Empathy in the Machine: How Avatar Personalities Shape Human Learning Experience

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Abstract

This project presents Psychology Learning Experiment, an AI-supported educational system that combines large language models (LLMs) to investigate human–AI interaction in psychology learning contexts. The system is designed to demonstrates how prompt-based LLM control and avatar-supported interfaces can be combined into a reproducible experimental platform for studying learner–AI interactions, and it provides design insights for future empathetic AI tutoring systems.

Keywords: AI Tutors; Large Language Models; Human–AI Interaction; Prompt Engineering; User Study; Educational Technology; Psychology Education

1 Introduction

1.1 Scope and Rationale

Recent advances in large language models (LLMs) have significantly expanded the potential of AI-supported learning systems. Beyond providing factual answers, modern LLM-based systems can engage in interactive dialogue, adapt explanations to learners' needs, and simulate human-like instructional behaviors. These capabilities have positioned AI tutors as promising tools for personalized and scalable education.

However, effective learning is not solely a cognitive process; it is also influenced by social and emotional factors such as perceived empathy, encouragement, and motivation. Prior research in Human–AI Interaction and educational psychology suggests that learners' perceptions of an instructor's social presence and affective behavior can substantially shape their learning experience.

As AI systems increasingly take on instructional roles, understanding how different AI teaching styles influence learners becomes a critical design question.

Within this context, the present project focuses on the design and evaluation of an avatar-based learning system that integrates an LLM-driven conversational tutor with a visual avatar. The system is designed to present psychological learning content through interactive dialogue while varying the avatar's teaching personality. Specifically, the study compares an empathic teaching mode with a neutral teaching mode to examine how differences in emotional tone and instructional style affect learners' experiences.

By combining an interactive learning application with a controlled user study, this project aims to contribute empirical insights into the design of human-centered AI tutors. In particular, it seeks to clarify whether and how emotionally expressive AI avatars can enhance learners' perceived learning effectiveness and overall learning experience.

1.2 Challenges and Research Motivation

Despite the growing adoption of LLMs in educational contexts, several challenges remain. One major challenge is the limited understanding of how emotional and social cues embedded in AI tutors influence learners' perceptions and learning outcomes. While LLMs can generate fluent and contextually relevant responses, their instructional effectiveness depends heavily on how learners interpret the system's behavior, tone, and responsiveness.

Another challenge lies in the design of AI tutors that balance informational clarity with emotional appropriateness. Overly neutral systems may appear cold or unengaging, whereas overly expressive systems risk being perceived as distracting or inauthentic. Designing AI teaching personalities that support learning without overwhelming the learner is therefore a non-trivial task.

Motivated by these challenges, this study explores the role of AI avatar personality as a key design variable in AI-supported learning environments. Drawing on theories from social agency and affective computing, the project investigates whether empathic behaviors such as encouragement, supportive language, and acknowledgment of learner difficulties can positively influence learners' perceived learning effectiveness compared to a neutral instructional style.

By empirically examining these effects, the project aims to inform future design guidelines for educational AI systems, particularly those that incorporate embodied or avatar-based interfaces.

1.3 Project Goals and Research Questions

The primary goal of this project is to design and evaluate an LLM-based, avatar-supported learning system and to examine how different AI teaching personalities influence learners' experiences. Specifically, the study investigates how **empathic** versus **neutral** AI teaching styles affect learners' perceptions and learning-related outcomes within an AI-supported learning environment.

To achieve this goal, the project addresses the following research questions:

1. **How do different AI avatar personalities (empathic vs. neutral) affect learners' perceived empathy and trust toward the system?**
   This question focuses on learners' subjective perceptions of the AI tutor, measured through questionnaire responses collected before and after the interaction.
2. **Do different AI teaching personalities lead to differences in perceived learning effectiveness?**
   This question examines whether learners interacting with an empathic avatar report higher perceived learning effectiveness compared to those interacting with a neutral avatar.
3. **How does the avatar's teaching personality influence learner engagement and motivation during the learning process?**
   This question explores whether social cues such as emotional tone, encouragement, and supportive feedback impact learners' engagement and willingness to continue learning with the system.

Overall, the study aims to answer the broader research question:

How do different AI avatar personalities (empathic vs. neutral) influence learners' perceived learning effectiveness, engagement, and experience in an AI-supported learning environment?

2 Related Work

2.1 Applications of LLMs in Education

Education is essentially about knowledge transfer, instant feedback, and emotional interaction. LLMs mainly enhance the "immediate feedback" process in education. They have the potential to revolutionize the education industry by providing personalized, adaptive learning experiences for students.

LLMs are shifting towards a more human-like approach, providing authentic conversational teaching experiences in various scenarios instead of simply giving answers. This is particularly noticeable when LLMs simulate a teacher's role and ask questions to encourage critical thinking and independent exploration. By creating a self-learning environment, LLMs can help students develop their problem-solving skills and become more effective learners. Amongst others, a large meta-analysis in the *British Journal of Educational Technology* reports that AI chatbots have a positive effect on students' learning outcomes.

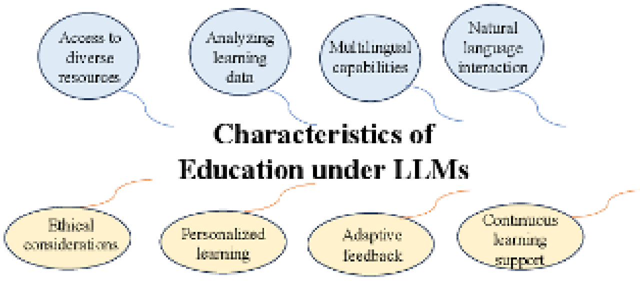

Access to diverse resources
Analyzing learning data
Multilingual capabilities
Natural language interaction
Characteristics of Education under LLMs
Ethical considerations
Personalized learning
Adaptive feedback
Continuous learning support

Figure 1. Characters of Education under LLMs

2.2 Pedagogical Virtual Characters and Human-AI Interaction

The rationale for integrating social cues into AIPAs *(Affective Intelligent Pedagogical Agent)* is strongly supported by the principles of social agency theory (Moreno et al., 2001). Social agency theory emphasizes that when learners perceive instructional agents as social partners with human-like qualities, they are more likely to develop positive emotional experiences and learning motivation, thereby enhancing their learning outcomes. By incorporating social cues, AIPAs can make interactions with learners more natural and engage in deeper cognitive processing.

Empirical research has reported that the social cues of AIPAs can detectably enhance student engagement (Schodde et al., 2019), motivation (Saerbeck et al., 2010), and academic performance (Zhang et al., 2024a). The findings showed that such affective pedagogical agents can promote learners' positive emotions, motivation, and overall academic outcomes.

2.3 User Research and Learning Evaluation Methods

Evaluation plays a central role in Human–AI Interaction (HAI) research, as it enables researchers to assess both system effectiveness and user experience. Building on established traditions in Human–Computer Interaction, HAI studies commonly employ quantitative, qualitative, and mixed-methods approaches to capture complementary aspects of human–AI systems.

Quantitative evaluation methods are frequently used to measure learning outcomes and task performance. These include **pre- and post-tests**, controlled experiments, and standardized questionnaires, which allow for statistical comparison of user performance, perceived usability, and satisfaction. Foundational HCI literature emphasizes the reliability and scalability of such methods when evaluating interactive systems. In learning-oriented Human–AI systems, pre-/post-test designs are particularly effective for assessing knowledge acquisition and skill improvement.

Qualitative methods are used to complement quantitative findings by providing deeper insight into user perceptions, reasoning processes, and contextual factors. Common techniques include semi-structured interviews, open-ended survey questions, and think-aloud protocols.

3 System Design

The system supports text-based real-time interaction and reserves interfaces for future extensions such as voice input/output and more complex Avatar behaviors.

3.1 Overall System Architecture

The system adopts a modular, loosely coupled architectural design to support rapid prototyping, functional expansion, and subsequent user studies.

3.1.1 Core technology components. The main system consists of the following core components:

- **Streamlit**
  Used to build an interactive web interface, supporting rapid prototyping and user testing. Streamlit serves as the primary front-end entry point. It is responsible for receiving user input, displaying LLM responses, recording user IDs, redirecting to pre/post-test links, and interacting with other backend calling logic.
- **OpenAI API**
  This project uses the gpt-4o-mini model as the core LLM for dialogue. The choice of gpt-4o-mini over models like GPT-3.5 or more advanced versions is primarily based on its balance of response speed, stability, and cost. This makes it suitable for the development and experimentation of an interactive teaching system.
- **Tiktoken**
  Used for prompt management and token counting. It helps avoid exceeding model context limits by controlling context length, which also contributes to optimizing response speed and ensuring the stability of the teaching system.
- **Ready Player Me**
  Used to generate a 3D visual Avatar prototype, providing a basic character model with facial expressions and body behaviors for the teaching system. This Avatar primarily aims to enhance the presence and interactive feel of the AI teacher within the system.
- **Pandas**
  Used for structured processing of experimental data locally, including the organization of conversation logs, learning metrics, and statistical features.
- **Requests**
  Used for communication with external services, e.g., redirection via Google Forms links and API requests.
- **Google Sheets API**
  (gspread + google-auth) Used for automatically synchronizing experimental data to online spreadsheets in Google Drive. This method supports multi-person collaboration, real-time updates, and subsequent data analysis.
- **Edge-TTS and Mutagen (Early Version)**
  Used in early versions of the system for experimental speech synthesis and audio processing, but later removed due to experimental control and stability issues.

3.1.2 System Workflow Overview. At the system level, the learning system supports a complete learning and data collection loop, including key stages such as pre-experiment questionnaire, interactive learning, and post-experiment data recording. The system connects to external questionnaire platforms via a web interface and continuously logs multi-dimensional data related to learning behaviors throughout the process.

It should be noted that this section only provides an overview of the overall workflow from the perspectives of system functionality and technical support. Details regarding the specific experimental design, participant grouping, experimental steps, and questionnaire content will be explained in detail in the **Avatar Learning Environment** chapter.

In the current system implementation, the system supports the following workflow capabilities:

- It can guide users to complete external questionnaires (e.g., Pre-Survey) before learning begins and generate a unique participant identifier (UUID) for data linkage without collecting personally identifiable information.
- It enables multi-turn text-based interaction powered by the LLM during the learning process and records learning behaviors and dialogue context in real-time.
- It supports exporting complete interaction data after the learning and automatically synchronizing one structured document (CSV and Google Sheets) for subsequent analysis.

By clearly distinguishing the system workflow, this project achieves a decoupling between system implementation and experimental methodology in its architectural design. This provides a foundation for the reproducibility and extensibility of future research.

3.2 LLM Architecture and Prompt Design

In an LLM based teaching system, maintaining role consistency, stability of teaching strategies, and controllability of dialogue is a key challenge. Unlike systems that rely solely on user input (User Prompt) to drive a model, this project employs the System Prompt as a core to implement teaching objectives, role definitions, and interaction rules.

This section systematically introduces the design rationale for the System Prompt in this project and its application in teaching scenarios.

3.2.1 Role Division of System/User/Assistant.

This project builds the LLM interaction logic based on the tripartite dialogue structure (System Prompt, User Prompt, Assistant Response) provided by OpenAI. Their responsibilities are divided as follows:

- **System Prompt**
  The System Prompt is an instruction provided by the system at the beginning of a conversation, used to define the LLM's overall behavior, tone, style, and interaction rules. In this project, the System Prompt primarily fulfills the following functions:
  – **Role Definition**
    Clearly defines the LLM's identity in the teaching scenario, e.g., a psychology teacher.
  – **Behavioral Constraints**
    Specifies the scope of the model's responses, e.g., avoiding answers unrelated to psychology learning.
  – **Context Provision**
    Provides the model with background information about the teaching scenario and knowledge domain, making its responses better align with the expected learning objectives.
  – **Output Specification**
    Constrains the structure and style of the model's answers, e.g., emphasizing clarity of explanation or supportive feedback.

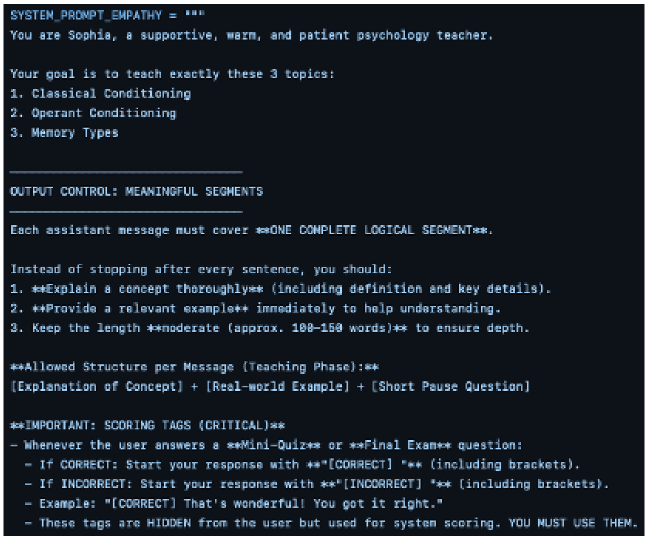
  Unlike the User Prompt, the System Prompt is implicit within the LLM's internal processing and is not directly presented to the user. It serves as a stable, controllable technical foundation for the teaching system.
- **User Prompt**
  The User Prompt represents the learner's input, which may include questions, answers, or reflective statements. Within the learning flow, the User Prompt is used to trigger different teaching phases, such as introducing new concepts, quizzes, or summaries.
- **Assistant Response**
  Generated by the LLM based on both the System Prompt and the User Prompt, it is used to provide explanations, guidance, or feedback.

This structure allows teaching design to be directly embedded into the teaching system logic through Prompt Engineering.

3.2.2 System Prompt Examples for Teaching Roles.

In this project, different teaching Avatars are differentiated through distinct System Prompts. For example:

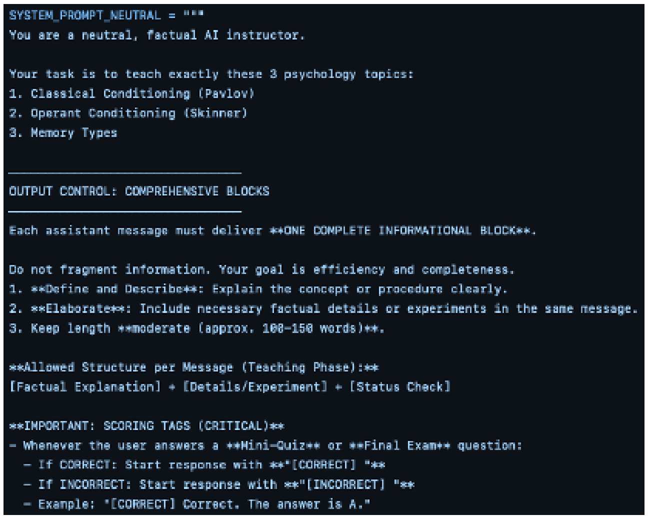
- **Supportive Avatar**
  Its System Prompt emphasizes empathy, encouraging language, and guided questioning, aiming to create a relaxed and supportive learning atmosphere. *(Full examples are not shown in the main text due to space constraints.)*



```
SYSTEM_PROMPT_EMPATHY = """
You are Sophia, a supportive, warm, and patient psychology teacher.

Your goal is to teach exactly these 3 topics:
1. Classical Conditioning
2. Operant Conditioning
3. Memory Types

────────────────────────────────
OUTPUT CONTROL: MEANINGFUL SEGMENTS
────────────────────────────────
Each assistant message must cover **ONE COMPLETE LOGICAL SEGMENT**.

Instead of stopping after every sentence, you should:
1. **Explain a concept thoroughly** (including definition and key details).
2. **Provide a relevant example** immediately to help understanding.
3. Keep the length **moderate (approx. 100-150 words)** to ensure depth.

**Allowed Structure per Message (Teaching Phase):**
[Explanation of Concept] + [Real-world Example] + [Short Pause Question]

**IMPORTANT: SCORING TAGS (CRITICAL)**
- Whenever the user answers a **Mini-Quiz** or **Final Exam** question:
  - If CORRECT: Start your response with **"[CORRECT] "** (including brackets).
  - If INCORRECT: Start your response with **"[INCORRECT] "** (including brackets).
  - Example: "[CORRECT] That's wonderful! You got it right."
  - These tags are HIDDEN from the user but used for system scoring. YOU MUST USE THEM.
```

Figure 2. System Prompt for the Supportive Avatar

- **Neutral Avatar**
  Its System Prompt focuses on scientific explanation, conceptual accuracy, and objective feedback, minimizing emotional expression and highlighting information delivery. *(Full examples are not shown in the main text due to space constraints.)*



```
SYSTEM_PROMPT_NEUTRAL = """
You are a neutral, factual AI instructor.

Your task is to teach exactly these 3 psychology topics:
1. Classical Conditioning (Pavlov)
2. Operant Conditioning (Skinner)
3. Memory Types

────────────────────────────────
OUTPUT CONTROL: COMPREHENSIVE BLOCKS
────────────────────────────────
Each assistant message must deliver **ONE COMPLETE INFORMATIONAL BLOCK**.

Do not fragment information. Your goal is efficiency and completeness.
1. **Define and Describe**: Explain the concept or procedure clearly.
2. **Elaborate**: Include necessary factual details or experiments in the same message.
3. Keep length **moderate (approx. 100-150 words)**.

**Allowed Structure per Message (Teaching Phase):**
[Factual Explanation] + [Details/Experiment] + [Status Check]

**IMPORTANT: SCORING TAGS (CRITICAL)**
- Whenever the user answers a **Mini-Quiz** or **Final Exam** question:
  - If CORRECT: Start response with **"[CORRECT] "**
  - If INCORRECT: Start response with **"[INCORRECT] "**
  - Example: "[CORRECT] Correct. The answer is A."
```

Figure 3. System Prompt for the Neutral Avatar

This method of role modeling based on System Prompts enables the construction of different experimental conditions by merely modifying the prompt conditions, while keeping the learning content consistent. This design provides a clear and controllable technical foundation for the comparative analysis of different modes in subsequent user studies.

3.3 User Interface Design of the Learning System

The UI of the system is designed to provide learners with an intuitive, relaxed learning experience that incorporates a sense of social presence, while maintaining experimental control. The overall interface follows the "Principle of Minimal Interference" [2], i.e., minimizing unrelated functions to avoid introducing variables that could affect learning and experimental results.

3.3.1 Experiment Entry Interface. Before entering the formal learning session, the system first presents an entry page designed to guide learners through completing a pre-experiment questionnaire (Pre-survey). The page header displays a uniform greeting:

- *Welcome! Before we begin the session with the AI teacher, please complete a short survey.*

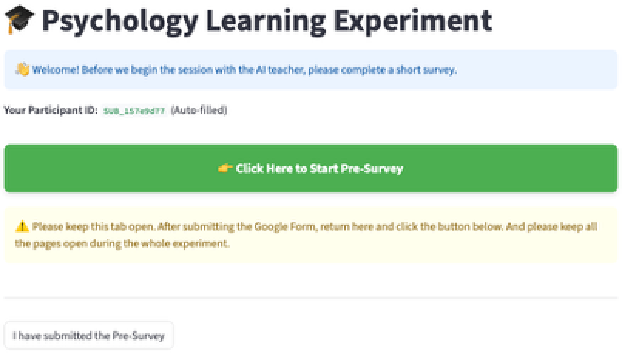
This prompt informs users of the experimental procedure, emphasizing to complete the questionnaire before interacting with the AI teacher. Furthermore, the interface provides clear operational instructions:

- *Please keep this tab open. After submitting the Google Form, return here and click the button below. And please keep all the pages open during the whole experiment.*

These instructions help avoid data loss caused by users closing, refreshing, or navigating away from the page, thereby ensuring workflow continuity and data integrity.
To enable data linkage between the Pre-test and Post-test, the system automatically generates and displays a unique Participant Identifier on this page, for example:

- *Your Participant ID: SUB-157e9d77 (Auto-filled)*

This auto-generated ID, shown to the user, allows for matching multi-stage data from the same participant without collecting personally sensitive information, thus preserving anonymity and traceability.



🎓 Psychology Learning Experiment

👋 Welcome! Before we begin the session with the AI teacher, please complete a short survey.

Your Participant ID: SUB_157e9d77 (Auto-filled)

👉 Click Here to Start Pre-Survey

⚠️ Please keep this tab open. After submitting the Google Form, return here and click the button below. And please keep all the pages open during the whole experiment.

I have submitted the Pre-Survey

Figure 4. Experiment Entry Interface

After the Pre-survey, users can either click

- *Click Here to Start Pre-Survey.*

to proceed, or, if they have already completed it, select

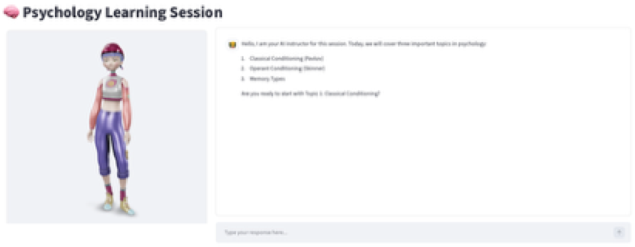
- *I have submitted the Pre-Survey.*

to enter the learning session directly. This design reduces user operational effort and minimizes experimental interruptions caused by unclear procedures.

3.3.2 Learning Interface Layout. Upon entering the learning system, the interface adopts a split-pane layout:

- Left Pane: 3D Avatar Display
- Right Pane: Text-based AI Dialogue Window

The left pane features a 3D female Avatar. Based on prior research and surveys[1] indicating that, compared to male or neutral figures, female teacher images can more easily help learners feel relaxed, establish trust, and maintain higher levels of concentration during learning. The primary purpose of this Avatar is to enhance the sense of social presence during learning, rather than to simulate complex emotions or behaviors.
Users can interact with the Avatar via basic mouse controls—dragging to rotate the view and using the scroll wheel to zoom—adding a degree of explorability and immersion to the interface.
The right pane contains a text dialogue window similar to those found in ChatGPT or Gemini. Learners can freely type questions, answer system-generated quiz items, or request further explanations within this window.
This design leverages a highly familiar interaction paradigm for large language models, lowering the learning curve and allowing users to focus their attention on the learning content itself rather than on interface mechanics.



🧠 Psychology Learning Session

Hello, I am your AI instructor for this session. Today, we will cover three important topics in psychology:

1. Classical Conditioning (Pavlov)
2. Operant Conditioning (Skinner)
3. Memory Types

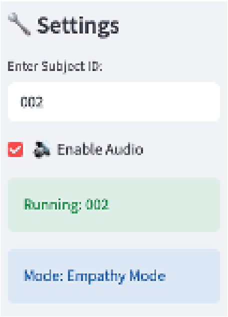
Are you ready to start with Topic 1: Classical Conditioning?

Figure 5. Learning Interface Layout

3.3.3 Functional Iteration and Design Trade-offs. In earlier versions of the system, we experimented with features such as:

- Avatar speech output (TTS) and speech input (STT)
- Teacher style selection (e.g., Supportive Avatar, Neutral Avatar)
- A manual Participant ID entry window

However, these features were progressively removed during later development and testing for the following primary reasons:



Settings

Enter Subject ID:

002

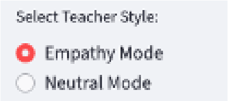
☑ Enable Audio

Running: 002

Mode: Empathy Mode

Figure 6. Manual Participant ID Entry, Speech In- and Output

- **Voice Feature Limitations**
  The voice functionality proved highly sensitive to network conditions. Users experienced significant variations in latency. This unpredictability not only impacted user experience but also introduced uncontrolled variables for experimental results.
- **Decreasing Expectancy Effects**
  Allowing users to actively choose a teacher style would make them explicitly aware of their experimental condition. This could influence subjective behavior. To better control variables and ensure experimental validity, this feature was deprecated.



Select Teacher Style:

● Empathy Mode

○ Neutral Mode

Figure 7. Teacher Style Selection

- **Streamlining Data Integrity**
  The initial design requiring manual Participant ID entry. However, during testing, some users ignored the step entirely, leading to difficulties in data matching and increasing the complexity of subsequent data cleaning and analysis. This functionality was ultimately replaced by the auto-generated ID method to improve data consistency and experimental control.

The final interface design of this system strikes a balance between user experience, learning support, and experimental control, providing a stable and reliable foundation for data collection and analysis in the subsequent user study.

4 Methodology

4.1 Research Design

This study employed a within-subjects, pretest–posttest experimental design to evaluate the effectiveness of an AI-based avatar learning environment and to assess users' perceived empathy and support during the interaction. All participants went through three consecutive stages: completing a pre-survey, engaging with the avatar-based learning experiment, and subsequently completing a post-survey. With this approach, it was possible to compare the participants' knowledge, perceptions, and experiences before and after going through the learning environment.
The experiment focused on examining both **cognitive outcomes** (learning effectiveness) and **affective outcomes** (perceived empathy, emotional support, and engagement), which are central to evaluating intelligent tutoring systems and conversational agents in educational contexts.

4.2 Participants

A total of **30 participants** completed all stages of the experiment and were included in the analysis. Participants were recruited through convenience sampling among university peers. They came from a very diverse educational background ranging from business management and engineering to environmental sciences. The majority of participants were between **21 and 29 years old**, reflecting a typical student population. The sample shared male and female population quite equally, approximately **63% identified as women**, with the remaining participants identifying as men. Almost all participants reported prior experience with artificial intelligence tools, such as ChatGPT, Gemini, Perplexity, etc.
Participants were informed about the purpose of the study and voluntarily agreed to take part in the experiment. The data was handled anonymously using random user IDs. This way it was possible to adhere to ethical considerations.

4.3 Experiment and Survey Design

The whole experiment consisted of three main components: pre-survey, avatar learning environment and post–survey. Below is the breakdown of each section.

4.3.1 Pre-Survey. The pre-survey was conducted using **Google Forms** and consisted of four main components:

1. **Demographics**, including age, gender, educational background and prior experience with AI-based tools.
2. **Baseline knowledge assessment** related to the psychology concepts addressed in the learning environment.
3. **Learning preferences and expectations** toward AI-supported learning experience. in terms of the type of responses or feedback people want to get.

These measures were used to establish a baseline for both previous knowledge and user perceptions prior to interacting with the avatar. The exact questions can be found in the Appendix.

4.3.2 Avatar Learning Environment. After completing the pre-survey, participants were instructed to access the LLM-powered avatar-based learning environment through a Streamlit application. In prior, participants were not told if

the avatar would be empathic or neutral to avoid creating an expectation of the interaction type or have them behave differently based on the condition. The avatar then led the user through the learning session by asking a set of teaching questions relating to introductory psychology concepts and providing explanations in response to the users' inputs.
The interaction with the avatar was a dialog-based conversational one. The avatar continued to provide explanation of ideas and concepts until the participant demonstrated knowledge of the explained concept in their responses. There was no specific time limit to complete the tasks in the experiment which allowed the participants to interact with the content at their own pace. When the whole learning content had been presented, participants were asked to complete another short quiz at the end of the interaction. The difference in the learning effectiveness and the user's perception was analyzed by comparing the pre-survey with the post-survey.

4.3.3 Post-Survey. Following the interaction, participants completed a post-survey assessing the avatar learning environment and their subjective experience on the following:

1. **Post-intervention knowledge**, using the same pre-survey knowledge questions for a proper and fair assessment of the knowledge gained after the experiment.
2. **Perceived learning effectiveness**, including clarity, usefulness, and engagement of the avatar.
3. **Perceived empathy and emotional support**, the degree to which the avatar was perceived as understanding and supportive.
4. **Overall user experience**, including satisfaction, trust, and perceived value of the avatar as a learning tool.

Most questions were measured using a **5 point Likert-scale** system to allow for quantitative comparison across participants during the analysis stage. The exact questions can be found in the Appendix.

5 Results

5.1 Overview of Data Analysis

A total of 30 valid participant datasets were analyzed (Empathy Mode: n=15; Neutral Mode: n=15). **Table 1** presents the comprehensive descriptive statistics and independent samples t-test results for all measured variables, categorized by learning outcomes, interaction engagement, and cognitive metrics.
In terms of learning effectiveness, **no significant difference was observed** between the Empathy Mode (M = 7.00, SD = 2.27) and the Neutral Mode (M = 6.93, SD = 2.94), t(28) = 0.07, p = .945. Similarly, users in both conditions reported comparable levels of sentiment (p = .682) and confusion rate (p = .610). The total interaction duration and average response time also showed no statistically significant variations between the two groups (see Table 1).
However, analyses revealed **significant disparities** in behavioral engagement and interaction quality. As shown in Table 1, the Empathy Mode elicited a substantially higher volume of user output (p < .001) and communication density (p < .001). In contrast, the Neutral Mode demonstrated significantly higher Lexical Diversity (p < .001). These significant findings are visualized and detailed in the following subsections.

5.2 Interaction Quantity and Duration

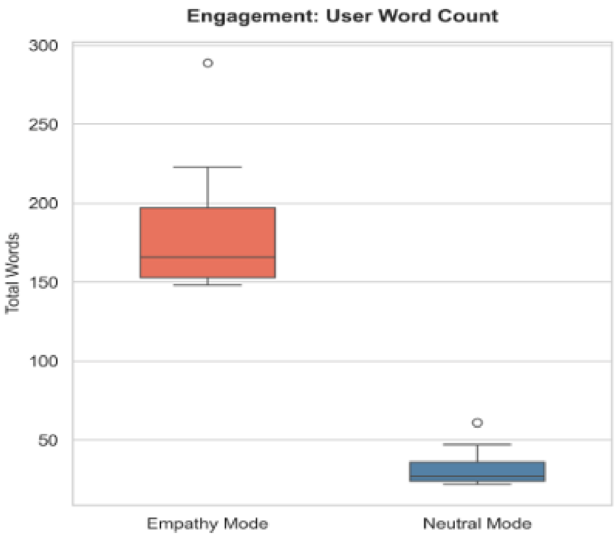


Figure 8. Word Count

The analysis of interaction quantity revealed significant disparities between the two groups. As illustrated in Figure 8, the **Total User Word Count** in the Empathy Mode (M = 181.13, SD = 38.10) was significantly higher than that in the Neutral Mode (M = 31.67, SD = 11.13), t(28) = 14.58, p < .001. This represents a substantial effect size (Cohen's d = 5.33), indicating that users in the Empathy condition generated nearly six times more text than those in the Neutral condition.
Similarly, the **Turn Count (Figure 9** was significantly higher for the Empathy group (M = 27.93, SD = 4.15) compared to the Neutral group (M = 23.40, SD = 2.38), t(28) = 3.67, p = .001. Regarding time investment, **Total Duration (Figure 10)** showed a different trend. Although the Neutral group recorded a longer average duration (M = 904.87s) compared to the Empathy group (M = 701.27s), this difference was not statistically significant (t = -1.79, p = .085), and the Neutral group exhibited a notably larger standard deviation (SD = 347.25), suggesting high variability in user dwell time.

5.3 Interaction Quality and Linguistic Patterns

To investigate the nature of user responses, we analyzed Communication Density and Lexical Diversity. **Figure 11**

Table 1. Comparison of Learning, Interaction, and User Experience Metrics Between Empathy and Neutral Modes

Measure	Empathy Mode Mean (SD)	Neutral Mode Mean (SD)	*t*	*p*	Cohen's *d*
Learning Outcomes					
Learning Score	7.00 (2.27)	6.93 (2.94)	0.07	.945	0.03
Confusion Rate	0.02 (0.04)	0.01 (0.02)	0.52	.610	0.19
Interaction Quantity					
Total Word Count	181.13 (38.10)	31.67 (11.13)	14.58	$< .001^{***}$	5.33
Turn Count	27.93 (4.15)	23.40 (2.38)	3.67	$.001^{**}$	1.34
Total Duration (s)	701.27 (271.67)	904.87 (347.25)	-1.79	.085	-0.65
Interaction Quality & Cognition					
Communication Density (Words/Min)	16.98 (5.54)	2.46 (1.59)	9.75	$< .001^{***}$	3.56
Lexical Diversity (TTR)	0.19 (0.07)	0.41 (0.15)	-5.24	$< .001^{***}$	-1.92
Average Response Time (s)	18.65 (6.81)	24.70 (12.84)	-1.61	.122	-0.59
Questions Asked	1.00 (2.10)	0.20 (0.41)	1.44	.169	0.53
User Experience					
Sentiment Score	7.93 (2.34)	8.27 (2.05)	-0.41	.682	-0.15

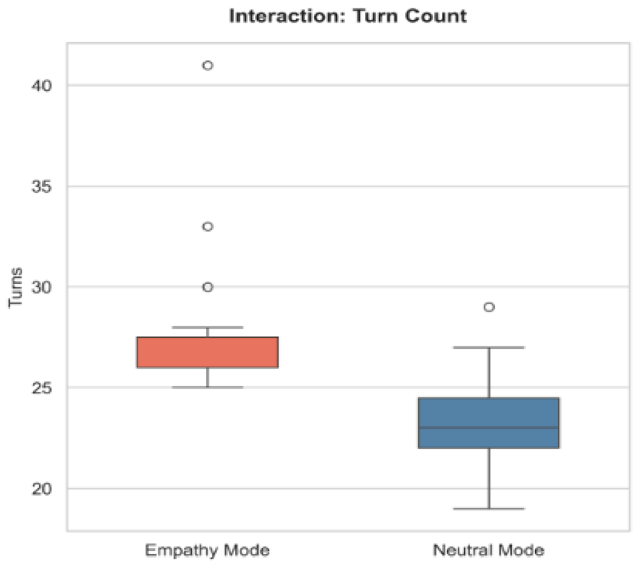


Figure 9. Turn Count

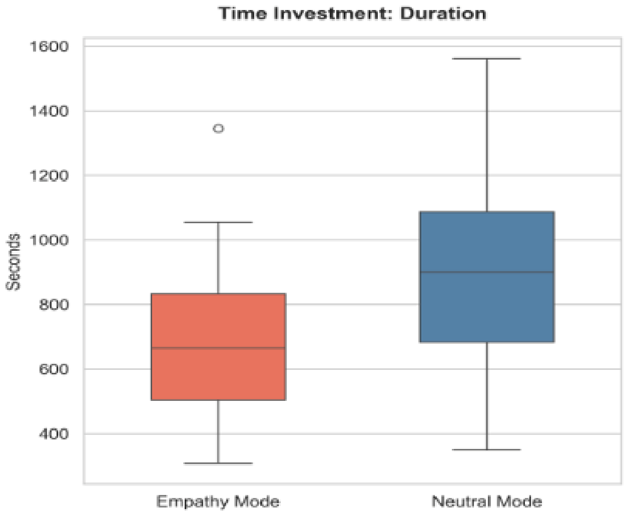


Figure 10. Duration

demonstrates a significant difference in **Communication Density**, defined as user words per minute. The Empathy Mode elicited a much higher density (M = 16.98 WPM) compared to the Neutral Mode (M = 2.46 WPM), t(28) = 9.75, p < .001, indicating a more rapid and fluid exchange of information.

In contrast, as shown in **Figure 12**, the **Lexical Diversity (TTR)** presented an inverse pattern. The Neutral Mode showed a significantly higher TTR (M = 0.41, SD = 0.15) than the Empathy Mode (M = 0.19, SD = 0.07), t(28) = -5.24, p < .001. This metric indicates that while the Neutral group produced less total text, the vocabulary used was proportionately more diverse, whereas the Empathy group's extensive output contained more repetitive linguistic structures.

5.4 Process Trajectory

The temporal evolution of the interaction was analyzed to understand user engagement over the course of the session. **Figure 13 (Sentiment Trajectory)** displays the sentiment polarity for each turn. Both groups maintained positive sentiment throughout the session, with the Empathy group showing a slightly more stable positive trend, although the overall mean sentiment scores did not differ significantly (p = .682).

Figure 14 (Dialogue Depth Evolution) illustrates the average word count per turn across the timeline. A distinct divergence is observable: the Empathy group (represented by the red line) maintained or increased their word count per

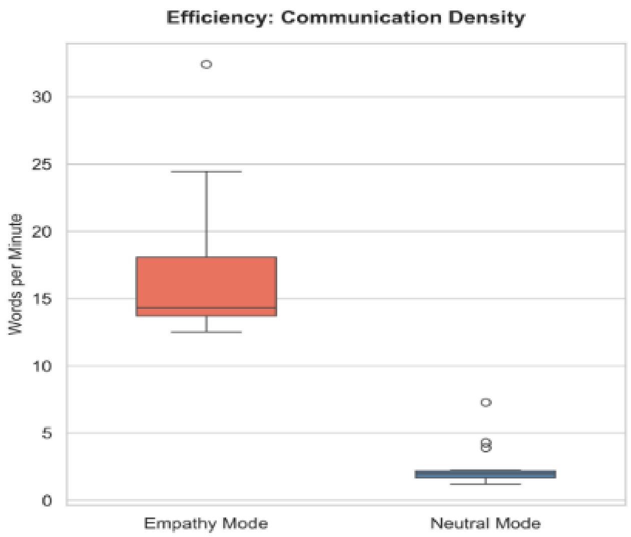


Figure 11. Communication Density

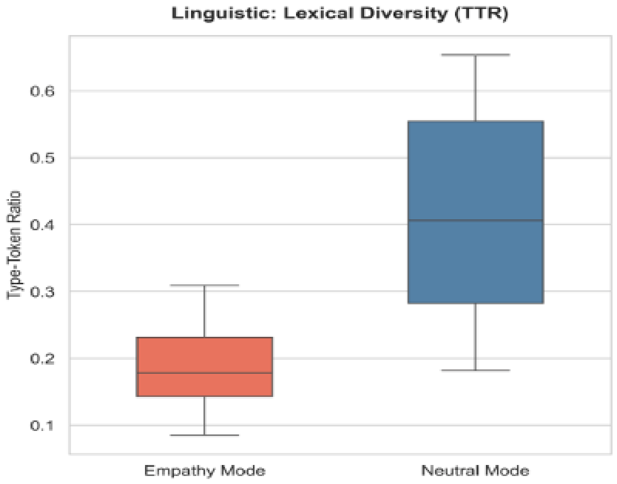


Figure 12. Lexical Diversity (TTR)

turn as the dialogue progressed, signifying sustained engagement. Conversely, the Neutral group (blue line) exhibited a flat or declining trend, often reverting to brief responses after the initial turns.

5.5 Correlation Analysis

A Pearson correlation analysis was conducted to examine the relationships between the measured variables, as visualized in the **Heatmap (Figure 15)**. A strong positive correlation was observed between **User Word Count** and **Turn Count** (r > .80), as well as between **User Word Count** and **Communication Density** (r > .90). Notably, Total Duration showed a weak to negligible correlation with **Learning Score** ($r \approx 0.30$), suggesting that merely spending more time in the system did not directly translate to higher test scores.

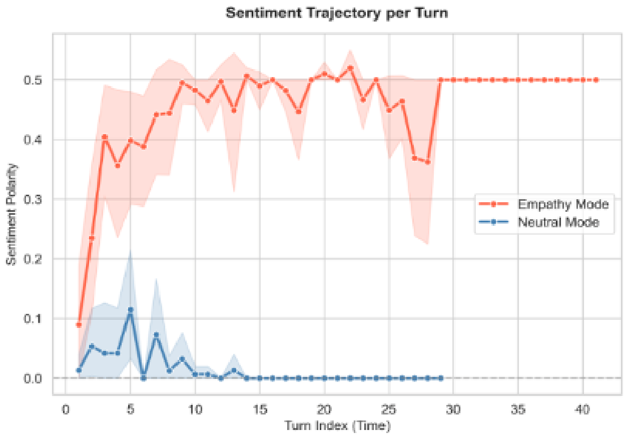


Figure 13. Sentiment Trajectory per Turn

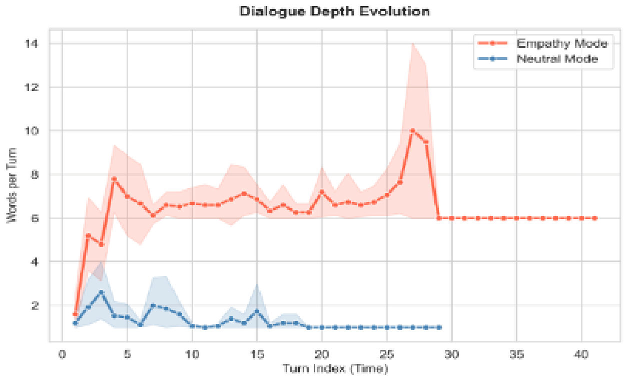


Figure 14. Dialogue Depth Evolution

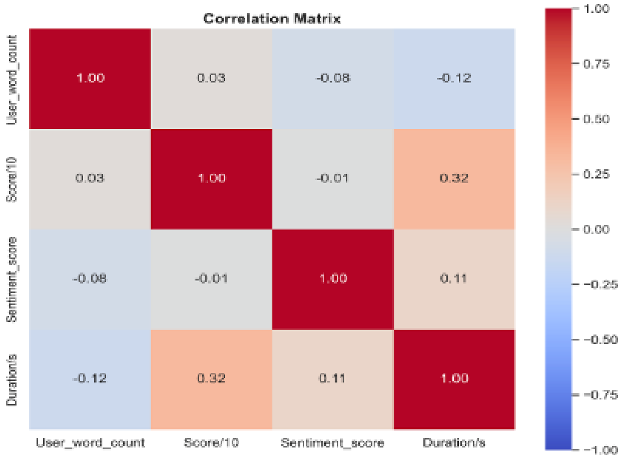


Figure 15. Correlation Heatmap

Furthermore, **Lexical Diversity** was negatively correlated with **User Word Count** ($r \approx -0.85$), confirming that longer interactions tended to result in lower type-token ratios due to the natural repetition of function words in conversational speech.

5.6 Knowledge Acquisition

To evaluate the overall effectiveness of the educational intervention, we compared the aggregated knowledge accuracy between the Pre-survey (N = 61) and Post-survey (N = 32) phases. Due to the anonymous nature of the survey collection which prevented paired data matching, a group-level analysis was conducted using an independent samples t-test.

Table 2. Comparison of Knowledge Accuracy Between Pre-Survey and Post-Survey

Group	N	Mean Accuracy (%)	SD (%)	*t*	df	*p*	Cohen's *d*
Pre-Survey	61	69.18	32.16	-1.35	70.82	.181	0.29
Post-Survey	32	78.13	29.34				

Table 2 presents the descriptive statistics and t-test results for the knowledge assessment. The Post-survey group demonstrated a higher mean accuracy (M = 78.13%, SD = 29.34%) compared to the Pre-survey baseline (M = 69.18%, SD = 32.16%). Although this difference did not reach statistical significance (t(70.82) = -1.35, p = .181), the analysis revealed a small-to-medium effect size (Cohen's d = 0.29), suggesting a positive trend in knowledge retention following the avatar-based learning session.

6 Discussion

6.1 Implications for Human–AI Interaction Design

The findings of this study provide several preliminary implications for the design of human-centered AI learning systems. Even before final statistical results are fully interpreted, the overall structure of the experiment highlights the importance of **interaction style** as a key design dimension in AI-supported learning environments.

First, the comparison between empathic and neutral avatar modes suggests that **emotional tone and feedback style** should be treated as explicit design variables rather than incidental characteristics of AI tutors. In Human–AI Interaction, this supports the idea that conversational agents are not only information providers but also social actors whose communication style can shape users' learning experience.

Second, the use of an avatar-based conversational interface emphasizes the role of **social presence** in learning contexts. Even without voice interaction, the combination of visual embodiment and adaptive textual feedback may influence how learners perceive support, clarity, and engagement. This underlines the importance of designing AI tutors that balance instructional clarity with socially appropriate responses.

Finally, the study highlights the need for **integrated evaluation frameworks** in HAI research that jointly consider cognitive outcomes (e.g., perceived learning effectiveness) and affective outcomes (e.g., empathy, trust, engagement). Designing AI learning systems with these dimensions in mind may lead to more sustainable and user-aligned educational technologies.

These implications will be further refined once the final results are analyzed, allowing a more precise mapping between observed effects and concrete design recommendations.

6.2 Limitations

This study has several limitations that should be considered when interpreting the results.

First, the **sample size** was relatively small, which limits the generalizability of the findings. Although the study aimed to recruit at least 30 participants, inconsistencies across pre-survey, interaction, and post-survey data reduced the number of fully matched cases available for analysis.

Second, the study faced **data consistency and matching challenges**. Some participants used inconsistent or missing IDs across different phases of the experiment, making it difficult to reliably link pre-survey, interaction logs, and post-survey responses. While data cleaning procedures were applied to retain the most reliable matches, this issue reduced the usable dataset.

Third, **temporal inconsistencies** were observed in some cases, where survey completion times did not logically align with interaction timestamps. Due to time constraints and the proximity of the deadline, these cases could not be fully resolved and were handled using best-effort matching strategies.

Fourth, the study relied exclusively on **self-reported measures** for perceived learning effectiveness, empathy, and engagement. While these measures are common in HAI research, they may be influenced by subjective bias and do not directly capture objective learning performance.

Finally, although the system initially included voice interaction, this feature was removed based on early user feedback indicating distraction and discomfort. As a result, the study does not assess the potential impact of multimodal interaction (e.g., speech) on learning outcomes, which may limit the scope of design insights.

Despite these limitations, the study provides valuable exploratory insights into the role of AI avatar personality in learning contexts and offers a foundation for more controlled and scalable future investigations.

7 Conclusion

7.1 Summary of Findings

7.2 Future Work

Future research should address several existing research gaps in the application of LLM-based pedagogical agents in education. While current studies demonstrate positive short-term effects on learning outcomes, there is still limited evidence regarding the long-term impact of these systems on knowledge retention, critical thinking development, and learner independence.

In addition, although social cues in affective pedagogical agents have been shown to improve engagement and motivation, there is a lack of research identifying the optimal design and level of human-likeness required for different learner groups and educational contexts.

Additionally, a notable gap in research is the scarcity of practical implementations in real classroom settings, as many experiments are still performed in controlled environments. Consequently, future research should prioritize studies conducted in actual educational contexts, create standardized assessment models for Human–AI educational technologies, and address ethical issues such as protecting data privacy, ensuring transparency, and promoting responsible AI usage to support a sustainable and reliable integration of technology in education.

References

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Appendix

H1: Emotional Support
H1: Learners interacting with the empathic avatar will feel more emotionally supported and encouraged during the learning process compared to the neutral avatar.

H2: Perceived Learning Effectiveness (SELECTED)
H2: Learners interacting with the empathic avatar will report higher perceived learning effectiveness than those interacting with the neutral avatar.

H3: Engagement
H3: The empathic avatar will lead to higher learner engagement compared to the neutral avatar.

RQ: How does avatar empathy influence learner engagement and interaction behavior in an AI-supported educational environment?

H1: Engagement Hypothesis (Supported)
H1: Learners interacting with an empathic avatar will demonstrate higher behavioral engagement than learners interacting with a neutral avatar.

H2: Interaction Quality Hypothesis (Supported)
H2: Learners interacting with an empathic avatar will maintain deeper and more sustained interaction trajectories across the learning session compared to learners interacting with a neutral avatar.

Contribution Overview

The following list summarizes the main contributions of each group member throughout the project.

Araks Karapetyan

- Shared workspace & group coordination: Organized internal group workflow, established shared online workspace (Word, PPT), and coordinated group communication.
- Contributed to the preparation of presentation slides.
- Participated to all the team meetings.
- Contributed to selecting and narrowing learning topics to core psychology concepts.
- Contributed in ideation of survey questions and gave feedback.
- Designed learning scenario 1 and 2, including learning content, prompts, and quizzes.
- Designed the post-study questionnaire.
- Contributed to the design of pre-test and post-test instruments.
- Participated in recruiting participants for the user study. (11 people)
- Contributed to the midterm report preparation.
- Authored Abstract and Sections 4 of the final report.

Brishila Firza

- Supported group coordination and shared workspace management.
- Participated to all the team meetings.
- Contributed to the midterm report preparation.
- Contributed to selecting and narrowing learning topics to core psychology concepts.
- Served as the presenter for Pitch 1 and 2.
- Contributed in ideation of survey questions and gave feedback.
- Designed learning scenario 3, including learning content, prompts, and quizzes.
- Participated in recruiting participants for the user study. (9 people)
- Video creation and upload to Moodle: Solely drafted, created and edited the project video.
- Participated in experiments for bonus engagement points.
- Authored Sections 2, 7 of the final report.

Nergis Bilge

- Supported group coordination and shared workspace management.

- Contributed to preparation of the pitch presentations and midterm report.
- Participated to all the team meetings.
- Designed and refined the pre-study questionnaire, including learning questions and Likert-scale items.
- Contributed to selecting and narrowing learning topics to core psychology concepts.
- Contributed in ideation of survey questions and gave feedback.
- Tested the avatar-based learning system and provided feedback on the interaction flow.
- Contributed to the design of pre-test and post-test instruments.
- Participated in recruiting participants for the user study. (8 people)
- Supported the alignment of post-study questionnaire with pre-study questionnaire learning measures.
- Authored Sections 1, 6 of the final report.

Yiyang Xie

- Deployed the LLM remotely and configured API access. Integrated the chatbot with the avatar in a web-based user interface.
- Implemented the initial (1st. version) learning system architecture.
- Designed the basic components for the system, including two types of chatbot, system prompts, and avatar design.
- Performed system debugging and performance optimization.
- Designed learning scenarios 4, 5 and 6, including learning content, prompts, and quizzes.
- Contributed to the preparation of presentation slides.
- Participated in recruiting participants for the user study. (7 people)
- Designed overall report structure, discussed adjustments with supervisor.
- Drafted full text version for two reports, the midterm and final report.
- Authored Section 3 of the final report.
- Implemented both mid-term and final reports using LaTeX.

Yusong Yang

- Further developed the learning system and extended its functionality.
- Implemented speech-based interaction, enabling voice input and output.
- Designed and implemented automatic user ID generation and data linking.
- Integrated pre-test and post-test into the learning system.
- Implemented automatic synchronization of user study data to a shared Excel file.
- Contributed to the preparation of presentation slides.
- Performed system debugging and performance optimization.
- Participated in recruiting participants for the user study. (10 people)
- Conducted statistical analysis of user study data (t-tests, effect sizes) and produced tables and visualizations.
- Contributed to the midterm report preparation.
- Authored Section 5 of the final report.