Designing Interactions Between Students and a Virtual Agent in Problem-Solving Contexts

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Abstract

This study explores the design and evaluation of interactions between undergraduate students and a virtual agent aimed at supporting literature review tasks in educational settings. Grounded in the principles of human-agent collaboration and interaction design, the project investigates how virtual agents can complement students' cognitive efforts and enhance problem-solving capabilities. Using the Wizard of Oz methodology, this research simulates student-agent interactions to identify preferences for structured guidance, feedback mechanisms, and adaptive interface designs. Findings emphasize the value of Localization Feedback and Direct Feedback, which provide actionable resources and clear explanations. A comparative usability analysis of movable widget and fixed sidebar interface designs reveals the advantages of flexibility and adaptability in enhancing user satisfaction and engagement. The results contribute to advancing human-AI collaboration in education, providing insights into optimizing virtual agent design for collaborative learning. Limitations and implications for future research are also discussed, highlighting the need for scalable implementations and expanded participant samples.

1 Introduction

The Interaction Design research group (IXD) and the Digital Communities program are working on ways for human and non-human agents (AI) to interact and collaborate in shared environments. These environments form Digital Communities, where agents access information, communicate with each other, and assist humans. The goal is for these digital agents to be integrated into collaborative platforms, acting as supportive members of the community.

This project aims to research and design interactions between students and a virtual agent. It seeks to demonstrate which interactions can support the execution of literature reviews in collaborative settings. By providing timely and relevant assistance, the virtual agent will act as a tool that complements rather than replaces students' cognitive efforts. To achieve these objectives, it is critical to understand the dynamics of human-agent and multi-agent collaboration in both individual and group settings.

Research on human-agent collaboration and multi-agent systems for assisting humans has been progressing. Agent cooperation and collaboration has been explored by Sioutis and Tweedale, where they highlighted the importance of communication, navigation, and trust in forming agent relationships

[12]. Furthermore, Tweedale investigated decision support systems that enable collaboration between intelligent agents and humans, emphasizing the role of cognitive hybrid reasoning and learning models [14].

This project seeks to address the following questions:

1. **How can interfaces be designed to facilitate real-time collaboration between students and virtual agents in problem-solving contexts?**
2. **What types of feedback are most valuable to students during educational problem-solving sessions?**
3. **Which interaction methods optimize usability and engagement in real-time collaboration with virtual agents?**

Recent research explores human-AI interaction in education, highlighting both potential benefits and challenges. Generative AI and conversational agents show promise for transforming educational practices [3]. However, designing effective human-AI interactions remains difficult due to uncertainty about AI capabilities and output complexity [15]. AI systems can support learning and teaching by analyzing large datasets, detecting patterns, and providing personalized recommendations [7]. This study aims to bridge gaps in understanding human-agent collaboration, with implications for the future of education and digital community design.

1.1 Related Work

Human-agent collaboration and interaction design have been extensively studied, with various frameworks and approaches contributing to our understanding of effective partnerships between humans and intelligent agents. This section reviews key research related to human-agent collaboration, AI in educational contexts, design challenges, and collaborative problem-solving, establishing the foundation for this study.

Human-agent collaboration has evolved as an interdisciplinary field exploring communication, coordination, and trust between humans and artificial agents. Sioutis and Tweedale emphasized the importance of communication, navigation, and trust in forming effective agent relationships [12]. Building on this, Cohen and Levesque highlighted the significance of shared intentions and responsive communication pathways for successful collaborations [6]. These frameworks underscore the need for mutual responsiveness, where agents actively adapt to human actions and intentions.

Bratman's Shared Cooperative Activity (SCA) theory further contributes to understanding collaborative dynamics, emphasizing commitment to shared goals, mutual responsiveness, and support [4]. These principles provide a foundation for designing virtual agents that foster collaboration in educational settings, particularly in tasks requiring joint problem-solving.

AI has emerged as a transformative tool in education, offering opportunities to enhance learning through personalization and adaptive support. Generative AI systems, such as conversational agents, have shown potential in creating engaging and interactive learning environments [3]. These systems analyze large datasets, detect patterns, and provide personalized recommendations, supporting students' cognitive and learning processes [7].

Research by Kim and Lee demonstrated that student-AI collaboration can significantly improve creativity and learning outcomes in tasks like problem definition and solution generation [8]. Their findings emphasize the importance of instructional strategies, such as scaffolding, to guide students in leveraging AI effectively. However, challenges remain in designing AI systems that preserve students' agency and encourage active participation [9].

Designing effective human-AI interactions involves addressing critical challenges such as explainability, usability, and trust. Tolzin and Janson identified mechanisms for establishing common ground in human-agent interactions, including embodiment, social features, and shared knowledge bases

[13]. These mechanisms enable virtual agents to align with users' social and cognitive expectations, fostering trust and engagement.

The "Guidelines for Human-AI Interaction" proposed by Amershi et al. emphasize the importance of making AI capabilities and limitations transparent, ensuring that users understand and trust the system [1]. Further, addressing cognitive overload and maintaining mutual responsiveness are critical for designing agents that effectively support collaborative tasks.

Collaboration in problem-solving contexts involves dynamic interactions between human and AI participants. Zhu et al. investigated human-AI collaboration in problem-solving and identified various interaction modes, including human-led, AI-led, and equal contribution [16]. Their findings reveal that while students appreciate AI's assistance, maintaining a balance between reliance on AI and independent problem-solving is essential for meaningful engagement.

Bratman's SCA theory provides additional insights into collaborative problem-solving, highlighting the role of shared intentions and interrelated subplans [4]. These principles align with this study's focus on designing virtual agents that complement students' cognitive efforts without undermining their autonomy.

While significant progress has been made in human-agent collaboration, AI in education, and interaction design, several gaps remain. Current research often lacks a detailed exploration of how virtual agents can facilitate collaborative tasks, such as literature reviews, in group settings. Additionally, there is a need to investigate interaction methods that optimize usability and engagement while preserving students' agency.

2 Methodology

2.1 User Evaluation

The evaluation involved undergraduate students from Fontys University of Applied Sciences. Five participants, aged between 19 and 22, were interviewed on campus. Participants were selected by approaching them directly and asking if they would want to participate in the study. The evaluation process comprised a questionnaire divided into two sections: the first focused on participants' experiences conducting a literature review without the assistance of artificial intelligence, while the second explored their experiences with AI support. The interviews were recorded using Otter, a mobile application designed for real-time transcription, and the resulting data was exported in *.txt* format. For qualitative analysis, Thematic Analysis was employed, using a color-coding method to facilitate the identification and clustering of recurring themes across participants' responses. Each theme was assigned a unique color for visual clarity.

2.2 Preliminary Human to Agent Interaction Evaluation

The *Wizard of Oz* methodology was employed to simulate preliminary interactions between participants and a virtual agent.

Niels Ole Bernsen, together with Hans Dybkjær and Laila Dybkjær, highlights the growing adoption of the Wizard of Oz (WOZ) simulation technique in systems design, driven by advancements in speech, language processing, and multimodal systems technologies. They explain that WOZ prototyping involves "wizards" simulating the system's functionality while interacting with users who ideally believe they are engaging with a fully operational system. Through iterative WOZ prototyping, they argue, it is possible to derive a detailed specification of the system's input/output behavior, enabling reliable implementation [2].

The Wizard of Oz methodology was utilized in this study due to the lack of a functional virtual assistant capable of listening to and responding to conversations between two students. In this approach, a human operator acted as the virtual agent, simulating the system's responses in real-time. This method allowed for the exploration and evaluation of the feasibility of interactions between students and a virtual agent, providing valuable insights into how such an AI system might influence collaborative conversations and learning dynamics.

The testing environment was established using the following technologies:

- **Matrix Protocol** [1]
- **Docker** [2]
- **Element** [3]

Once the server was operational, two participant accounts and one "Wizard" account were created. Students collaborated on a 10-minute literature study task via the Element platform, engaging in real-time verbal discussions. The virtual agent, operated by a human (the Wizard), generated context-sensitive responses informed by AI tools (*ChatGPT* and *Gemini*) and human-written guidance in natural language. Additionally, links to scientific papers were sourced using *Elicit*, and three pre-selected papers were provided to participants.

The experiment was conducted at TQ5 at Fontys University of Applied Sciences, chosen for its controlled environment, quiet atmosphere, and technical infrastructure. Participants were placed in two separate meeting rooms to minimize distractions and maintain the integrity of the test. Once the video call was initialized through the Element platform, participants began working collaboratively on the assignment. The virtual agent monitored participants' discussions in real-time, providing context-aware outputs via the Element platform chat interface.

The virtual agent's responses focused on the following areas:

1. **Guidance:**
   - How to read a scientific paper.
   - Key terms to focus on.
   - Pointing out where to find different chapters.

Upon task completion, participants were interviewed to evaluate the virtual agent's interactions. The interviews were structured in both topic and order. The focus was on two primary factors:

- **User Satisfaction:** Participants' overall contentment with the virtual agent's assistance.
- **Perceived Helpfulness:** The extent to which the virtual agent's responses facilitated the task.

A questionnaire was designed to collect subjective data from participants and was divided into three sections:

1. Interaction with the virtual agent.
2. Quality of virtual agent's responses.
3. Overall experience and suggestions.

The questionnaire primarily included open-ended questions to allow for rich, qualitative responses. An example question was: *"How did the virtual agent's guidance influence your approach to the literature study task?"* Thematic Analysis, supported by a color-coding technique, was used to analyze the qualitative data, highlighting key patterns and recurring themes in participant feedback.

[1]The Matrix protocol is an open standard for decentralized, real-time communication, allowing users to exchange messages and data securely across platforms and applications. It is widely used for chat, voice calls, and file sharing.

[2]Docker is a platform that allows developers to package applications and their dependencies into containers—lightweight, portable units of software that ensure consistency across different environments.

[3]Element is a secure, open-source client for the Matrix protocol, offering encrypted messaging, group chats, and integration with other platforms, aimed at fostering seamless communication.

2.3 Types of Feedback

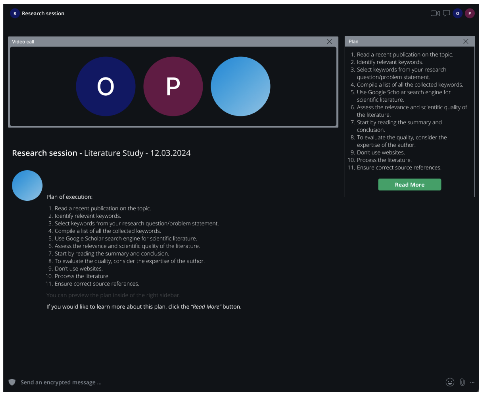
This study employed a quantitative and qualitative survey-based research design to investigate the types of feedback most valuable to students in the context of educational problem-solving sessions. The survey targeted undergraduate students from Fontys University of Applied Sciences, selected through a convenience sampling method to ensure accessibility and participation from students with relevant academic experience. The survey was conducted online using Google Forms, chosen for its ease of use, accessibility, and ability to ensure participant anonymity. The online format also allowed participants to respond asynchronously, minimizing scheduling conflicts and increasing response rates.

The survey instrument was divided into five key sections, including demographic information, ratings of five feedback types (Indirect, Direct, Localization, Summary, and Explanation), open-ended justifications for these ratings, feedback importance at different problem-solving stages, and suggestions for improvements. These feedback types were chosen based on a foundation of feedback literature, which developed five main predictions regarding feedback features: summarization, identifying problems, providing solutions, localization, explanations, scope, praise, and mitigating language [11]. Participants were provided clear instructions at the beginning of the survey to ensure consistency in responses.

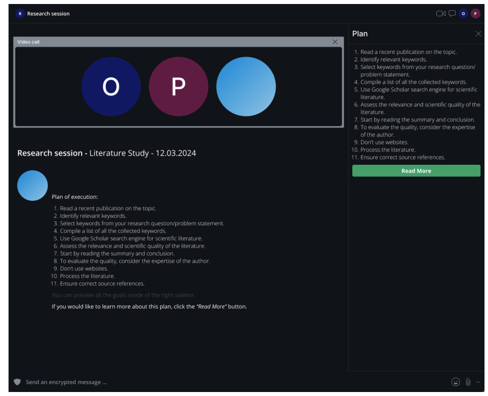
Data collection was conducted over a two-week period, and participation was entirely voluntary, with informed consent obtained before survey initiation. The data analysis process was conducted using Python, involving cleaning, organization, and structural preparation. Quantitative data were statistically analyzed.

2.4 Interactions Evaluation

User interaction interfaces were designed and prototyped using Figma. Each interaction scenario was developed with two distinct approaches: one using movable widgets and the other using fixed components. These alternatives offered participants different interaction methods to evaluate. The prototypes were presented to a group of 10 participants, aged between 19 and 24 years, recruited from the student population. Participants were instructed to observe the functionality demonstrated in the interfaces and to actively engage by clicking through the prototypes to explore their features. A detailed comparison of these approaches is visualized in Figure 1 and Figure 2. Upon completing the review of both interaction approaches, participants were asked to complete the System Usability Scale (SUS) questionnaire, the most well-known and widely used questionnaire for evaluating the usability of interactive systems [5]. This questionnaire provided a standardized measure of participants' perceived usability of the interfaces. Many variations of the SUS have replaced the term 'system' in the original statements with terms like 'website' or 'mobile app' to make them suitable for their respective application domains [10].

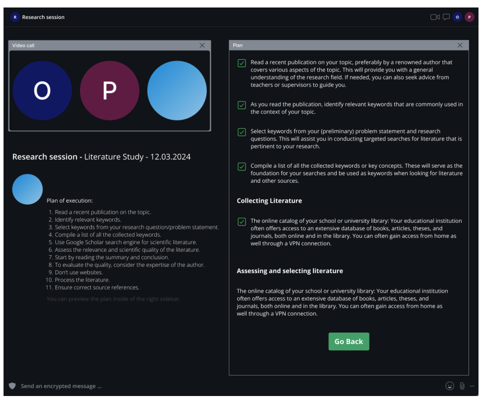


(a) Prototype showcasing the design and functionality of a movable widget, allowing users to interact and reposition it dynamically within the interface.



(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 1: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction



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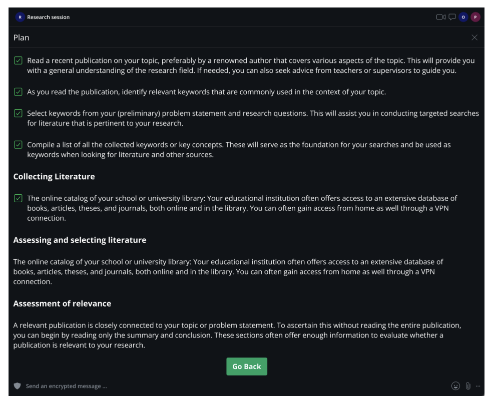

(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 2: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction

3 Results

3.1 Users Evaluation

The evaluation employed a qualitative approach, including user interviews and a structured questionnaire, to identify key frustrations and motivations related to the literature review process. Data collected from participants informed the development of a representative persona, illustrating demographic attributes, work methods, and recurring concerns. These concerns included encountering outdated sources through both traditional search engines and AI tools, questioning the reliability of AI-generated content, and the need for thorough information validation. The persona further highlighted preferences for collaborative work, efficient task management, and transparent AI support. This composite character thus reflects the shared experiences of the focus group and serves as a reference for addressing user needs and refining literature review workflows.

3.2 Interactions

The resulting interactions focus on three primary components: guidance, shared goal setting, and virtual agent invocation. The guidance component structures the literature review process by proposing a plan, identifying key terms, and presenting relevant sources, accompanied by explanations of their importance. The shared goal setting feature supports alignment between the user and the virtual agent, clarifying objectives at the outset. Finally, the invocation mechanism enables users to engage the agent, either via text or speech, thus providing a streamlined approach to initiating support. This integrated design aims to enhance the literature review process by reducing cognitive load and ensuring users understand both the rationale and objectives behind each recommended action.

3.3 Types of Feedback

In the analysis of feedback types, the data reveals distinct preferences and perceptions among respondents regarding the value of various types of feedback provided by virtual agents. Respondents were predominantly undergraduate students (73%), with a majority being in the 18–24 age group (73%), and most reported having used a virtual agent or AI-based assistant for studying or problem-solving (91%). These demographic factors provide context for understanding how different feedback types were perceived.

Localization Feedback, characterized by pointing to specific references or sources to help solve the problem, received the highest average rating of 4.45. This indicates that respondents highly value feedback that provides concrete and actionable resources. Direct Feedback, which provides clear explanations of why information is relevant, followed closely with an average rating of 4.36, reflecting a strong preference for feedback that is both informative and explanatory. Indirect Feedback, which offers useful information without explaining its relevance, was rated more moderately, with an average rating of 2.73, indicating that respondents found it less valuable compared to other feedback types. Summary Feedback and Explanation Feedback had average ratings of 3.91 and 3.55, respectively, suggesting a generally positive but more mixed perception of these types of feedback.

The bar chart in Figure 3 further supports these trends, illustrating the relatively high consistency in the ratings for Localization Feedback and Direct Feedback. In contrast, the ratings for other feedback types showed a broader spread, signaling differing opinions on their utility. Additionally, the data shows that respondents who were more familiar with AI tools tended to rate feedback types more positively, suggesting that experience with virtual agents may influence perceptions of feedback quality.

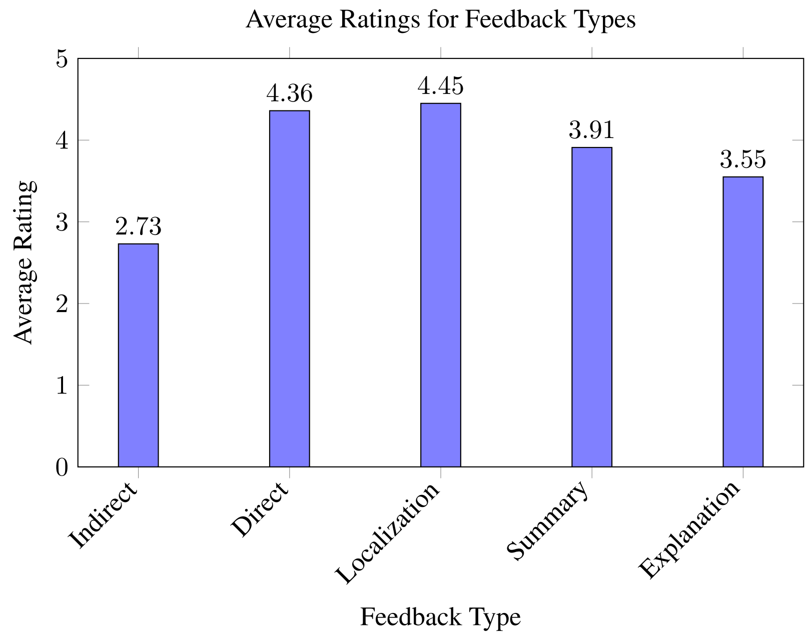

Figure 3: Bar Chart of Average Ratings for Feedback Types

3.4 UI for Interactions

The usability evaluation of the interaction components was conducted using the System Usability Scale (SUS). The results, as depicted in Figures 4, provide a comparative overview of the average SUS scores and their distribution across all tested scenarios. The focus was on assessing the user experience (UX) of fixed bar and movable widget designs for three primary functionalities: plan creation, key terms exploration, and shared goal setting.

3.4.1 Average SUS Scores

The bar chart in Figure X illustrates the average SUS scores for all components. The Plan - Movable Widget achieved the highest usability score (65), reflecting a robust and user-friendly interface that aligns with user expectations for plan creation. The Key Terms - Movable Widget followed with a score of 62.5, indicating good usability with minimal improvements needed. The Shared Goal - Movable Widget, although scoring lower (60), still demonstrated satisfactory usability. In contrast, the fixed bar and modal components consistently scored lower across all functionalities, reaffirming the advantage of flexibility in interface design.

These findings suggest that movable widgets significantly enhance user satisfaction by providing adjustable and multitasking-friendly interfaces. This aligns with prior research emphasizing the importance of interface adaptability in improving the user experience (Reference to related work).

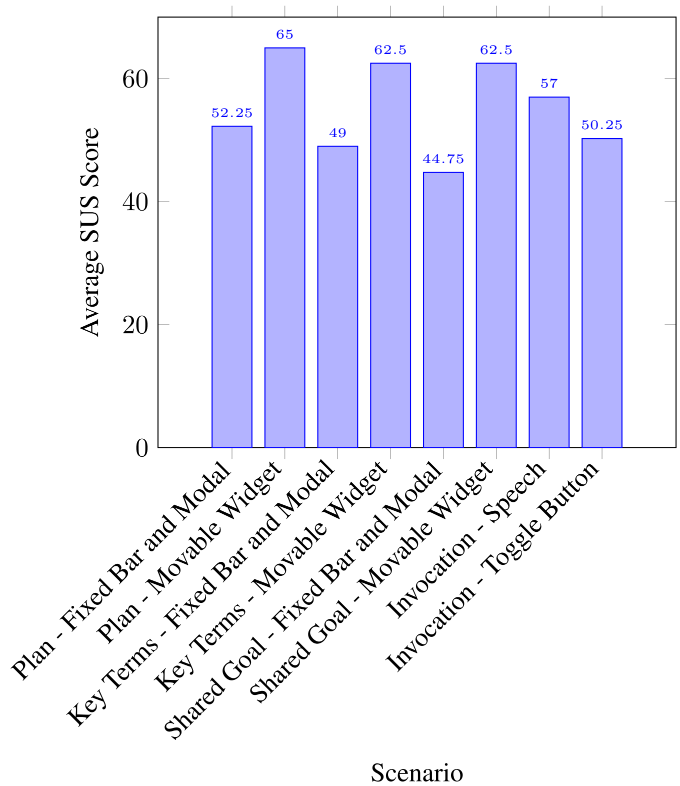

Figure 4: Average SUS Scores Across Scenarios

3.4.2 Distribution of SUS Scores

The box plot in Figure Y visualizes the distribution of SUS scores, highlighting variability and consistency across scenarios. The Plan - Movable Widget demonstrated a compact distribution around the median, suggesting a consistently positive user experience among participants. Similarly, the Key Terms - Movable Widget showed minimal variability, indicating that most users found it intuitive and efficient.

Conversely, the Shared Goal - Fixed Bar and Modal exhibited wider variability, suggesting mixed reception among participants. The Invocation - Toggle Button scenario also showed outliers, which may indicate usability challenges for specific user groups. These variations highlight areas where targeted redesign efforts may enhance the overall experience.

4 Discussion

The study focused on evaluating interactions between undergraduate students from Fontys University of Applied Sciences and a virtual agent designed to assist with literature reviews. The participants, primarily with limited experience using AI tools, highlighted the potential of such interactions to enhance collaborative educational tasks. Notably, types of feedback such as Localization Feedback and Direct Feedback were perceived as the most beneficial, offering actionable resources and clear explanations.

The Wizard of Oz methodology [2] provided a unique perspective on the interaction dynamics, allowing participants to engage with the simulated virtual agent in real-time. This approach effectively revealed preferences for structured guidance, shared goal setting, and intuitive invocation mechanisms. The usability assessment of interface designs further confirmed the importance of adaptability, with movable widgets receiving higher usability scores compared to fixed bar and modal components.

4.1 Implications and Limitations

Given the demographic characteristics of the focus group, which consisted of undergraduate students with basic exposure to AI tools, the findings underscore the need for virtual agents tailored to early adopters of AI in education. The students valued feedback mechanisms that were clear, specific, and immediately applicable to their tasks, reflecting their need for direct support without undermining their autonomy. The study's sample size, limited to five participants for interviews and ten for interaction evaluations, restricts the generalizability of the findings. Additionally, the Wizard of Oz methodology, while insightful, relies on simulated interactions that may not entirely replicate real-world AI behaviors

5 Conclusion

This study aimed to explore the interactions between undergraduate students from Fontys University of Applied Sciences and a virtual agent designed to assist with literature reviews in educational contexts. The central problem addressed was the design of effective human-AI collaboration, specifically in how AI agents can support students during problem-solving tasks without diminishing their cognitive engagement.

The findings of the study revealed several critical insights. First, feedback types such as Localization and Direct Feedback were valued most by students, highlighting the importance of providing clear, actionable, and relevant information in educational interactions with AI. Furthermore, the Wizard of Oz methodology used for simulating real-time interactions allowed for valuable insights into the dynamics between students and virtual agents, revealing preferences for structured guidance, clear goal-setting, and intuitive agent invocation mechanisms.

Interface design played a significant role in shaping the user experience. The study found that flexible and adaptable interfaces, such as movable widgets, consistently outperformed fixed bars and modal components in usability evaluations. Participants appreciated the ability to tailor their interaction with the virtual agent to their preferences and workflows, further emphasizing the critical role of interface design in ensuring engagement and satisfaction in human-AI interactions.

Additionally, the study found that while the sample size was small, the results indicated that students with basic experience with AI tools could significantly benefit from a virtual agent designed to complement their cognitive efforts. The usability evaluation and interaction analysis demonstrated that an intuitive and adaptable interface is just as important as the quality of the agent's feedback in promoting effective collaboration.

Overall, this study contributes to the growing body of research on human-agent collaboration in education, offering a foundation for future development in this field. Further exploration with a larger sample and fully functional AI agents will provide deeper insights into the potential of virtual agents to support collaborative learning and educational problem-solving.

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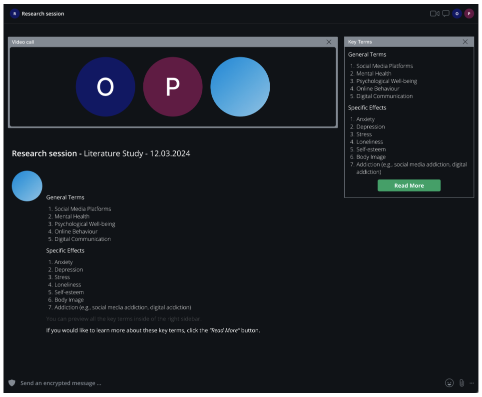
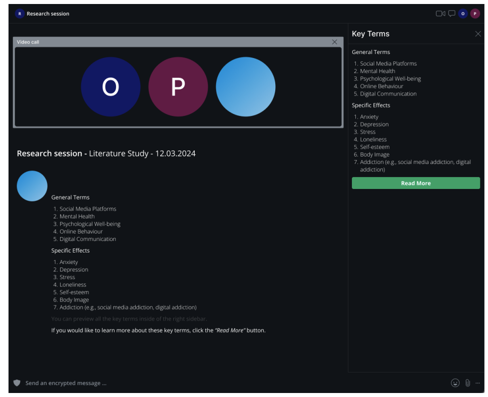
A Appendix

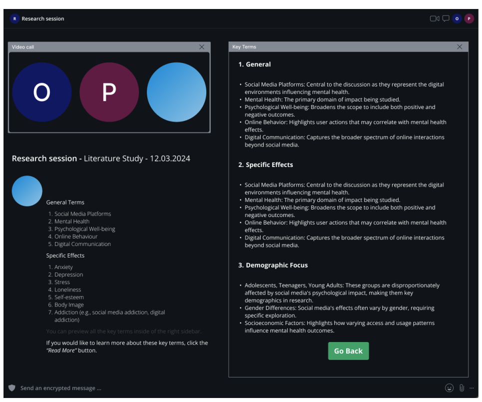


(a) Prototype showcasing the design and functionality of a movable widget, allowing users to interact and reposition it dynamically within the interface.



(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 5: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction



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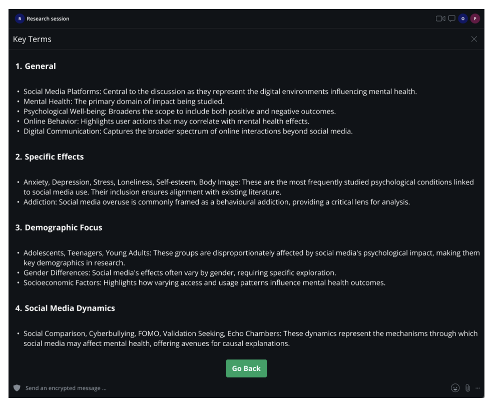
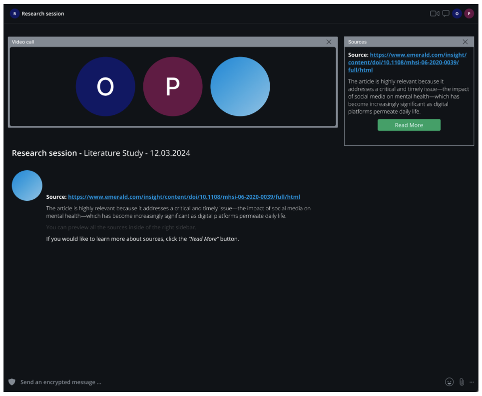


(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 6: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction



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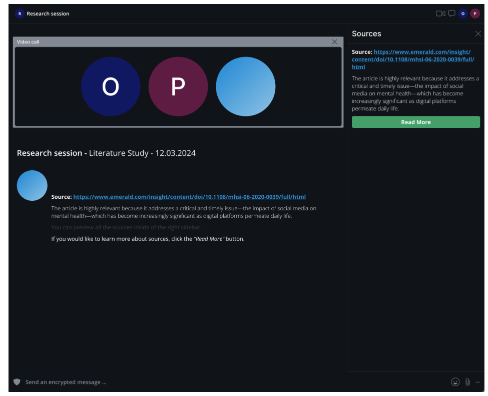
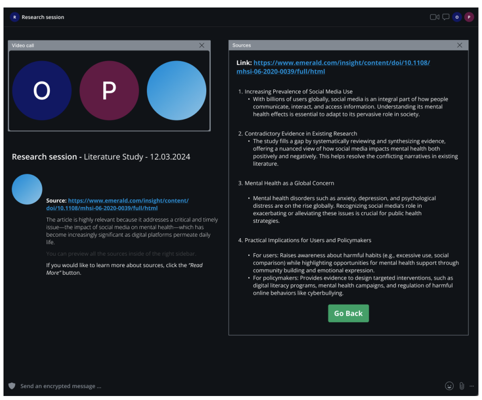
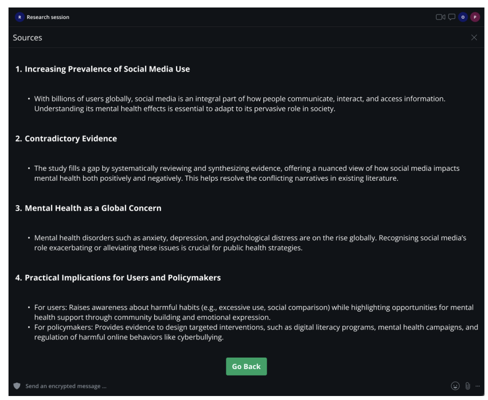


(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 7: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction

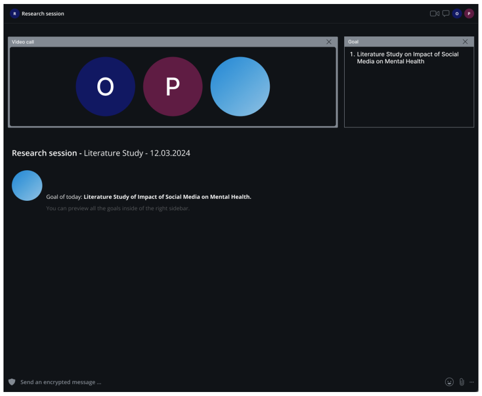


(a) Prototype showcasing the design and functionality of a movable widget, allowing users to interact and reposition it dynamically within the interface.

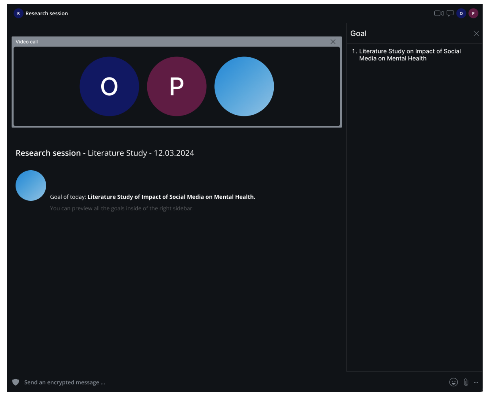


(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 8: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction

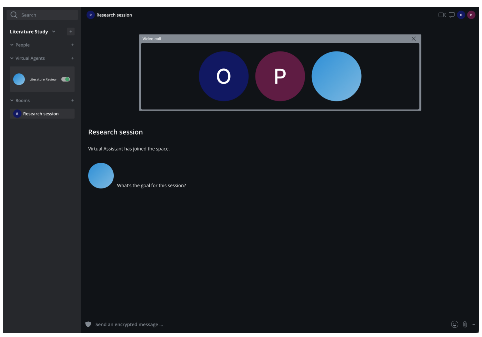


(a) Prototype showcasing the design and functionality of a movable widget, allowing users to interact and reposition it dynamically within the interface.

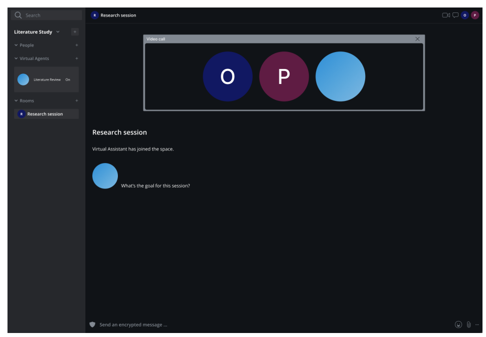


(b) Illustration of a fixed sidebar designed for consistent accessibility, providing a static location for key navigation or information.

Figure 9: Comparison of prototypes for usability testing, featuring a movable widget and a fixed sidebar to evaluate user interaction



(a) Prototype showcasing the design and functionality of a virtual agent invocation, allowing users to invoke it by speech.



(b) Prototype showcasing the design and functionality of a virtual agent invocation, allowing users to invoke it by toggling the left-side button.

Figure 10: Comparison of prototypes for usability testing, featuring manual and speech invocation.