CTE Workshop Proceedings, 2025, Vol. **12**, pp. 63–77 https://doi.org/10.55056/cte.939

Educational game for conflict mediation training in wartime conditions using large language models

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Abstract. Interpersonal conflicts increase significantly during wartime, negatively impacting psychological well-being and social cohesion. This research introduces an innovative educational game that teaches mediation skills through interactive dialogue with characters generated by large language models (LLMs). The game features dynamically generated conflicts and personalized responses based on player actions, allowing users to practice mediation strategies in a safe and repeatable environment. The game has been implemented with PyGame and Gemini 1.5 Flash LLM. We conducted an experiment to evaluate the effectiveness of different mediation strategies in the same conflict scenario. Our results demonstrate that the compensation strategy proves most effective in our generated conflict scenario. What is more important, the game provides a quantitative method for evaluating mediation strategies, which has been impossible in real world conflicts. This novel approach fills a significant gap in mediation education, offering an accessible tool for training mediators, particularly in conflict sensitive regions such as Ukraine.

Keywords: educational game, mediation training, conflict resolution, large language models, Gemini API, wartime education

1. Introduction

War is an extraordinarily powerful stressor that destroys not only physical infrastructure but also social connections between people. According to reports from national and international monitoring agencies, since the beginning of the war in Ukraine, 21.3 million Ukrainian citizens have suffered from its consequences and need humanitarian assistance, of which 57% are children [1]. The constant anxiety, fear for the future, uncertainty, and loss of familiar lifestyles become the dominant emotional state. These changes affect people's psychological state, making them irritable, aggressive, and less tolerant of each other.

Children and adolescents are particularly vulnerable to the negative impacts of war events, as their psyche is at a stage of active formation. Under war conditions, this natural developmental process becomes complicated, as stressful situations and traumatic experiences significantly worsen emotional state and mental health. Without timely and qualified psychological assistance, traumatized children may experience serious disruptions in normal psychological development, which can have significant negative consequences for their psyche in adulthood and contribute to the development of interpersonal conflicts in the future [12].

Mediation has proven to be an effective tool for peacefully resolving disputes, but there is a lack of accessible and interactive tools to learn these skills, especially in conflict zones. This gap is particularly problematic in Ukraine, where the ongoing war has increased interpersonal conflicts and created an urgent need for conflict resolution

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skills. Addressing this need requires innovative approaches that combine educational theory with modern technology.

Large language models (LLMs) offer unique opportunities for creating interactive learning experiences [17]. They can generate dynamic content, respond to user input, and simulate complex social interactions, making them ideal for training social skills like mediation. However, while LLMs have been integrated into various educational applications [16], their potential for teaching conflict resolution skills remains largely unexplored.

This paper presents a novel educational game designed to teach mediation skills through interactive dialogue with characters powered by LLMs. The game creates realistic conflict scenarios relevant to wartime conditions and allows users to practice different mediation strategies in a safe, repeatable environment. In addition, our game provides metrics for a quantitative evaluation of the effectiveness of the different mediation strategies.

The primary contributions of this research are:

- A novel educational game for teaching mediation skills using LLM-generated dialogues
- LLM prompts for conflict participants simulation
- A technique for evaluating different mediation strategies through quantitative metrics
- Empirical findings on the effectiveness of various mediation approaches in simulated conflict scenarios

2. Background and related work

2.1. Interpersonal conflicts in wartime conditions

Wartime conditions create unique challenges for interpersonal relationships. Brulin, Brulin-Solignac and Bouchard [5] emphasize that war is a major and long-lasting polytraumatic event with deleterious psychological consequences affecting a very large number of people both within and outside the country. These psychological disorders can have lasting effects on children, adolescents, and adults who are direct or indirect victims.

The psychological impact extends beyond the immediate trauma of war. According to Semigina [21], Ukrainian social services and social workers were largely unprepared to act in emergency situations, leading to structural and ethical complexities, including value conflicts. This situation creates additional barriers to resolving interpersonal conflicts, as the traditional support systems are themselves under strain.

Research by Burgos-Calvillo, Vasquez-Salgado and Greenfield [6] indicates that socioeconomic differences significantly impact conflict resolution styles among university students, with individualistic strategies proving more effective in improving roommate relations and reducing psychological distress. These findings suggest that conflict resolution approaches must be adapted to the specific social and cultural context, particularly in wartime conditions where these factors are in flux.

2.2. Mediation education and training

Mediation is defined as “an extrajudicial voluntary, confidential, structured procedure during which the parties, with the help of a mediator, try to prevent or resolve a conflict through negotiations” [24]. Traditional mediation training methods have relied heavily on face-to-face role-play exercises and theoretical models such as the Riskin Grid [8]. While effective for experiential learning, these methods are resource-intensive and may not adequately prepare students for the dynamic and interactive nature of actual mediation sessions.

Devinatz [11] identifies several key attributes required for effective mediators, including strong communication skills, flexibility, neutrality, composure, and ethicality during the mediation process. These skills can be attained through participation in mediation training programs, but traditional programs often struggle to provide sufficient opportunities for practice and feedback.

In Ukraine, mediation as a practice has been developing since independence, but only in autumn 2021 was the definition of mediation, its basic principles and procedures, and the status of mediator officially enshrined in the Law of Ukraine "On Mediation" [24]. Since 2018, thousands of Ukrainian schools have established "Reconciliation Services" that actively work to prevent and respond quickly to conflicts in the educational environment [4].

Recent initiatives in Ukraine demonstrate growing recognition of the importance of mediation. In 2024, several new projects aimed at implementing mediation and developing a culture of negotiation and conflict resolution were launched, including the Erasmus+ project "The Art of Negotiation and Conflict Resolution (Mediation)/ArtNoConflict" and a joint project between Kharkiv National University and UNICEF on trauma-oriented approaches to mental health, psychological support, and mediation [18, 19].

2.3. Large language models in educational applications

Large language models (LLMs) have demonstrated significant potential for enhancing educational experiences. Bewersdorff et al. [2] highlight how LLMs, particularly Multimodal Large Language Models (MLLMs) like GPT-4 Vision, can process multimodal data to create enriched, personalized, and interactive learning landscapes in education. These applications range from content creation to tailored support for learning, fostering engagement in scientific practices, and providing assessments and feedback.

In the context of educational games, LLMs have been used to enhance player experiences by creating dynamic, responsive environments. Gatti Junior et al. [13] explore the application of LLMs such as ChatGPT in designing educational board games, guiding educators through phases of ideation, customization, and prototype feedback. Similarly, Todd et al. [23] investigate the use of LLMs to generate functional video game levels, finding that their performance scales dramatically with dataset size.

The integration of LLMs with game-based learning environments has shown particular promise. Goslen et al. [14] introduced a plan generation framework that leverages a text representation of students' interactions in a game-based learning environment to generate plans for accomplishing given target goals. Their results indicate that generated plans can guide students to achieve their goals more efficiently.

However, challenges remain in implementing LLMs in educational contexts. As noted by Huber et al. [15], while LLMs provide many opportunities, they also introduce risks of over-reliance that could potentially limit the development of domain expertise. Furthermore, Gatti Junior et al. [13] identify challenges such as biases from training datasets, generation of inaccurate details, counter-intuitive rules, and misinterpretation of feedback, which can result in unintended dynamics.

2.4. LLMs for conflict resolution and negotiation training

Recent research has begun to explore the potential of LLMs for conflict resolution and negotiation training. Bianchi et al. [3] developed NEGOTIATIONARENA, a flexible framework for evaluating and probing the negotiation abilities of LLM agents. Their findings indicate that LLMs can significantly improve their negotiation outcomes by employing certain behavioral tactics, though they also exhibit irrational negotiation behaviors similar to those seen in humans.

In the context of conflict resolution, Shaikh et al. [22] introduced Rehearsal, a system that allows users to practice handling conflicts with a simulated interlocutor, explore alternative conversational paths, and receive feedback on conflict strategies. Their approach conditions the output of an LLM on the Interest-Rights-Power (IRP) theory from conflict resolution, guiding users towards strategies that help de-escalate difficult conversations.

However, to our knowledge, no existing work has specifically addressed the use of LLMs for teaching mediation skills in the context of wartime conflicts. This gap represents an important opportunity to leverage the capabilities of LLMs to address a pressing social need.

3. Methodology

3.1. Game design and architecture

The educational game was designed to provide users with a safe environment to practice mediation skills through interaction with AI-generated characters in conflict situations. The game features a 2D environment where players can move around and interact with different characters, each with unique personalities and conflict scenarios. The primary goal is to help players develop effective mediation strategies by applying theoretical knowledge in simulated real-world situations.

Key design requirements included:

- An intuitive Ukrainian interface
- Moderate system requirments
- AI-generated characters with unique backgrounds and conflict situations
- Dynamic dialogue generation based on player actions
- Quantitative feedback on mediation effectiveness
- Assistance features to guide players in making decisions

The game architecture consists of several components: a 2D game environment built with Pygame, character generation system, dialogue management system, and LLM integration for content generation. Figure 1 shows the game interface.

3.2. LLM selection and integration

After evaluating several LLMs, we selected Gemini 1.5 Flash for our implementation. This decision was based on comparative research on the performance capabilities of ChatGPT-4o and Gemini 1.5 Flash [20], which showed that while ChatGPT-4o has high baseline indicators, specialized training does not significantly increase its accuracy. In contrast, Gemini 1.5, despite lower initial performance, demonstrates substantial improvements after training, especially with TXT files. These findings indicate Gemini 1.5's excellent ability to store and retrieve information, making it potentially more effective for dialogue generation.

Additional factors in our selection included:

- Cost-effectiveness compared to competitors
- High-quality text generation capabilities
- Contextual adaptation
- Ability to model human communication
- Speed and accuracy
- Official Python API support

Integration with the Gemini API involved several steps:

1. Creating an API key through Google AI Studio

Figure 1: Game interface showing the player character and environment.

2. Installing the Python google.generativeai library
3. Configuring system instructions for character-specific information
4. Implementing a dialogue management system to handle user input and LLM responses
5. Processing LLM output to extract character responses and update game state

The integration used Gemini's system instructions mechanism to provide character-specific information that is processed by the model before handling the main request. A custom prompt template was designed to describe the generated character, their conflict, and response format instructions. Special formatting using the "^" symbol was implemented to split the received response into three parts: the character's textual response, a trust score (from -5 to 5), and a willingness-to-compromise score (from -3 to 3).

3.3. Parameter optimization

LLM performance is significantly influenced by various parameters, particularly the temperature setting, which controls the randomness level in generated responses. To identify the optimal temperature value for our game, we conducted a user study where respondents evaluated the naturalness of responses generated with different temperature settings.

The temperature parameter affects the Softmax function as follows:

```
# Model preparation
def set_context():
    genai.configure(api_key=api_key)
    MODEL = 'gemini-1.5-flash'
    SYSTEM_INSTRUCTION = current_character.get_prompt() + \
            "Conflict essence: " + \
            conflict.description + \
            " \nFORMAT OF YOUR RESPONSES: three lines separated by '^'
                character. \n1. First line - text response of your character
                ." + \
            " \n2. Second line - integer from -5 to 5, which shows whether
                your TRUST towards the player has changed." + \
            " -5 means significantly decreased, 5 means significantly
                increased." + \
            " \n3. Third line - integer from -3 to 3, which shows whether
                your WILLINGNESS TO COMPROMISE has changed." + \
            " -3 means significantly decreased, 3 means significantly
                increased."

    print (SYSTEM_INSTRUCTION)
    global model
    global chat
    model = genai.GenerativeModel(MODEL, system_instruction=
        SYSTEM_INSTRUCTION)
    chat = model.start_chat()
```

Figure 2: Code snippet showing model configuration for character-specific dialogue generation.

$$p_i(T) = Softmax(z_i/T) = \frac{\exp(z_i/T)}{\sum_{j=1}^{n} \exp(z_j/T)} \tag{1}$$

Where z_i represents the logit (unnormalized prediction) for the i-th class of the model, and p_i are the probabilities of choosing the i-th class, which sum to 1.

Increasing T increases the chances of selecting less probable words in dialogue. Thus, low values make responses predictable and precise, medium values balanced, and high values more creative but less logical. Since this parameter critically affects text quality, we conducted a survey to determine the optimal value for our game.

The survey involved 15 participants who evaluated 50 dialogue responses generated with different temperature settings on a 10-point scale, where 1 meant "not at all like human language" and 10 meant "very similar to human language". The results were averaged and plotted as shown in figure 3.

Based on respondent evaluations, responses with a temperature value of 0.8 were rated as most natural for text generation. This setting provides a balance between logical coherence and creative diversity, allowing for meaningful yet varied responses. This temperature value was adopted for the final implementation.

3.4. Mediation strategy evaluation

To evaluate the effectiveness of different mediation strategies, we designed an experiment comparing four distinct approaches (table 1).

In each experiment, we used the same pair of characters and the same conflict scenario. For each strategy, 20 dialogue turns were executed, carefully following the principles of that strategy. The effectiveness of each strategy was measured using the

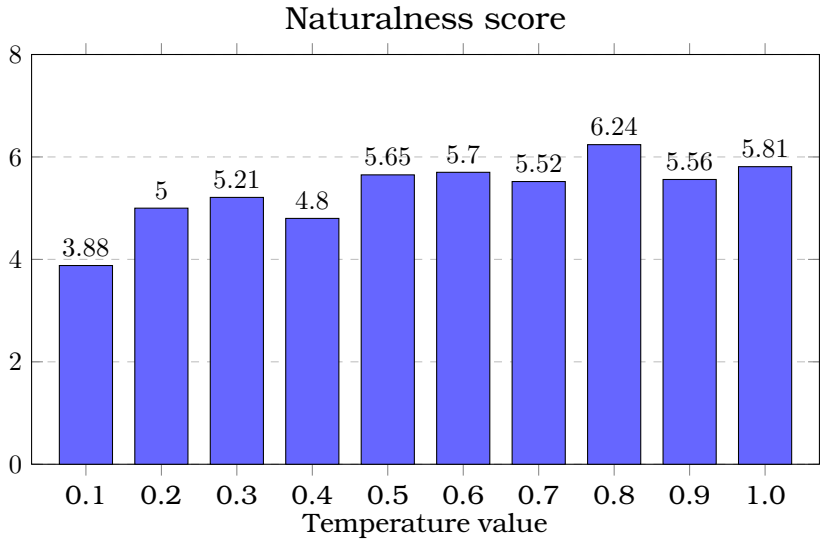

Figure 3: Results of temperature parameter optimization survey.

Table 1
Mediation strategies evaluated in the experiment.

Strategy	Description
Integration	Focuses on finding solutions within the shared interests of parties. The mediator helps participants find points of contact and form a compromise that satisfies both sides.
Pressure	Involves narrowing the options where no agreement exists. The mediator can reduce the attractiveness of alternatives that do not include an agreement, motivating parties to seek compromise.
Compensation	Involves expanding possible agreement options. The mediator looks for additional incentives or benefits for each party to increase the likelihood of agreement.
Inaction	Involves non-interference in the negotiation process, allowing parties to resolve the dispute independently. This strategy is used when participants have the potential for self-resolution of the conflict.

game's trust and willingness-to-compromise metrics, which were updated after each player interaction based on the LLM's assessment of the interaction quality.

The experiment was designed to demonstrate the potential of quantitative strategy evaluation, which is nearly impossible in real-world where conflicts cannot be reset to test alternative approaches. The results provide insights into which mediation strategies might be most effective in certain conflict types.

4. Implementation

4.1. Game development

The game was developed using Python and the Pygame library. For easier code management, the implementation was divided into six main files:

- `main.py`: contains main settings, movement mechanics, and AI requests
- `aicharacter.py`: responsible for character generation
- `player.py`: handles player appearance and animations
- `conflict.py`: defines conflicts

- `obstacle.py`: creates obstacles for the player
- `spritesheet.py`: helps load and process sprites

The game initialization involves setting up the Pygame environment and creating the game window with specified dimensions. The graphical user interface is managed using the pygame_gui library, which provides a dialogue window for communication with characters. This window can be hidden rather than closed, maintaining usability throughout the game session.

Character generation is handled by the AICharacter class, which defines behavior and properties for game characters. The class includes functions for randomly generating character traits and updating game metrics based on player interactions.

```
class AICharacter:
        color = (255, 0, 0)
        width, height = 50, 50
        x, y = 100,100
        tile = ""
        sprite = None
        name = "Anonymous"
        age = 20
        gender = "male"
        description = ""
        manner_of_speech = ""
        objective = ""
        trust = 0  #trust towards player
        consent = 0  #willingness to compromise
```

Figure 4: AICharacter class definition for handling character behavior in the game.

Movement is implemented through keyboard input to move the player in different directions. The game restricts movement while the dialogue console is open, ensuring players focus on the mediation process during character interactions.

The conflict generation system creates varied conflict scenarios by combining different conflict descriptions, participant characteristics, and contextual factors. This ensures each playthrough provides unique mediation challenges.

4.2. Dialogue system

The dialogue system is central to the game's mediation training functionality. When a player collides with a character, the current_character variable is initialized, which triggers the preparation of the AI model for dialogue with the user. This opens the console window to begin communication with the character.

For processing user input and obtaining AI responses, we build a request in the PROMPT variable that includes the current trust level, willingness to compromise, and the new input message. The chat.send_message(PROMPT) method sends the request to the AI and receives a response. When the character responds, a sound is played, and the data is displayed in the game's console window, with character characteristics updated accordingly.

This dialogue system creates a dynamic interaction experience where the player's choices directly influence character trust and willingness to compromise, providing immediate feedback on mediation effectiveness.

```
conflict_descriptions=["p1 and p2 work at...",
        "p1 and p2 had an argument about...",
        "p1 and p2 have a joint business,"]

class Conflict:
        side1=None  #conflict party 1
        side2 = None  #conflict party 2
        description = ""

        def generate(self):
                self.description = random.choice(conflict_descriptions)
                self.description = self.description.replace("p1", self.
                    side1.name)

        def __init__(self, s1:AICharacter, s2:AICharacter):
                self.side1, self.side2 = s1,s2
                self.generate()
```

Figure 5: Creation of conflict scenarios with multiple sides and random generation.

```
if (event.type == pygame_gui.UI_CONSOLE_COMMAND_ENTERED and
        event.ui_element == console_window):
    command = event.command
    if current_character:
        PROMPT = "Your current TRUST level is " + str(current_character.
            trust) + " out of 100." + \
                "Your WILLINGNESS TO COMPROMISE is currently " + str(
                    current_character.consent) + " out of 100." + "The next
                    player's reply: " + command + " "
        response = chat.send_message(PROMPT)
        print (response.text)
        talk_sound.play() # sound on response
        console_window.add_output_line_to_log(response.text.split("^")[0],
            is_bold=True)
        try:
            # Change trust level and willingness to compromise
            current_character.change_trust(int(response.text.split("^")[1])
                )
            current_character.change_consent(int(response.text.split("^")
                [2]))
        except:
            pass
        console_window.set_display_title(current_character.name + \
                            " | Trust: " + str(current_character.trust) + \
                            " | Willingness to compromise: " + str(
                                current_character.consent))
```

Figure 6: Request formation and response processing for character dialogue.

5. Results

5.1. Temperature parameter optimization

Our survey on temperature parameter optimization yielded clear results regarding which settings produce the most natural-sounding dialogue responses. As shown in figure 3, respondents rated responses with a temperature value of 0.8 most favorably,

with an average score of 8.2 out of 10.

Lower temperature values produced responses that felt too mechanical and predictable. Higher temperature values (1.0 and beyond) introduced too much randomness, making responses occasionally miss the required format, so they were not included into our survey.

The chosen temperature value of 0.8 provides an optimal balance between consistency and creativity. Responses at this setting maintain logical coherence while introducing enough variability to feel naturalistic and engaging. This finding aligns with research by De Nadai [9, p. 4-5], who found that intermediate temperature values generally produce the most human-like text for conversational applications.

5.2. Mediation strategy evaluation

The evaluation of different mediation strategies revealed substantial differences in effectiveness as measured by the game's trust and willingness-to-compromise metrics. Figure 7 shows the comparative effectiveness of each strategy based on our experiments.

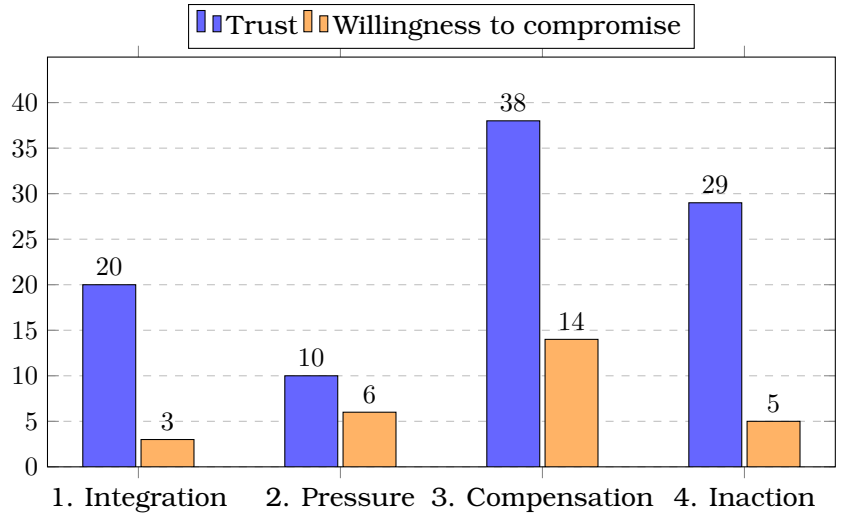

Figure 7: Results of testing different mediation strategies

The compensation strategy proved most effective in our generated conflict scenarios, achieving a trust score of 38 (out of 100) and a willingness-to-compromise score of 14 (out of 100) after 20 dialogue turns. This strategy, which focuses on expanding possible agreement options by identifying additional incentives for each party, appears particularly well-suited to the types of conflicts generated in our system.

The inaction and integration strategies were less effective and scored 29 and 20 trust points out of 100. These strategies proved moderately successful but did not match the effectiveness of the compensation approach.

The pressure strategy showed limited effectiveness, with scores of 10 for trust and 6 for willingness to compromise. This suggests that approaches emphasizing the narrowing of options where no agreement exists may be less effective in building trust in our simulated conflicts.

Interesting enough, despite its poor trust building performance, the pressure strategy was the second most effective in encouraging conflict resolution. It overperformed both inaction and integration strategies.

These findings align with research by Carnevale [7], who identified compensation as a particularly effective strategy in certain conflict types. However, it's important to

note that our results are specific to the conflict scenarios generated in our system and may not generalize to all real-world conflicts.

6. Discussion

6.1. Implications for mediation training

Our research demonstrates the potential of LLM-based educational games for teaching mediation skills, particularly in contexts where traditional training methods are limited or inaccessible. The game provides several advantages over conventional approaches:

1. *Accessibility and scalability* – the digital format allows for widespread distribution, making mediation training accessible to individuals who might otherwise lack access to formal instruction. This is particularly valuable in war-affected regions like Ukraine, where the need for mediation skills is high but resources for training are constrained.
2. *Safe practice environment* – the game creates a risk-free space for users to experiment with different mediation strategies without fear of real-world consequences. This encourages experimentation and learning through trial and error, which is essential for developing effective mediation skills.
3. *Quantitative feedback* – unlike traditional role-play exercises, our system provides immediate, quantitative feedback on the effectiveness of different approaches through the trust and willingness-to-compromise metrics. This allows users to gain concrete insights into which strategies work best in different scenarios.
4. *Repeatability and variety* – the ability to generate diverse conflict scenarios and reset interactions enables users to practice the same mediation techniques across different contexts or try alternative approaches with the same characters. This reinforces learning and helps users develop adaptable skills.

The finding that the compensation strategy proved most effective in our experiments has interesting implications for mediation training. While traditional mediation education often emphasizes integration strategies (focusing on shared interests), our results suggest that exploring expanded options and additional incentives may be more effective in certain conflict types. This aligns with emerging research in the field [10] but provides a novel quantitative validation of these theoretical approaches.

6.2. LLMs for educational game development

Our experience developing an LLM-powered educational game offers several insights for similar projects:

1. Our findings on temperature optimization highlight the importance of fine-tuning LLM parameters for specific applications. The optimal temperature value of 0.8 identified in our research balances coherence and creativity in a way that enhances the educational experience. This suggests that educational applications of LLMs may benefit from different parameter settings than those used for general-purpose applications.
2. The design of effective prompts proved crucial for generating appropriate character responses. Our approach of using system instructions to establish character context and specifying a structured output format (with trust and compromise scores) enabled us to create a consistent, educational experience. This demonstrates how careful prompt engineering can transform general-purpose LLMs into specialized educational tools.

3. While the Gemini API provided powerful capabilities, integrating it into a real-time game environment presented technical challenges, particularly in handling response timing and error cases. These challenges highlight the need for robust integration patterns when building interactive applications with LLMs.
4. The API-based approach allowed us to leverage sophisticated LLM capabilities without requiring high-end hardware for end-users. However, it also introduces dependencies on external services and potential costs for API usage at scale. Future educational applications may need to balance these factors when deciding between API-based and local deployment models.

6.3. Limitations and future work

While our research demonstrates the potential of LLM-based games for mediation training, several limitations should be acknowledged:

1. The current implementation focuses on conflicts typical in the Ukrainian context during wartime. The effectiveness of different mediation strategies may vary across cultural contexts and conflict types. Future work could expand the range of scenarios to address a wider variety of cultural settings and conflict situations.
2. Despite ongoing advances, LLMs still face challenges in maintaining perfect coherence across extended dialogues and may occasionally generate inappropriate responses. More sophisticated filtering and safety mechanisms could be implemented to address these issues.
3. While our quantitative metrics provide valuable insights, they are based on the LLM's assessment rather than external validation. Future studies could incorporate expert evaluations or real-world outcomes to further validate the effectiveness of the training.
4. As with any simulation-based training, the transfer of skills from the game environment to real-world mediation scenarios requires further study. Further research on how game-based training affects actual mediation performance would provide valuable insights.

Future directions for this research include:

- Testing a wider range of mediation strategies across diverse conflict types could provide more nuanced insights into which approaches work best in specific contexts.
- Implementing adaptive difficulty and personalized feedback based on user performance could enhance the educational value of the system.
- Extending the system to support multiplayer interactions, where users can practice mediation with both AI characters and other players, could create more authentic learning experiences.
- Developing curriculum materials and instructor guides to integrate the game into formal mediation education programs could amplify its impact.

7. Conclusion

This paper has presented a novel educational game for teaching mediation skills using LLM-generated dialogues. The system leverages the capabilities of the Gemini 1.5 Flash LLM to create dynamic, responsive characters engaged in realistic conflict scenarios. Through careful parameter optimization and prompt engineering, we created an engaging learning environment that provides immediate feedback on mediation effectiveness.

Our experimental evaluation of different mediation strategies revealed that the compensation approach, which focuses on expanding possible agreement options, was

most effective in our generated conflict scenarios. This finding provides quantitative support for theoretical perspectives on mediation strategy and offers practical guidance for mediators in similar conflict types.

The system addresses a critical need for accessible mediation training, particularly in war-affected regions such as Ukraine, where interpersonal conflicts have increased due to wartime conditions. By creating a safe, repeatable environment for practicing mediation skills, our game offers an innovative solution to the challenge of mediation education in resource-constrained settings.

Future work will focus on expanding the range of conflict scenarios, implementing more sophisticated feedback mechanisms, and validating the effectiveness of training through longitudinal studies. These enhancements will further strengthen the system's value as an educational tool and contribute to the growing body of knowledge on both mediation practice and LLM applications in education.

Declaration on generative AI: During the preparation of this work, the authors used Claude 3.7 Sonnet to enhance content and improve writing style. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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