Designing AI Voice Agents for Users with Attentional Vulnerabilities: The Role of Proactivity and Interaction Structure

Short Paper

Subin Kim
Department of Industrial and Management Engineering, POSTECH
Pohang, Republic of Korea
tnqlsi12@postech.ac.kr

Tingru Cui
School of Computing and Information Systems, The University of Melbourne
Melbourne, Australia
tingru.cui@unimelb.edu.au

Jorge Goncalves
School of Computing and Information Systems, The University of Melbourne
Melbourne, Australia
jorge.goncalves@unimelb.edu.au

Abstract

As conversational AI becomes increasingly integrated into everyday digital environments, designing effective voice-based interactions has become an important challenge in human–AI interaction. In particular, the way conversational agents proactively guide users and structure interactions may strongly influence users' perceived control and experience. These challenges may become especially important for users with attentional vulnerabilities, who may experience difficulties maintaining focus during digital interactions. This study investigates how AI proactivity and interaction structure influence user experience in voice-based conversational interactions. A mixed-design experiment with 24 participants examined the effects of three levels of AI proactivity (low, medium, high) and two interaction structures (step-by-step vs. freeform) on perceived intrusiveness, task effectiveness, and emotional support. The results suggest that step-by-step interaction structures may help reduce perceived intrusiveness while maintaining the benefits of proactive guidance. These findings provide practical implications for designing more manageable and supportive voice-based conversational systems.

Keywords: Conversational AI, Voice Interaction, AI Proactivity, Interaction Structure, User Experience

Introduction

Digital technologies increasingly rely on conversational interfaces that enable users to interact with systems through natural language. With the rapid development of large language models (LLMs), voice-based conversational agents are becoming increasingly capable of supporting dynamic and context-aware dialogue. Compared with traditional graphical or text-based interfaces, voice interaction allows users to communicate with systems in a more natural and hands-free manner. However, voice interaction unfolds sequentially through conversational turn-taking and provides limited visual scaffolding, requiring users to process information in real time. These characteristics make conversational pacing and information delivery important design challenges in voice-based AI systems.

A key design challenge in conversational agents concerns the degree to which systems proactively guide interaction. Modern AI assistants increasingly take initiative by suggesting options, asking follow-up questions, or guiding users through tasks. Such proactive behaviors can improve interaction efficiency by reducing users' effort and helping them navigate complex decisions (Miksik et al., 2020; Zargham et al., 2022; Deng et al., 2025). However, excessive system initiative may also create negative experiences. When conversational agents intervene too frequently or dominate the interaction, users may perceive the system as intrusive or overly controlling, which can undermine their overall experience (Oh et al., 2024; Deng et al., 2025; Munz et al., 2025). This tension reflects an important trade-off between helpful guidance and users' sense of autonomy during interaction.

These design challenges may be particularly important for users with attentional vulnerabilities, such as individuals who experience difficulties maintaining focus during digital interactions, including those with ADHD-like characteristics (Kofler et al., 2020; Bozhilova et al., 2021). In voice-based interaction, where information is delivered sequentially and cannot be easily revisited, these users may be particularly sensitive to conversational pacing, prompt density, and system initiative. While conversational agents may provide helpful guidance that supports task progression, overly proactive or poorly structured interactions may increase cognitive burden and disrupt users' sense of control. Designing conversational agents that balance helpful guidance with users' autonomy therefore represents an important challenge in human–AI interaction. This study investigates how AI proactivity and interaction structure jointly influence user experience in voice-based conversational interactions, with a specific focus on individuals with attentional vulnerabilities.

Literature Review

AI Proactivity in Conversational Agents

Proactivity refers to the extent to which an AI system initiates suggestions, prompts, or guidance without explicit user input. In conversational interfaces, proactive behaviors may include asking follow-up questions, suggesting options, or guiding users through task steps (Miksik et al., 2020; Zargham et al., 2022; Deng et al., 2025).

Prior research suggests that proactive conversational systems can enhance user engagement and task performance by providing timely assistance and maintaining conversational momentum (Deng et al., 2025; Liu et al., 2025). For instance, conversational agents may help users clarify preferences, explore alternatives, or complete tasks more effectively when they proactively provide suggestions or ask clarifying questions. In voice-based interactions, where users rely primarily on sequential dialogue rather than visual navigation, proactive prompts may be particularly helpful for guiding interaction flow (Clark et al., 2019; Mahmood et al., 2025).

However, proactivity also introduces potential risks. When systems take excessive initiative, users may perceive the interaction as intrusive or overly controlling (Oh et al., 2024). Instead of feeling supported, users may experience interruptions, unwanted prompts, or an imbalance in conversational control. Research on proactive technologies suggests that poorly timed or overly frequent interventions can negatively influence users' perceptions of intelligent systems (Zargham et al., 2022; Deng et al., 2025). In the present study, AI proactivity reflects a broader set of conversational support behaviors, including prompting style, response elaboration, and follow-up guidance. As a result, the effectiveness of AI proactivity likely depends not only on whether systems initiate actions, but also on how such initiative is integrated into the conversational interaction.

Autonomy and Psychological Reactance in Human-AI Interaction

User responses to proactive technologies can be understood through the lens of psychological reactance theory. Psychological reactance theory proposes that individuals experience motivational resistance when they perceive that their freedom of choice or autonomy is threatened (Brehm, 1966). When external agents attempt to control behavior or limit perceived freedom, individuals may respond negatively in order to restore their sense of autonomy.

In digital environments, perceived autonomy plays an important role in shaping how users evaluate intelligent systems. Studies of automation and intelligent decision support systems suggest that users respond more positively to technologies that provide assistance while preserving their sense of control (Lee & See, 2004; Huang et al., 2025). Conversely, when systems appear overly directive or intrusive, users may perceive a loss of autonomy and develop negative attitudes toward the system.

Within conversational AI interactions, proactive system behavior may influence users' perceptions of autonomy during dialogue. When conversational agents frequently interrupt, offer unsolicited suggestions, or dominate the conversation, users may perceive the system as interfering with their preferred interaction style. This perception is commonly described as perceived intrusiveness, which reflects the extent to which users feel that a system disrupts their sense of control during interaction (Oh et al., 2024). Such perceptions may negatively influence users' evaluation of the interaction, including their satisfaction with the system and their perception of its effectiveness (Chen et al., 2023).

Interaction Structure in Voice-Based Communication

In addition to system initiative, the structure of conversational interaction may influence how users perceive AI behavior. Voice-based communication typically unfolds through sequential turn-taking, in which information is exchanged incrementally rather than presented simultaneously (Clark et al., 2019). Designers of conversational agents therefore face decisions about how conversational information should be organized and delivered during dialogue.

One important design distinction concerns whether interactions are structured step-by-step or presented in a more freeform manner. In step-by-step interactions, the system guides the conversation through a sequence of short exchanges, asking one question at a time and responding incrementally to user input. This structure can help maintain conversational clarity and provide manageable guidance throughout the interaction. In contrast, freeform interactions may involve longer responses or multiple prompts delivered within a single conversational turn, allowing greater flexibility but potentially requiring users to process more information simultaneously (Liu et al., 2025; Qu et al., 2026).

The structure of dialogue may influence how users interpret proactive system behaviors. When proactive prompts are delivered within a clear sequential structure, they may be perceived as helpful guidance that supports task progression. However, when multiple suggestions or prompts are presented at once, the same level of system initiative may appear overwhelming or intrusive (Munz et al., 2025).

Research Gap and Model Development

Prior research highlights both the benefits of proactive conversational agents and the importance of preserving user autonomy during interaction (Oh et al., 2024; Deng et al., 2025). However, limited research has examined how AI proactivity and interaction structure jointly influence users' perceptions in voice-based conversational interactions, particularly through the mechanism of perceived intrusiveness.

This issue may be especially relevant for users with attentional vulnerabilities who experience difficulties maintaining focus and processing conversational information during digital interactions. In voice-based communication, where users must process sequential information without persistent visual support, overly proactive or poorly structured interactions may increase cognitive burden and disrupt users' sense of autonomy. This study therefore examines how AI proactivity and interaction structure influence perceived intrusiveness and user experience in voice-based interactions.

Research Model and Hypotheses

Building on prior research on conversational AI and user autonomy, this study proposes a research model explaining how conversational design influences user experience in voice-based AI interactions. Specifically, the model conceptually proposes that AI proactivity and interaction structure may influence perceived intrusiveness during interaction. In addition, interaction structure is expected to moderate the relationship between AI proactivity and perceived intrusiveness. **Figure 1** illustrates the proposed research model.

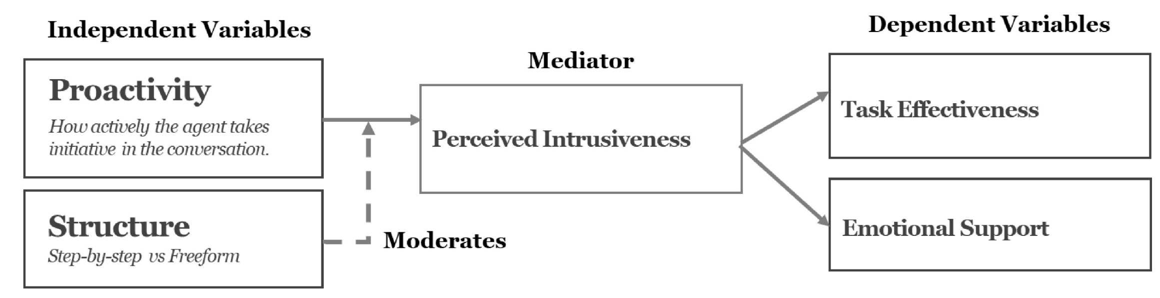

Figure 1. Proposed Research Model

Effects of AI Proactivity

AI proactivity refers to the extent to which a conversational agent initiates prompts, suggestions, or guidance without explicit user requests (Deng et al., 2025). Proactive behaviors such as follow-up questions or unsolicited suggestions may help maintain conversational flow and support task progression. However, excessive system initiative may particularly interfere with perceived autonomy in voice-based interactions that require continuous attention and sequential information processing.

Prior research suggests that when conversational agents frequently introduce prompts or dominate the dialogue, users may perceive the system as intrusive or overly controlling (Oh et al., 2024). Such responses are consistent with psychological reactance theory, which suggests that individuals experience resistance when their perceived freedom is threatened (Brehm, 1966). In conversational settings, these autonomy threats may manifest as perceived intrusiveness.

H1: *Higher AI proactivity will increase perceived intrusiveness during conversational interaction.*

Effects of Interaction Structure

Interaction structure determines how conversational information is organized and delivered during dialogue. In voice-based interactions, prompts may be delivered sequentially through step-by-step exchanges or presented in a more open freeform format (Clark et al., 2019; Liu et al., 2025).

Step-by-step interactions guide users through the conversation incrementally, allowing them to respond to one prompt at a time. This structure may provide clearer conversational pacing and reduce the cognitive demands associated with processing multiple suggestions simultaneously (Sweller, 1988; Qu et al., 2026). Such structured interaction may be particularly helpful for users who experience difficulty managing conversational information during voice interaction. In contrast, freeform responses may present multiple prompts within a single conversational turn, which can make the interaction appear more system-driven and potentially more intrusive (Munz et al., 2025).

H2: *Step-by-step interaction structures will reduce perceived intrusiveness compared to freeform interaction structures.*

Effects of Perceived Intrusiveness on User Experience

Perceived intrusiveness reflects the extent to which users feel that a system interferes with their autonomy during interaction. In conversational settings, maintaining a sense of control over the dialogue is an important component of positive user experience. When users perceive a conversational agent as intrusive, they may evaluate the interaction less positively. Prior studies suggest that intrusive system behaviors can reduce users' perceptions that a system effectively supports their task goals (Chen et al., 2023; Deng et al., 2025). Intrusive conversational behaviors may also negatively affect users' emotional experiences during interaction by reducing perceptions of support or empathy (Chen et al., 2023; Wong et al., 2024).

H3: *Perceived intrusiveness will negatively affect perceived task effectiveness.*

H4: *Perceived intrusiveness will negatively affect emotional support.*

Moderating Role of Interaction Structure

The perceived intrusiveness of proactive system behavior may depend on how conversational prompts are structured during interaction. When proactive suggestions are delivered sequentially through step-by-step exchanges, users may perceive them as supportive cues that help organize the conversation. Because prompts are presented incrementally, users can respond at their own pace and maintain a sense of conversational control. In contrast, when proactive suggestions are delivered simultaneously in freeform responses, users may perceive the system as introducing multiple directions at once. This presentation may increase the likelihood that proactive system behavior is interpreted as intrusive or overwhelming (Liu et al., 2025; Munz et al., 2025).

H5: *Interaction structure moderates the relationship between AI proactivity and perceived intrusiveness such that the effect of proactivity on intrusiveness is stronger in freeform interactions than in step-by-step interactions.*

Method

Experimental Design

To test the proposed model, we conducted a 3 × 2 mixed-factorial experiment. The first independent variable, AI proactivity (low, medium, high), was manipulated within subjects and represented the degree to which the conversational agent-initiated prompts and guidance during interaction. The second independent variable, interaction structure (step-by-step vs. freeform), was manipulated between subjects and determined whether conversational prompts were delivered sequentially or presented in a more open conversational format. Participants interacted with LLM-powered voice agents across multiple conversational tasks. After each interaction, participants evaluated their experience by rating perceived intrusiveness, task effectiveness, and emotional support. This design allowed us to examine how conversational design factors influence user experience outcomes in voice-based AI interactions.

Participants

This study is part of a larger research project investigating conversational AI design for users with attentional vulnerabilities. The data reported in this paper represent an initial exploratory data collection. Twenty-four participants (16 female, 8 male), aged 18–34 years ($M = 24.0$, $SD = 4.4$), voluntarily participated in the study. All participants self-reported experiencing attention-regulation difficulties in their daily digital use, which served as a screening criterion rather than a clinical diagnosis. Most participants were university students or recent graduates and fluent in English. A demographic survey indicated that participants were highly digitally literate, with 95.8% reporting confidence in using digital technologies. While 62.5% reported rarely using voice assistants, more than 90% reported using large language models (e.g., ChatGPT, Copilot) daily or several times per week. Ethical approval was granted by the University of Melbourne Human Research Ethics Committee, and written informed consent was obtained prior to participation. Participants received a Woolworths gift card (AUD $16) as compensation.

Materials, Tasks and Procedure

Six conversational agents were implemented using ChatGPT Voice Mode, representing all combinations of three levels of AI proactivity (low, medium, high) and two interaction structures (step-by-step vs. freeform). Each agent followed predefined dialogue rules controlling how it initiated prompts, responded to user input, and managed conversational turn-taking. Low-proactivity agents produced short responses with minimal prompts. Medium-proactivity agents asked concise, goal-oriented questions that guided the interaction. High-proactivity agents provided multiple options, follow-up prompts, and more elaborated responses. In the step-by-step condition, agents asked questions sequentially, whereas in the freeform condition prompts were presented within a single conversational turn. **Table 1** summarizes the dialogue rules used to operationalize proactivity and interaction structure.

To evaluate these conversational styles, two types of tasks were designed: goal-oriented and reminiscence. Goal-oriented tasks involved functional scenarios such as product recommendation, restaurant booking, or navigation, while reminiscence tasks prompted participants to share personal stories such as a happy memory, hobby, or first job. Each task contained three topic-specific success criteria (e.g., type of drink, size, temperature), which participants memorized beforehand and addressed naturally during the conversation. The dialogue continued until all criteria were mentioned and participants confirmed completion. Each session lasted approximately 30-40 minutes and included six experimental trials. The order of proactivity conditions was counterbalanced across participants to reduce potential order and fatigue effects. In each trial, participants completed a conversational task and then provided post-interaction ratings.

Table 1. Experimental conditions of proactivity and interaction structure across six prompt-engineered voice agent conditions.

	Low	**Medium**	**High**
Step-by-Step	• Step-by-step responses • Short reaction • Minimal prompts	• *One-by-one questions* • *Steady conversation*	• *One-by-one questions with several options* • *Active reactions & empathy*
Freeform	• Freeform responses • Short reaction • Minimal prompts	• *All questions at once* • *Steady conversation*	• *All questions at once with several options* • *Active reactions & empathy*

Measures and Analysis

After each interaction, participants rated perceived intrusiveness, task effectiveness, and emotional support using 7-point Likert scales. Task effectiveness and emotional support were included to capture functional and affective dimensions of user experience in conversational AI interactions. Perceived intrusiveness measured the extent to which participants felt that the system interfered with or dominated the interaction, whereas task effectiveness and emotional support reflected perceived interaction quality and affective response. Quantitative data were analyzed using two-way ANOVA to examine the main effects of AI proactivity and interaction structure, as well as their interaction effects on perceived intrusiveness, task effectiveness, and emotional support. The significance level was set at $p < .05$. In addition, brief post-task interviews were conducted after each interaction to collect qualitative feedback regarding conversational flow, system initiative, and perceived conversational control.

Preliminary Results

Quantitative Results

To provide an initial examination of the proposed research model, a two-way ANOVA was conducted to examine the effects of AI proactivity (low, medium, high) and interaction structure (step-by-step vs. freeform) on perceived intrusiveness, task effectiveness, and emotional support. **Table 2** summarizes the p-values for the main and interaction effects.

Table 2. Two-way ANOVA p-values for Proactivity, Structure, and their interaction.

P-Value	**Proactivity**	**Structure**	**Interaction** (Proactivity × Structure)
Intrusiveness	<0.001**	0.024*	0.026*
Task Effectiveness	0.006**	0.011*	0.757
Emotional Support	<0.001**	0.298	0.284

* $p < .05$, ** $p < .01$

For perceived intrusiveness, significant main effects of AI proactivity, $F(2,138)=16.61$, $p<.001$, and interaction structure, $F(1,138)=5.21$, $p=.024$, were observed. In addition, a significant interaction effect between proactivity and interaction structure was found, $F(2,138)=3.73$, $p=.026$. Task effectiveness was also significantly influenced by AI proactivity, $F(2,138)=5.24$, $p=.006$, and interaction structure,

$F(1,138)=6.57$, $p=.011$. However, no significant interaction effect between proactivity and interaction structure was observed for task effectiveness, $F(2,138)=0.28$, $p=.757$. Emotional support showed a significant main effect of AI proactivity, $F(2,138)=27.71$, $p<.001$, whereas neither interaction structure nor the interaction effect significantly influenced emotional support.

As illustrated in **Figure 2**, perceived intrusiveness decreased more substantially under step-by-step interactions as proactivity increased, whereas freeform interactions showed a weaker reduction pattern. In comparison, both task effectiveness and emotional support generally increased as proactivity increased across interaction structures.

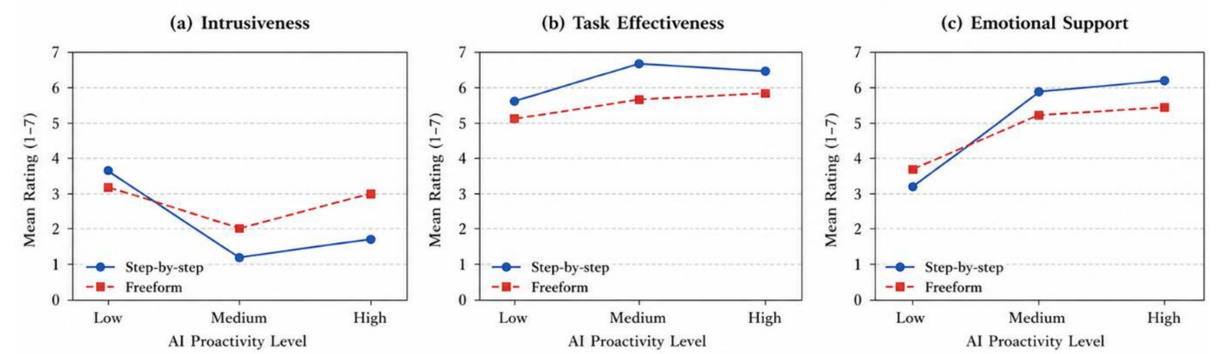

Figure 2. Effects of AI proactivity and interaction structure on (a) Intrusiveness, (b) task effectiveness and (c) emotional support.

Qualitative Findings

Qualitative interview responses were analyzed to identify recurring perceptions of conversational behavior. Across conditions, participants emphasized the importance of balanced system initiative. Low-proactivity interactions were often described as passive or unhelpful. In contrast, medium proactivity was frequently perceived as the most balanced interaction style, with participants describing these interactions as clear, efficient, and easy to follow. High proactivity sometimes supported decision-making and emotional engagement but could also increase cognitive effort when responses became overly long or detailed.

Interaction structure also shaped how proactive behavior was experienced. Participants generally reported that step-by-step interactions helped maintain a clearer conversational rhythm and allowed information to be processed incrementally. In contrast, freeform responses occasionally presented multiple prompts simultaneously, which some participants described as more demanding to process.

Task context further shaped participants' experiences. In goal-oriented tasks, participants tended to focus on clarity and efficiency in completing the task, whereas in reminiscence tasks they were more sensitive to conversational tone and emotional responsiveness.

Discussion

This study provides a preliminary examination of how AI proactivity and interaction structure influence user experience in voice-based conversational interactions. The results suggest that higher levels of system proactivity were generally associated with higher perceived task effectiveness and emotional support, while interaction structure significantly influenced perceived intrusiveness. In particular, step-by-step interaction structures appeared to reduce perceived intrusiveness more effectively as proactivity increased, suggesting that structured conversational pacing may help users manage proactive system behavior more comfortably.

From a theoretical perspective, this study contributes to the literature on human–AI interaction by integrating insights from psychological reactance theory and cognitive load theory to explain how users respond to proactive conversational systems (Deng et al., 2025; Chen et al., 2023). The findings suggest that proactive assistance does not necessarily increase perceived disruption when conversational guidance is delivered through a structured interaction flow. Instead, step-by-step dialogue may help users perceive proactive system behavior as more manageable and less intrusive by providing a clearer conversational rhythm and allowing information to be processed incrementally. These findings suggest that users may evaluate proactive conversational behavior through multiple dimensions simultaneously, including both perceived disruption and perceived usefulness. While structured interactions appeared to reduce perceived intrusiveness more effectively, higher levels of proactivity were also associated with increased task effectiveness and emotional support across conditions, suggesting a potential trade-off between guidance and autonomy in proactive voice interactions.

From a practical standpoint, the results highlight the importance of balancing system initiative with structured dialogue pacing in conversational AI design. Voice interfaces that provide proactive guidance through step-by-step conversational flows may support task completion while reducing perceived intrusiveness, particularly in interactions that require sustained attention. These findings suggest that conversational structure itself may function as an important design mechanism for improving user experience in proactive voice interactions.

These findings highlight the importance of conversational pacing as a key design dimension in proactive voice interactions. As an initial exploratory analysis based on a relatively small sample, this study primarily focused on examining the direct effects of conversational design factors on user experience outcomes. Although perceived intrusiveness emerged as a significant factor associated with conversational structure and proactivity, future research with larger samples is needed to further examine the role of perceived intrusiveness within the proposed research model. In addition, because many participants reported limited prior experience with voice assistants, the findings may not fully generalize to highly experienced voice assistant users.

Conclusion

This study examined how AI proactivity and interaction structure shape user experience in voice-based conversational interactions. The findings suggest that higher levels of system proactivity may support both task effectiveness and emotional support, while interaction structure plays an important role in shaping perceived intrusiveness. In particular, step-by-step interaction structures appeared to reduce perceived intrusiveness more effectively as proactivity increased. By integrating perspectives from psychological reactance theory and cognitive load theory, this research highlights the importance of balancing proactive system initiative with structured conversational pacing. Overall, the study suggests that well-structured conversational guidance may help users experience proactive voice interactions as both supportive and manageable, particularly in cognitively demanding interaction contexts.

Acknowledgments

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP)-Global Data-X Leader HRD program grant funded by the Korea government (MSIT) (IITP-2026-RS-2024-00441244). The authors also acknowledge the support provided by the School of Computing and Information Systems at the University of Melbourne during the study.

References

Bozhilova, N., Kuntsi, J., Rubia, K., Michelini, G., & Asherson, P. (2021). Electrophysiological modulation of sensory and attentional processes during mind wandering in attention-deficit/hyperactivity disorder. NeuroImage: Clinical, 29, 102547. **https://doi.org/10.1016/j.nicl.2020.102547**

Brehm, J. W. (1966). A theory of psychological reactance. Academic Press. **https://doi.org/10.1016/C2013-0-10423-0**

Chen, Q., Gong, Y., & Lu, Y. (2023). User experience of digital voice assistant: Conceptualization and measurement. ACM Transactions on Computer-Human Interaction, 31(1), 1-35. **https://doi.org/10.1145/3622782**

Clark, L., Pantidi, N., Cooney, O., Doyle, P., Garaialde, D., Edwards, J., ... & Cowan, B. R. (2019, May). What makes a good conversation? Challenges in designing truly conversational agents. In Proceedings of the

2019 CHI conference on human factors in computing systems (pp. 1-12). **https://doi.org/10.1145/3290605.3300705**

Deng, Y., Liao, L., Lei, W., Yang, G. H., Lam, W., & Chua, T. S. (2025). Proactive conversational ai: A comprehensive survey of advancements and opportunities. ACM Transactions on Information Systems, 43(3), 1-45. **https://doi.org/10.1145/3715097**

Huang, Y., Zhou, Q., & Piper, A. M. (2025, April). Designing conversational AI for aging: a systematic review of older adults' perceptions and needs. In Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (pp. 1-20). **https://doi.org/10.1145/3706598.3713578**

Kofler, M. J., Singh, L. J., Soto, E. F., Chan, E. S., Miller, C. E., Harmon, S. L., & Spiegel, J. A. (2020). Working memory and short-term memory deficits in ADHD: A bifactor modeling approach. Neuropsychology, 34(6), 686. **https://doi.org/10.1037/neu0000641**

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. Human factors, 46(1), 50-80. **https://doi.org/10.1518/hfes.46.1.50_30392**

Liu, C., Su, M., Xiang, Y., Huang, Y., Yang, Y., Zhang, K., & Fan, M. (2025, April). Toward enabling natural conversation with older adults via the design of LLM-powered voice agents that support interruptions and backchannels. In Proceedings of the 2025 CHI conference on human factors in computing systems (pp. 1-22). **https://doi.org/10.1145/3706598.3714228**

Mahmood, A., Cao, S., Stiber, M., Antony, V. N., & Huang, C. M. (2025, April). Voice assistants for health self-management: designing for and with older adults. In Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (pp. 1-22). **https://doi.org/10.1145/3706598.3713839**

Miksik, O., Munasinghe, I., Asensio-Cubero, J., Bethi, S. R., Huang, S. T., Zylfo, S., ... & Swietojanski, P. (2020). Building proactive voice assistants: When and how (not) to interact. arXiv preprint arXiv:2005.01322. **https://doi.org/10.48550/arXiv.2005.01322**

Munz, L. P. M., Neef, C., Preusser, I., & Richert, A. (2025, November). The Double-Edged Sword: Exploring Older Adults' Interaction and Imagination with an LLM-Enhanced Health Agent. In Proceedings of the 13th International Conference on Human-Agent Interaction (pp. 95-104). **https://dl.acm.org/doi/10.1145/3765766.3765779**

Oh, J., Kim, W., Kim, S., Im, H., & Lee, S. (2024, May). Better to ask than assume: Proactive voice assistants' communication strategies that respect user agency in a smart home environment. In Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (pp. 1-17). **https://doi.org/10.1145/3613904.3642193**

Qu, N. Z., Li, J., & Chignell, M. (2026). Voice-Powered Assembly: Boosting Self-Efficacy in Older Adults with "Build2Race". ACM Transactions on Accessible Computing. **https://doi.org/10.1145/3789501**

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive science, 12(2), 257-285. **https://doi.org/10.1207/s15516709cog1202_4**

Wong, N., Jeong, S., Reddy, M., Stamatis, C. A., Lattie, E. G., & Jacobs, M. (2024, July). Voice assistants for mental health services: Designing dialogues with homebound older adults. In Proceedings of the 2024 ACM Designing Interactive Systems Conference (pp. 844-858). **https://doi.org/10.1145/3643834.3661536**

Zargham, N., Reicherts, L., Bonfert, M., Voelkel, S. T., Schoening, J., Malaka, R., & Rogers, Y. (2022, July). Understanding circumstances for desirable proactive behaviour of voice assistants: The proactivity dilemma. In Proceedings of the 4th conference on conversational user interfaces (pp. 1-14). **https://doi.org/10.1145/3543829.3543834**