering and judgment)” and “Goal setting” ($r= -0.521$, $p<0.01$).

3.2.2 Correlation between the percentage of dialogue content and trust. The correlations between the occurrence rate of dialogue content labels and the trust that the interviewees felt towards the interviewer were as follows (Table 2). The analysis focused only on the trust that was correlated with behavior change. There was a moderate positive correlation ($r=0.440$, $p<0.05$) between “This interviewer puts my interests first” and “Providing tailored insights”. There was also a weak negative correlation ($r= -0.374$, $p<0.1$) between “This interviewer puts my interests first” and “Assessment (interviewee’s information gathering and judgment)”. There was no significant correlation between “This interviewer puts my interests first” and “Building a trust relationship with the interviewee” or “Goal setting”. There was a strong positive correlation ($r=0.565$, $p<0.01$) between “I consider this interviewer to possess integrity” and “Providing tailored insights.” There was also a weak negative correlation ($r= -0.395$, $p<0.05$) between “The interviewer is a sincere person” and “Building a trust relationship with the interviewee.” On the other hand, there was no significant correlation between “I consider this interviewer to possess integrity” and “Assessment (interviewee’s information gathering and judgment)” or “Goal setting”.

Table 1: Correlation between trust relationship and behavior change

	Trust relationship items									
	Competence -expertise	Competence -ability	Competence -good knowledge	Competence -considering	Benevolence -puts my interests first	Benevolence -keeps in mind	Benevolence -wants to understand	Integrity -unbiased	Integrity -honest	Integrity -integrity
Behavior change	0.251	0.068	0.050	0.114	0.384 †	0.301	0.012	0.261	0.158	0.375 †
† p<0.1										

Table 2: Correlation between the percentage of dialogue content and trust

		Dialogue content labels			
		Building a trust relationship	Assessment	Providing tailored insights	Goal setting
Trust	Benevolence -puts my interests first	-0.066	-0.374 †	0.440*	0.059
	Integrity -integrity	-0.395*	-0.170	0.565**	0.062
				† p<0.1 * p<0.05 ** p<0.01	

3.3 The overall relationship between dialogue content, trust relationship, and behavior change

As an explanatory factor for behavior change, we adopted the trust and the occurrence rate of dialogue content labels, which showed a correlation in Sections 3.1 and 3.2. We then set up a path diagram hypothesizing the process leading to behavior change, as shown in Figure 1, and conducted path analysis. First, to verify the fit of this model to the data, we checked the goodness-of-fit indices. The chi-square value was 9.230, the degrees of freedom were 6, and the p-value was 0.161. The Comparative Fit Index (CFI) was 0.925, the Tucker-Lewis Index (TLI) was 0.813, the Root Mean Square Error of Approximation (RMSEA) was 0.144 (90% CI [0.000, 0.316]), and the Standardized Root Mean Square Residual (SRMR) was 0.099. The model did not fit well according to the criteria (CFI>=0.95, TLI>=0.95, RMSEA<=0.06, SRMR<=0.08) indicated in a previous study [9]. Therefore, we referred to the modification index (MI) and adjusted the model. Specifically, we added the path where the occurrence rate of dialogue content label “Assessment (interviewee’s information gathering and judgment)” (MI=1.645) directly explains “I will work towards the goals I have set,” the path where the occurrence rate of dialogue content label “Providing tailored insights” (MI=1.390) directly explains “I will work towards the goals I have set,” and the path where the occurrence rate of dialogue content label “Building a trust relationship with the interviewee” (MI=0.119) directly explains “I will work towards the goals I have set” (Figure 2. The values in the figure are the results of the path analysis). When we checked the goodness-of-fit indices for the new model, we found that the chi-square value was 0.598, the degrees of freedom were 2, the p-value was 0.742, the CFI was 1.000, the TLI was 1.243, the RMSEA was 0.000 (90% CI [0.000, 0.270]), and the SRMR was 0.025, so we judged that the model had sufficient goodness of fit.

As shown by the bold line and numbers in Figure 2, in this model, there is a negative correlation (standardized coefficient estimate = -0.530, p<0.05) between the occurrence rate of dialogue content label “Providing tailored insights” and the occurrence rate of dialogue

content label “Assessment (interviewee’s information gathering and judgment)”, and a negative correlation (standardized coefficient estimate = 0.676, p<0.01) between the occurrence rate of dialogue content label “Providing tailored insights” and the occurrence rate of dialogue content label “Building a trust relationship with the interviewee.” The path from the occurrence rate of dialogue content label “Providing tailored insights” to “I consider this interviewer to possess integrity” (standardized coefficient estimate = 0.444, P < 0.05) and the path from “I consider this interviewer to possess integrity” to “I will work towards the goals I have set” (standardized coefficient estimate = 0.597, p<0.01) were significant. Therefore, it was shown that when the time spent by the interviewer on “Assessment (interviewee’s information gathering and judgment)” and “Building a trust relationship with the interviewee” was shorter than for other interviews, and the time spent on “Providing tailored insights” was longer than for other interviews, the degree to which the interviewee felt that the interviewer possessed integrity increased. The degree to which the interviewee felt that the interviewer possessed integrity also increased the degree to which they felt that they wanted to work towards their goal.

4 DISCUSSION

Regarding the relationship between the trust relationship and behavior change, there was a correlation between the trust that “I consider this interviewer to possess integrity” and “This interviewer puts my interests first”, and only “I consider this interviewer to possess integrity” was significant as a factor explaining “I will work towards the goals I have set.” The impression of “I consider this interviewer to possess integrity” is a type of trust that belongs to the category of integrity, one of the three categories of trust (competence, benevolence, integrity). Hildegard [20] argued that nurses are not friends of patients, and that as professional staff they should provide information directly using responsible language for treating individuals and improving behavior rather than chatting. In the results of this survey, the reason that the integrity, rather than the competence or benevolence, of the interviewer affected

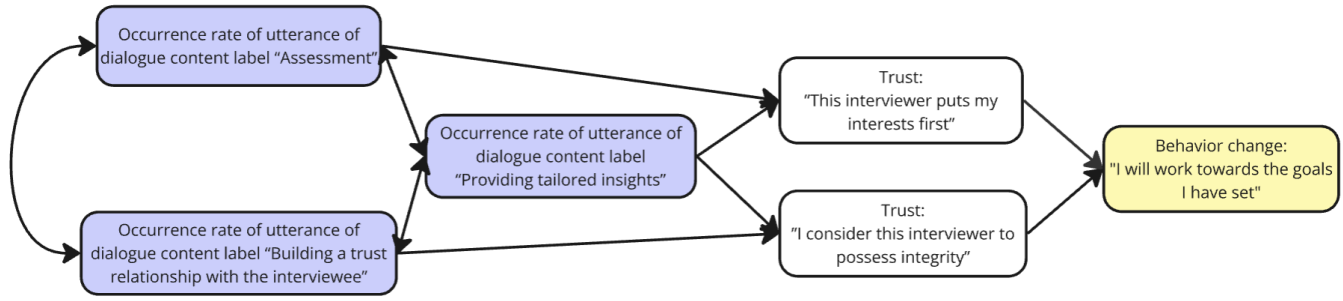


Figure 1: Path diagram created on the basis of correlation analysis results

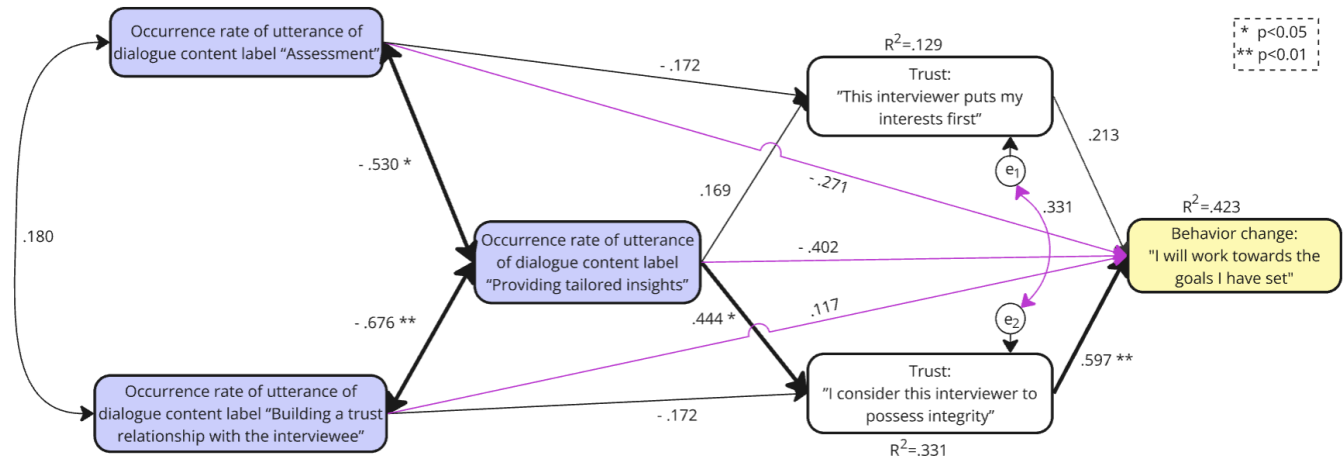


Figure 2: Path diagram and path analysis results after model modification

behavior change ("I will work on my goal") was possibly that the interviewees felt that the interviewer's behavior as a health guidance specialist demonstrated integrity (i.e., they were conscientious and responsible), and this led to a desire to change their behavior.

Regarding the relationship between dialogue content and trust relationship, the occurrence rate of dialogue content label "Engaging awareness" was positively correlated with the impressions "This interviewer puts my interests first" and "I consider this interviewer to possess integrity" and was a significant factor in explaining the impression "I consider this interviewer to possess integrity". The percentage of dialogue content of "Building a trust relationship with the interviewee" was negatively correlated with but was not a significant factor in explaining the impression of "I consider this interviewer to possess integrity." Additionally, the percentage of dialogue related to "Building a trust relationship with the interviewee" was negatively correlated with the percentage of dialogue related to "Providing tailored insights." As shown in the results in Section 3.2.1, the average percentage of dialogue related to "Providing tailored insights" was 17.8%, with a maximum of 34.3%, while the average occurrence rate of dialogue related to building a trust relationship with the interviewee was 21.2%, with a minimum of 8.9%. From the above, although "Building a trust relationship with the interviewee" is clearly not unnecessary for interviewees, they

feel more trust (impression of integrity) when more time is spent on "Providing tailored insights" than "Building a trust relationship with the interviewee" as a relative balance.

An interesting point is that, in the results of path analysis, the path directly explaining the dialogue content ("Providing tailored insights" and "Building a trust relationship with the interviewee") did not show any significant results, while the path via the trust relationship ("possessing integrity") did. Therefore, the trust relationship ("possessing integrity") elicited from the dialogue content is thought to play an important role as an essential "glue" for promoting behavior change.

Chen et al.[5] have demonstrated that empathic communication by chatbots—such as expressing empathy and acceptance toward users' statements—enhances user behavior change, and in this study, we further revealed that such conversations are predominantly included in utterances labeled as "Building a trust relationship with the interviewee". The results of this study suggest that while utterances involving building trust with the interviewee are essential, allocating time to utterances related to "Providing tailored insights" may further enhance trust and promote behavior change. Here, "empathic communication" refers to a style of dialogue and is not in opposition to the content of the dialogue. Therefore, an empathic communication style can be adopted across a wide range

of dialogue content. In other words, even in utterances aimed at "Providing tailored insights," incorporating an empathic communication style may further enhance user trust and promote behavior change. For example, it may be effective to empathize with the user's chronic disease or discomfort and then convey the causes, improvement measures, and ideas for action that are appropriate for their situation.

5 FUTURE DIRECTIONS

Future work should integrate insights from previous research on effective communication styles with the findings of this study—specifically, the combination of dialogue content—to clarify the effectiveness and challenges of chatbot interactions. This will contribute to new knowledge on chatbot design that facilitates user behavior change. While this study adopted an approach that derives chatbot design directionality from human-human communication [7, 17], previous research [23] has highlighted differences between users' perceptions of humans and chatbots. Therefore, when applying these findings, chatbot-specific characteristics and constraints should be considered in the design of chatbot interactions. We hope this study contributes to the field of Human-Computer Interaction (HCI) by advancing research on chatbot design.

References

- [1] Abhishek Aggarwal, Cheuk Chi Tam, Dezhi Wu, Xiaoming Li, and Shan Qiao. 2023. Artificial Intelligence-Based Chatbots for Promoting Health Behavioral Changes: Systematic Review. *Journal of Medical Internet Research* 25 (2023). doi:10.2196/40789
- [2] Sangnam Ahn, Rashmita Basu, Matthew Smith, Luohua Jiang, Kate Lorig, Nancy Whitelaw, and Marcia Ory. 2013. The impact of chronic disease self-management programs: Healthcare savings through a community-based intervention. *BMC public health* 13 (12 2013), 1141. doi:10.1186/1471-2458-13-1141
- [3] Izak Benbasat and Weiquan Wang. 2005. Trust In and Adoption of Online Recommendation Agents. *J. Assoc. Inf. Syst.* 6 (2005), 4. <https://api.semanticscholar.org/CorpusID:7030200>
- [4] Benjamin Chaix, Jean-Emmanuel Bibault, Arthur Pienkowski, Guillaume Delamon, Arthur Guillemassé, Pierre Nectoux, and Benoît Brouard. 2019. When Chatbots Meet Patients: One-Year Prospective Study of Conversations Between Patients With Breast Cancer and a Chatbot. *JMIR cancer* (2019) 5, 1 (May 2019), e12856. doi:10.1007/s10916-019-1237-1
- [5] Zhiyun Chen, Xinyue Zhao, Min Hua, and Jian Xu. 2024. Building Bonds Through Bytes: The Impact of Communication Styles on Patient-Chatbot Relationships and Treatment Adherence in AI-Driven Healthcare. In *HCI International 2024 – Late Breaking Papers: 26th International Conference on Human-Computer Interaction, HCII 2024, Washington, DC, USA, June 29 – July 4, 2024, Proceedings, Part III* (Washington DC, USA). Springer-Verlag, Berlin, Heidelberg, 32–52. doi:10.1007/978-3-031-76809-5_3
- [6] Elia Grassini, Marina Buzzi, Barbara Leporini, and Alina Vozna. 2024. A systematic review of chatbots in inclusive healthcare: insights from the last 5 years. *Univ Access Inf Soc* (2024) (May 2024). <https://doi.org/10.1007/s10209-024-01118-x>
- [7] Jeffrey T Hancock, Mor Naaman, and Karen Levy. 2020. AI-Mediated Communication: Definition, Research Agenda, and Ethical Considerations. *Journal of Computer-Mediated Communication* 25, 1 (01 2020), 89–100. doi:10.1093/jcmc/zmz022 [arXiv:https://academic.oup.com/jcmc/article-pdf/25/1/89/32961176/zmz022.pdf](https://academic.oup.com/jcmc/article-pdf/25/1/89/32961176/zmz022.pdf)
- [8] Christina N. Harrington and Lisa Egede. 2023. Trust, Comfort and Relatability: Understanding Black Older Adults' Perceptions of Chatbot Design for Health Information Seeking. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI '23). Association for Computing Machinery, New York, NY, USA, Article 120, 18 pages. doi:10.1145/3544548.3580719
- [9] Li-tze Hu and Peter Bentler. 1998. Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *Psychological Methods* 3 (12 1998), 424–453. doi:10.1037/1082-989X.3.4.424
- [10] Labour Japanese Ministry of Health and Welfare. [n. d.]. Standard Health Checkup and Health Guidance Program (2024 Edition). <https://www.mhlw.go.jp/content/10900000/001231390.pdf> (accessed 2024-12-26).
- [11] Theodore Jensen, Mohammad Maifi Hasan Khan, Md Abdullah Al Fahim, and Yusuf Albayram. 2021. Trust and Anthropomorphism in Tandem: The Interrelated Nature of Automated Agent Appearance and Reliability in Trustworthiness Perceptions. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference* (Virtual Event, USA) (DIS '21). Association for Computing Machinery, New York, NY, USA, 1470–1480. doi:10.1145/3461778.3462102
- [12] Courtney O. Jordan, Megan E. Slater, and Thomas E. Kottke. 2008. Preventing chronic disease risk factors: rationale and feasibility. *Medicina* 44 10 (2008), 745–50. <https://api.semanticscholar.org/CorpusID:23593495>
- [13] Tobias Kowatsch, Theresa Schachner, Samira Harperink, Filipe Barata, Ullrich Dittler, Grace Xiao, Catherine Stanger, Florian V Wangenheim, Elgar Fleisch, Helmut Oswald, and Alexander Möller. 2021. Conversational Agents as Mediating Social Actors in Chronic Disease Management Involving Health Care Professionals, Patients, and Family Members: Multisite Single-Arm Feasibility Study. *J Med Internet Res* 23, 2 (Feb 2021), e25060. doi:10.2196/25060
- [14] Yi-Chieh Lee, Naomi Yamashita, and Yun Huang. 2020. Designing a Chatbot as a Mediator for Promoting Deep Self-Disclosure to a Real Mental Health Professional. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW1, Article 31 (May 2020), 27 pages. doi:10.1145/3392836
- [15] Yi-Chieh Lee, Naomi Yamashita, Yun Huang, and Wai Fu. 2020. "I Hear You, I Feel You": Encouraging Deep Self-disclosure through a Chatbot. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '20). Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3313831.3376175
- [16] David Mechanic. 1998. The Functions and Limitations of Trust in the Provision of Medical Care. *Journal of health politics, policy and law* 23 (09 1998), 661–86. doi:10.1215/03616878-23-4-661
- [17] Yi Mou and Kun Xu. 2017. The Media Inequality: Comparing the Initial Human-human and Human-AI Social Interactions. *Computers in Human Behavior* 72 (2017), 432–440. <https://doi.org/10.1016/j.chb.2017.02.067>
- [18] Yoo Jung Oh, Min-Lin Fang Jingwen Zhang, and Yoshimi Fukuoka. 2021. A systematic review of chatbots in inclusive healthcare: insights from the last 5 years. *International Journal of Behavioral Nutrition and Physical Activity* (2021) 160 (May 2021), 18. <https://doi.org/10.1186/s12966-021-01224-6>
- [19] Jeanette M Olsen and Bonnie J Nesbitt. 2010. Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *American journal of health promotion : AJHP* 25, 1 (Sep-Oct 2010), e1–e12. doi:10.4278/ajhp.090313-LIT-101
- [20] Hildegard E Peplau. 1960. Talking with Patients. *The American journal of Nursing* 60 (1960), 964–966. <https://doi.org/10.2307/3418512>
- [21] Juanan Pereira and Óscar Díaz. 2019. Using Health Chatbots for Behavior Change: A Mapping Study. *Journal of medical systems* (2019) 43 (Apr 2019), 135. doi:10.1007/s10916-019-1237-1
- [22] Pouya Saeedi, Inga Petersohn, Paraskevi Salpea, Belma Malanda, Suvi Karuranga, Nigel Unwin, Stephen Colagiuri, Leonor Guariguata, Ayesha A Motala, Katherine Ogurtsova, Jonathan E Shaw, Dominic Bright, and Rhys Williams. 2019. Global and regional diabetes prevalence estimates for 2019 and projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition. *Diabetes Res Clin Pract* 157 (Nov 2019), 107843.
- [23] Lennart Seitz, Sigrid Bekmeier-Feuerhahn, and Krutika Gohil. 2022. Can we trust a chatbot like a physician? A qualitative study on understanding the emergence of trust toward diagnostic chatbots. *International Journal of Human-Computer Studies* 165 (2022), 102848. doi:10.1016/j.ijhcs.2022.102848
- [24] Rebecca Wald, Evelien Heijlselaar, and Tibor Bosse. 2021. Make your own: The Potential of Chatbot Customization for the Development of User Trust. In *Adjunct Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization* (Utrecht, Netherlands) (UMAP '21). Association for Computing Machinery, New York, NY, USA, 382–387. doi:10.1145/3450614.3463600
- [25] World Health Organization. [n. d.]. Noncommunicable diseases. <https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases> (accessed 2024-12-26).