POSTER

Comparing Text-Only and Virtual Reality-Embodied Conversational AI Agents for Interpersonal Skills Training

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Figure 1: Side-by-Side Simulation Views of the AI Agent Conditions: Text-Only AI Agent (Left) and VR-Embodied AI Agent (Right)

Abstract

Conversational AI agents powered by large language models (LLMs) have the potential to support the development of interpersonal skills, which are essential for navigating diverse situations and engaging effectively with a variety of people. However, text-based AI agents often lack crucial nonverbal cues such as facial expressions, body gestures, and tone of voice. In this study, we present a VR simulation featuring an embodied AI agent that leverages nonverbal cues to train interpersonal skills across various scenarios. We compare its efficacy to a Text-Only AI agent in a between-subjects study with twenty-four participants. We find that participants preferred the embodied agent condition, and their initial scores were significantly higher than those of participants in the text condition. However, the difference between the initial and final scores was not statistically significant.

CCS Concepts

• **Human-centered computing** → **Empirical studies in HCI**.

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Keywords

Embodied AI Agent, Large Language Models, Virtual Reality, Interpersonal Skills Training, Conflict Resolution, Human-AI Interaction, Nonverbal Communication

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1 Introduction

In the past year, large language models (LLMs) have demonstrated their utility for education in a number of settings [9]. While they are frequently used for teaching factual knowledge [10, 18, 20, 22], LLMs have also shown promise in supporting the development of soft skills. For instance, LLMs were used in teacher assistant training with GPT-simulated students [17]. In particular, their ability to simulate naturalistic human interaction can make them a tireless and discreet partner for practicing social skills [14, 15, 21]. LLMs have also proven strong potential for personalizing learning experiences by adapting content and feedback to individual learners' needs [1, 13].

Despite these advances, most prior work on LLM-powered learning remains text-based and lacks the embodied, nonverbal components that are critical in social interactions. Words are only one facet of effective conflict resolution. Nonverbal cues, including gesture, posture, and tone of voice, convey a substantial amount of information and significantly shape interpersonal experiences [5]. To successfully defuse a conflict, a person must deal with their conversational partner's nonverbal expressions of anger while also controlling their own behavior [11].

Virtual Reality (VR) offers many advantages for social skills training [8, 12, 19], as it allows people to practice their communication skills and learn to regulate their own responses to emotional situations in a controlled environment [6] that supports representative practice [7]. Inspired by Rehearsal [21], we created an embodied version of conflict resolution training simulation that incorporates nonverbal cues through an AI agent avatar in a virtual environment (Figure 1). These cues are essential for managing conversational dynamics, interpreting emotional intent, and enhancing engagement. By displaying nonverbal cues through the VR-embodied AI agent, the simulation more accurately reflects real-world interactions and helps participants learn both verbal and nonverbal aspects of communication. While most LLM-powered AI agents used in interpersonal skills training remain text-based, our work explores the impact of embodiment by incorporating real-time verbal interaction, facial expressions, and gestures. Conflict resolution is particularly difficult to train in real-life settings due to emotional intensity, social risk, and logistical constraints. By simulating these challenging scenarios in virtual reality, our embodied AI agent offers a safe, repeatable, and accessible environment for practicing conflict resolution strategies. Prior VR-based training tools typically utilized pre-scripted agents; in contrast, our study integrates real-time conversational AI, personalized feedback grounded in conflict resolution theory, and a direct comparison between embodied and text-only modalities. We present the results of a small pilot study investigating the following research questions:

- ***RQ1***: Does the embodiment of a conversational AI agent in conflict simulations enhance participants' use of cooperative conflict resolution strategies compared to a Text-Only AI agent?
- ***RQ2***: Do participants prefer the VR-Embodied or the Text-Only AI agent for learning conflict resolution strategies?

2 Methodology

We recruited 29 participants through the university SONA system. Five were excluded due to technical issues, leaving 24 participants (8 men and 16 women).

The virtual role-playing simulation for the VR-Embodied condition was developed in Unity 3D using both pre-existing and custom-built assets. The Oculus Unity Plugin was used for HMD integration. The AI agent avatar was created by generating a high-fidelity 3D model of the first author's face using Reallusion software, with facial features and hair modified to reduce the resemblance. Animations for gestures, such as open arms, crossed arms, were imported from ActorCore.com and Mixamo.com. In addition to these gestures, a custom script was implemented to animate the agent's facial expressions, including smiling, neutral, and frowning states. The script also enabled the agent to display a set of nonverbal cues corresponding to different affective states: positive (open arms and smile), neutral (neutral stance and facial expression), and negative (crossed arms and frown). The simulation relies on the *Interests-Rights-Power (IRP)* framework from the conflict resolution theory [16]. The IRP framework codes individuals' utterances into three broad categories—cooperative, neutral, or competitive—based on Brett et al.'s conflict resolution strategies and examples [4], as organized into a detailed table by Shaikh et al. [21] (Table 1 in [21]). The agent gradually transitions from negative to neutral and then positive cues when the participant employs cooperative strategies aligned with the IRP framework. Conversely, the agent reverts to negative cues when the participant uses competitive strategies.

We integrated OpenAI API into the Unity 3D projects of both VR-Embodied and Text-Only agent conditions, and used GPT-4 to facilitate conversations between the agent and the participant. Shaikh and colleagues developed a set of LLM prompting techniques for their Rehearsal simulation, designed to generate dialogues grounded in the IRP conflict resolution framework [21]. This approach employs three prompts that contextualize the conversation, generate counterfactual responses aligned with the IRP framework, and produce corresponding responses to both user inputs and counterfactuals [21]. Building on this work, we developed a separate set of prompts that generate tailored feedback on participants' responses. This technique has three components: detecting the conflict resolution strategy used by the participant, generating counterfactual responses, and providing concise, strategy-based feedback. Both sets of prompting techniques were integrated into the simulation to facilitate interpersonal skill training through LLM-powered interaction and feedback. Four different scenarios, three from the Rehearsal simulation [21] (Work Performance, Blender Return, Undercooked Meal) and a new scenario (Noise Complaint), were assigned across the four simulation rounds (First Test, Practice Round, Final Test, Experience Round), with the order randomized for each participant.

To enable verbal communication in the VR-Embodied AI agent simulation, we developed a pipeline integrating OpenAI's Speech-to-Text (STT) and Text-to-Speech (TTS) technologies. Participants' voice inputs are transcribed into text using STT, and then sent to LLM (GPT-4). The model generates a response, which is converted into speech using OpenAI's Nova voice via TTS and saved as an MP3 file. This audio is played through the embodied AI agent's avatar in the virtual environment. We also recorded filler sounds such as "umm," "uhh," "I mean," and "you know" with the Nova voice and used these recordings during response latency to indicate that the agent was about to respond. The Unity SALSA plugin was used to synchronize the avatar's lip movements with the generated verbal responses. In the Text-Only AI agent simulation, we created a text-based interface to display the conversation history, allow participants to type their responses, and present tailored feedback during the practice and experience rounds, with a pipeline that sends text input to the LLM, generates a response, and displays it within the interface.

In the VR-Embodied condition, participants wore an Oculus Quest 2 headset and used its controllers to launch the simulation and operate the microphone to verbally interact with the AI agent. They did not have a full avatar but instead saw semi-transparent ghost hands in the virtual environment. In the Text-Only condition, participants completed the simulations on the researcher's laptop, typing their responses to interact with the AI agent.

2.1 Procedure

Upon arrival, participants received an overview of the study, had the opportunity to ask questions, and signed an informed consent form. They were informed that they would complete four role-playing simulations with LLM-powered AI agents, each based on a distinct conflict scenario. In the first three simulations, each participant experienced the same condition, either the Text-Only AI agent or the VR-Embodied AI agent. In the fourth simulation, participants switched to the alternate condition (i.e., those who began with the Text-Only agent then interacted with the VR-Embodied agent, and vice versa). In the **first test (Simulation 1)**, participants were required to complete 10 dialogue turns within a maximum of 10 minutes. This served as a baseline to assess their initial conflict resolution skills. Following this, participants watched an instructional video on the IRP framework and reviewed a summary of it on a laptop screen. In the **practice round (Simulation 2)**, participants engaged in another 10-turn simulation, during which they received AI-generated, tailored feedback showing the strategies they used and suggesting improvements for resolving the conflict. They again had up to 10 minutes to complete the task. In the **final test (Simulation 3)**, participants were required to complete 10 dialogue turns within 10 minutes. This simulation measured improvements in test scores compared to the first test. In the **experience round (Simulation 4)**, participants engaged in a different type of simulation from the previous three, designed to contrast the interaction experience across agent modalities. Finally, all participants completed a Qualtrics survey reflecting on how they interacted with the AI agents. We collected three types of data: Participants' *test scores*, measured by the number of cooperative strategies used in each 10-turn round; *behavioral data* tracked in the VR-Embodied condition; and *self-report* data based on participants' responses at the end of the study.

3 Results

3.1 Comparison of Learning Outcomes

The test score was measured by the number of cooperative conflict resolution strategies used by participants, as defined by the IRP framework, across their 10 dialogue turns in each simulation. Mean test scores were calculated separately for the VR-Embodied and Text-Only conditions, each based on 12 participants (n=12 per condition; N=24) (Figure 2). In the first test (Simulation 1), participants in the VR-Embodied condition exhibited a higher mean test score (M=7.50) compared to the Text-Only condition (M=4.58). After receiving AI-generated tailored feedback in the practice round (Simulation 2), participants' mean test score in the VR-Embodied condition increased to M=8.58. Participants in the Text-Only condition improved more dramatically, to (M=6.50). In the final test (Simulation 3), test scores for the VR-Embodied condition increased marginally to M=8.67. However, the Text-Only condition test score significantly increased to M=7.50 compared to the first test. Using paired t-tests, we examined changes in test scores between the first and final tests of each condition. For *VR-Embodied*, the comparison

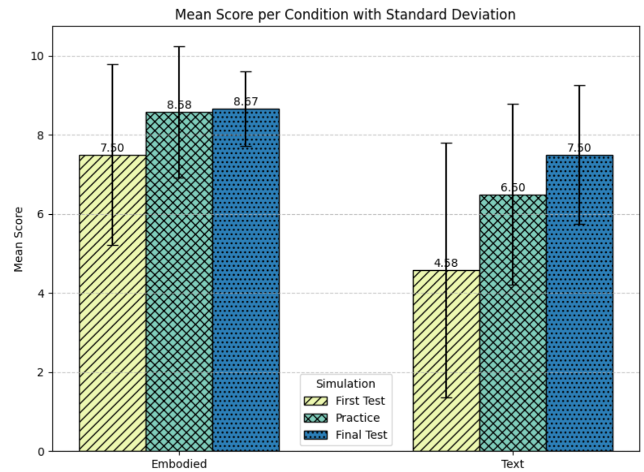

Figure 2: A bar graph of the participants' mean test scores by condition with standard deviations

between the first test and final test revealed no statistically significant difference (p=0.1159). However, the increase in test scores from first to final test (p=0.0111) in *Text-Only* was statistically significant. The *VR-Embodied* participants performed well on their first attempt and improved only marginally thereafter. The *Text-Only* participants scored lower, but the increase in their use of cooperative strategies was statistically significant.

3.1.1 Behavioral Changes. After conducting paired t-tests on all axes, only the right controller's y-axis showed a significant change between the first test and the final test (p=0.0428), reflecting a shift toward a more open and relaxed posture over the course of the training sessions. This suggests that participants may have changed their nonverbal behavior during their practice. Participants remained relatively stationary in space, moving only their arms subtly.

3.2 Survey Results

Twenty-one participants preferred the VR-Embodied condition, while three participants preferred the Text-Only condition. However, we saw no significant differences between conditions across the survey questions (Table 1), including the participants' familiarity with AI and VR. Questions 1 through 5 in Table 1 were adapted from Biocca et al.'s [3], and Questions 6 and 7 were adapted from Basdogan et al.'s questionnaire on togetherness [2].

3.2.1 Qualitative data. For the question "How effective did you find the AI agent during the conflict resolution task? Why?", most participants across two conditions reported that the simulation was effective (n=18). Reasons included receiving real-time feedback, preparing for real-life situations, learning conflict resolution strategies, and reflecting on past experiences. Participants who found the simulation somewhat effective (n=5) or ineffective (n=1) reported that the AI agent's responses became repetitive and that real conflicts are "much more complicated typically."

When asked "Did you feel the AI Agent simulation improved your conflict resolution skills? Why?", most participants said the

Survey Questions (5-point scale unless being called out)	Text M(SD)	VR M(SD)	p-value
How easily distracted were you during the interaction?	1.833(0.577)	2.083(0.669)	0.349
How easy was it for you to tell how the AI Agent felt?	4.167(0.577)	3.917(0.900)	0.558
How responsive was the AI Agent?	4.167(0.718)	4.000(0.603)	0.535
How often were the AI Agent's behaviors clearly a reaction to your own behaviors?	3.917(0.900)	3.833(0.718)	0.684
How often were the AI Agent's verbal response clearly a reaction to your verbal input?	4.583(0.515)	4.583(0.515)	1.000
When you think back about your experience, do you remember this as more like just interacting with a computer or working with another person?	3.083(0.900)	2.917(0.793)	0.734
To what extent were you and the AI Agent in harmony during the course of conflict resolution?	3.917(0.900)	3.500(0.522)	0.138
I consider the tool extremely useful. (7-point scale)	5.417(1.240)	5.500(0.798)	0.802
With the help of this product I will improve my social interaction skills in the future. (7-point scale)	5.667(1.435)	5.417(0.996)	0.366

Table 1: Survey results for the text and the VR conditions

simulation improved skills by providing feedback and opportunities to practice and reflect on their responses (n=18). Three participants somewhat agreed, while another three disagreed, reporting that the simulation included too much text and made it "difficult to feel a sense of empathy that is necessary in real life conflict resolution."

For the question "How easy was it to interact with the AI agent during the conflict resolution task? Why?", thirteen participants found the agent's replies clear and tailored. Ten participants noted response delays, repetitive responses, and "pressure to respond" in the VR-Embodied condition. One participant described the agent as "not very interactive."

When asked "Do you think the embodiment of the AI agent was easier to interact with compared with a Text-Only interface? Why?", most participants reported finding the AI agent easier because the body language and facial expression made them feel like they were interacting with a real person (n=18). Six participants reported finding it more difficult, stating that they "got nervous while speaking," the agent responded "slowly," or the agent seemed "fake."

For the question "How did the verbal response of the embodied AI agent affect your verbal response?" in the VR-Embodied condition, most participants reported that the verbal response did impact their own responses. For example, they "responded based on the tone of the embodied AI agent," "used the tone of the AI agent to determine my approach with my next response," and stated that the verbal response "made me more engaged in the conversation."

When asked "How did the facial expressions of the embodied AI agent affect your facial expression?" responses were mixed. Half of the participants described the agent's facial expressions as hard to understand, "limited and delayed" or "creepy." But, half of the participants liked the facial expression. Some noticed the agent's facial expression changed throughout the conversation, especially when a solution was suggested. Most participants stated that the facial expression did not impact their own facial expression, and one reported that the headset hindered facial expressions.

For the question "How did the gestures of the embodied AI agent affect your gestures?" most participants noticed the agent crossed "her" arms, and inferred that the agent was still unsatisfied or in disagreement. But that did not impact participants' own gestures. The reasoning could be "as I stayed still with the controllers" as one participant put it. One participant noticed more eye contact towards the end. However, another reported ignoring the gestures completely.

4 Discussion

In this paper, we explored using a VR-Embodied AI agent for conflict resolution training; comparing results to a Text-Only condition. In both conditions, participants' test scores improved. Most participants preferred the VR-Embodied AI agent, and their test scores were overall slightly higher than those in the Text-Only condition. However, the improvement between the first and final tests in the VR-Embodied condition was not statistically significant. In contrast, participants in the Text-Only condition began with significantly lower test scores than the VR-Embodied condition, but their final test score was statistically significantly different.

Although the current VR-Embodied AI agent simulation shows potential in enhancing participants' conflict resolution skills, it also presented areas for improvement. Some participants commented on response latency due to the speech-to-text (STT) and text-to-speech (TTS) processing pipeline, although we used filler sound recordings to mitigate this. Participants were required to wear a headset and hold controllers to activate the microphone, reducing the interactions' naturalism. This was reflected in the tracked movement data, as participants did not approach the agent or make active gestures. Furthermore, the appearance and nonverbal behaviors of the AI agent avatar could appear uncanny at times. Despite these factors, the higher initial scores, even in our small sample, point to potentially increased engagement in the embodied agent condition. Future work will also compare time-to-next-turn across conditions, examine response edits in the text-based setting, and recruit a larger, more diverse sample to enhance the study's validity.

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