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Interactive AI Learning Through Game Play: Engaging K-8 Students with Tic-Tac-Toe AI Game

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***Abstract*— This work focuses on the "Tic-Tac-Toe AI Game", a key exhibit at a recent educational technology exhibition, designed as an interactive introduction to the capabilities and applications of artificial intelligence (AI) and machine learning (ML) systems. The interactive game engaged K-8 students in strategic gameplay, helping them develop a deeper understanding of AI's potential through themes such as perception, trust, practical application, and specialization. The game allowed students aged 7 to 14 to engage with AI opponents at three difficulty levels: Olivia (Easy), Emma (Medium), and Chris (Advanced). Throughout the two-day exhibit, 56 students played a total of 150 rounds against the AI opponents, with each session lasting one to three minutes, providing an engaging introduction to AI gameplay and strategy development. To analyze player strategies, movement tracking was implemented using the LabelImg graphical annotation tool. Each move was documented with bounding boxes and sequential numbering, distinguishing between player and AI moves. This method provided a detailed dataset for evaluating player strategies and decision-making patterns. While we observed the gameplay performance of all participants across different grade levels, our detailed strategy analysis focused specifically on first-grade students due to the availability of screen recording data. Findings showed that first graders preferred the top-left and center squares, possibly mimicking successful AI moves or displaying cognitive biases influenced by game design. A decision tree model was applied to predict gameplay outcomes, achieving a 66% accuracy rate in determining the success of first graders' strategic success against the AI opponents. The exhibit highlighted how young learners adapted to AI strategies, particularly when facing the advanced AI, Chris. This research demonstrates how interactive AI tools can transform abstract AI concepts into tangible, engaging experiences, fostering curiosity, adaptability, and strategic thinking in young learners.**

Keywords—Tic-Tac-Toe; Educational Technology; Artificial Intelligence; AI-driven Gameplay

I. Introduction

Artificial Intelligence (AI) is transforming education by introducing interactive and hands-on learning experiences. AI-powered tools are being used in classrooms to provide personalized learning pathways, automate assessment tasks, and enhance student engagement [1]. Studies have shown that AI-driven educational environments increase student motivation and improve retention rates compared to traditional instruction methods [2]. However, traditional AI education still largely depends on abstract theories, text-heavy explanations, and coding exercises, which can be difficult for young learners to grasp [3]. Many children struggle to develop an intuitive understanding of how AI makes decisions, adapts, and learns from patterns [4]. A more effective approach involves game-based learning, where children engage with AI through interactive play rather than passive instruction. Research in educational technology has demonstrated that incorporating AI-driven gameplay into learning environments enhances problem-solving abilities, critical thinking, and computational reasoning [5]. Gamification elements such as real-time feedback, adaptive AI difficulty levels, and competition create an engaging experience that improves curiosity and deeper cognitive processing [6]. One example of this approach is Tic-Tac-Toe, a simple yet strategic game that reflects fundamental AI decision-making processes [7]. The game provides a structured environment where students can observe how AI systems analyze game states, predict possible moves, and adjust strategies dynamically. Research on game-based AI education suggests that simple, rule-based games like Tic-Tac-Toe serve as effective models for introducing algorithmic thinking to young learners [8]. By interacting with AI opponents, students gain direct exposure to machine learning principles, such as pattern recognition, reinforcement learning, and decision trees [9]. Studies have demonstrated that AI-driven games improve strategy development, cognitive flexibility, and problem-solving skills [10]. For instance, research on AI-enhanced educational games found that students who interacted with adaptive AI developed more sophisticated decision-making strategies compared to those who engaged in non-adaptive, traditional gameplay [11]. Further investigations have highlighted that integrating machine learning principles into structured games like Tic-Tac-Toe allows students to develop an intuitive understanding of AI's capabilities and limitations [12].

This work expands on previous research by examining how K-8 students interact with AI opponents of varying difficulty levels in Tic-Tac-Toe. The analysis focuses on how students adapt to AI strategies, recognize patterns in AI behavior, and develop an understanding of AI-based decision-making. By evaluating gameplay interactions, movement tracking, and post-game surveys, this paper provides insights into the effectiveness of AI-driven games in early education and their potential to enhance AI literacy among young learners. To explore this hypothesis, we conducted an interactive study with 56 K-8 students, where they played against three distinct AI opponents of varying difficulty: Olivia (Easy), Emma (Medium), and Chris (Advanced). The students had full autonomy in choosing their AI opponent, and their gameplay experiences were analyzed through movement tracking, survey responses, and strategic decision analysis. This approach provided valuable insights into students' perception of AI intelligence, and their ability to adapt to AI strategies.

II. LITERATURE REVIEW

Tic-Tac-Toe, a classic two-player game, is widely used in education to introduce logic, strategy, and problem-solving. When integrated with AI, it becomes a powerful tool for teaching computational thinking and decision-making [13]. Integrating AI-driven educational tools has transformed learning methodologies, particularly in game-based learning. One study by S. Jain and N. Khera highlights that adapting Tic-Tac-Toe into an AI-driven experience reinforces educational paradigms and develops cognitive learning [14]. AI-powered games promote logical reasoning, outcome anticipation, and strategic decision-making [15]. Some studies show that AI-powered learning programs can improve test scores by up to 62% [16][17]. Additionally, AI-assisted game-based learning can predict student performance with high accuracy [18].

One of the key benefits of AI-powered Tic-Tac-Toe is its ability to improve critical thinking and cognitive development. The game requires students to analyze AI responses, adjust their strategies, and develop problem analysis. By interacting with AI, students deepen their understanding of AI decision-making principles. However, engagement levels differ across age groups. Elementary school students benefit from its simplicity as an introduction to AI concepts. High school students, however, may find it less stimulating. They often require more complex challenges to stay engaged [19]. Therefore, advanced AI applications and additional activities can enhance high school learning experiences.

Reinforcement learning and neural networks offer deeper insights into machine learning and help students connect basic gameplay mechanics to more advanced applications [20][21]. Decision-making algorithms further strengthen the educational value of AI-driven Tic-Tac-Toe by promoting interactive, strategic gameplay. For example, the widely used minimax algorithm enables optimal decision-making and teaches structured problem-solving approaches [22][23]. Also, reinforcement learning and neural networks extend AI capabilities by learning from past experiences, giving learners a clear view of how AI adapts and refines its strategies. These algorithms are observed in AI Chess games.

Educators can also use decision trees to assess a child's learning progress by identifying areas where students consistently make suboptimal moves. The analyzed data helps educators implement targeted interventions to improve students' strategic thinking [24]. Decision trees effectively teach students the logic behind AI predictions which bridge the gap between theoretical concepts and practical applications.

In addition to decision trees, advancements in image processing provide new opportunities to track student progress in AI-powered Tic-Tac-Toe [25]. By analyzing changes in a child's gameplay over time, image processing techniques such as object detection or heat map analysis offer educators a data-driven approach to assessing student development. AI-powered image recognition can monitor decision patterns, learning curves, and adaptive strategies. This allows teachers to customize lesson plans based on individual learning trajectories [26][27]. What begins as a simple AI-driven game transforms into a powerful tool for cognitive skill assessment and personalized learning.

While Tic-Tac-Toe AI games effectively introduce students to AI principles, their long-term impact on AI learning and career development remains uncertain [28]. Studies suggest that while initial engagement levels are high, it is unclear whether this translates into sustained interest in AI or improved academic performance in advanced AI courses [29]. In addition to improving engagement, AI-driven Tic-Tac-Toe teaches students about the limitations of AI. While AI can calculate the best moves based on the current game state, it cannot predict human decision-making with absolute certainty. This aligns with findings by F. Pedro, M. Subosa, A. Rivas, and P. Valverde, which emphasizes the limited nature of AI in educational contexts [30]. Recognizing these constraints helps students develop a more meaningful understanding of AI. It teaches them that AI decision-making is structured but still influenced by the unpredictability of human behavior [31]. Given these complexities, longitudinal studies could provide valuable insights into how early exposure to AI through interactive games influences students' academic trajectories in STEM fields and their eventual career choices [32][33].

III. METHODOLOGY

The design of the Tic-Tac-Toe AI game was created as an interactive, user-friendly, and educational tool. A significant aspect of the game design was its simplicity, with straightforward visuals and easy interactions so that children of all ages could play in one to three minutes overall. By playing against the computer AI characters, children can observe AI's moves without being involved in technical details. The game board consists of a 3x3 grid where each cell is initially blank and turns into an 'X' or 'O' whenever a move is made by the player or the AI. The player's moves are represented by 'X', while the AI's moves are represented by 'O'.

A. *Promoting Engagement*

As part of our mission to engage and educate children in the realm of AI, we created an attractive and informative trifold poster as shown in Fig. 1. This promotional tool captured students' curiosity and encouraged interaction. The study took place at a public K-8 school in an urban setting. Students participated in different grade levels. We introduced the game to all groups through a brief one to two minutes session using the trifold poster. This short introduction was designed to spark interest without overwhelming the students.

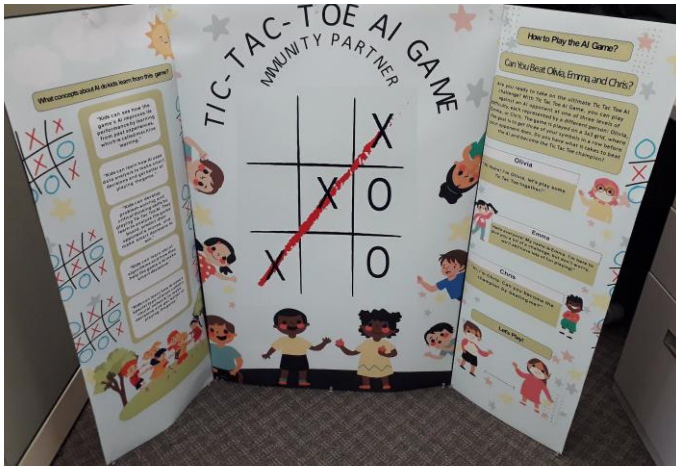

Fig. 1. Tic-Tac-Toe Trifold poster; the right-side features AI characters Olivia (Easy), Emma (Medium), and Chris (Advanced). The center showcases a diverse representation of players with an overall visualization of Tic-Tac-Toe. The left-side provides useful information on how the game works and its benefits for children.

The poster prominently featured and introduced the AI characters, Olivia, Emma, and Chris. This allowed the players to familiarize themselves with the characters before diving into the game. Each character had a unique identity and backstory. This encouraged players to engage with them on a more personal level. However, we intentionally omitted information about the characters' associated difficulty levels on the poster. This design choice was meant to evoke curiosity in players. It motivated students to play against each character and explore their unique play styles and difficulty levels. In addition, this poster aligned with our goal to celebrate diversity and inclusivity. The AI characters were carefully designed to represent a variety of ethnic backgrounds, including Black and Latinx communities. This broad representation not only served to make the game more relatable to a diverse group of players but also promoted a sense of inclusion and equality within the AI and gaming world. The children were asked to type their name and grade level with help into the designed interface of the computer game using a keyboard before starting. This personalized interaction encouraged player engagement and allowed us to adjust the game settings based on the age and educational level of the player. We incorporated a dynamic difficulty setting. Then, players could select the AI opponent based on their preferred challenge level. Players could freely choose an AI opponent from three difficulty levels: easy (Olivia), medium (Emma), and advanced (Chris). To provide a learning experience, Olivia, the easy level, incorporates random moves to offer a beginner-friendly challenge. Emma, the medium level, employs a basic version of the Minimax algorithm with a limited search depth (e.g., 3 moves ahead) and a simple evaluation function that allows players to experience a more structured decision-making process in AI. Chris, the advanced level, uses a highly optimized Minimax algorithm with alpha-beta pruning, a deeper search depth (e.g., 5 moves ahead), and a sophisticated evaluation function that considers multiple strategic factors, such as board control and positional advantage. We chose the Minimax algorithm because it is effective for deterministic, turn-based games in Tic-Tac-Toe. Unlike machine learning models that require large datasets for training, Minimax applies a structured decision-making process based on game rules. It guarantees optimal moves by evaluating all possible outcomes rather than relying on pattern recognition. These varied approaches enhance the game's replay-ability and serve as a step-by-step guide to help players develop an intuition about the complexity and strategy involved in AI. The structure of the Minimax algorithm is depicted in Fig. 2 below.

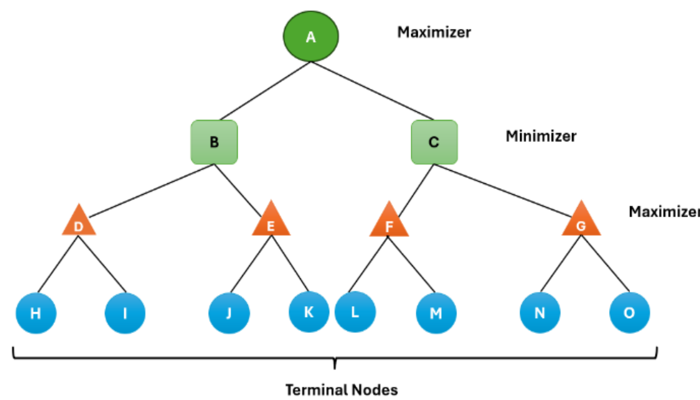

Fig. 2. Minimax decision tree illustrating the alternation between maximizer and minimizer nodes. Terminal nodes represent possible outcomes, with decisions propagated upward to determine the optimal move.

B. *Level of Difficulties*

Understanding the different levels of difficulty in the Tic-Tac-Toe AI game is the key to appreciating the underlying AI techniques implemented and the unique challenges they offer. Here, we will discuss more about the AI characters "Olivia", "Emma", and "Chris", who represent the different levels as AI opponents. The user interface is shown in Fig. 3.

Fig. 3: User interface with AI opponent options. Players enter their name and grade level before selecting an AI opponent: Olivia (Easy), Emma (Medium), or Chris (Advanced).

Olivia (Easy): In the "easy" level, represented by the AI character "Olivia", the AI does not use any advanced strategy to make its moves. The goal at this level is to make the game easy and enjoyable for beginners. Olivia's moves are mostly random, not guided by any sophisticated algorithm. This gives the K-8 students a fair chance to understand the game's rules and strategies without being overwhelmed by a strong AI opponent.

Emma (Medium): In the "medium" level, the AI character "Emma" uses a simplified version of the Minimax algorithm combined with alpha-beta pruning. Unlike Olivia, Emma does not make random moves. Instead, Emma evaluates all possible moves and assigns a score to each based on the current state of the game. The Minimax algorithm functions by recursively traversing the game tree. At each level, the process alternates between maximizing Emma's score and minimizing the human player's score. This alternation is based on the assumption that the human player will always try to maximize their score while Emma will try to minimize it. The traversal continues until it reaches a maximum depth or the game ends. Subsequently, the algorithm evaluates the game state and returns a score based on whether Emma won, lost, or tied. The score propagates back up the tree and guides Emma's decision on the best move. According to Fig. 4, it illustrates how the Minimax algorithm with alpha-beta pruning eliminates unnecessary branches. The dashed red lines indicate pruned moves, improving efficiency. The figure also illustrates how Emma evaluates game states while balancing between optimal and suboptimal moves due to the introduced randomness factor.

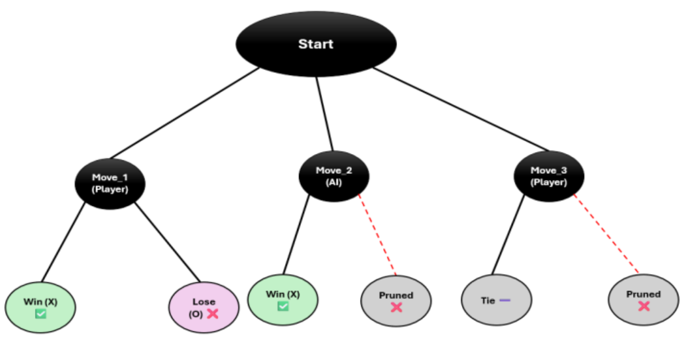

Fig. 4: Minimax decision tree with alpha-beta pruning (shown with red dashed lines). The diagram represents Emma's decision-making process.

To make the game a bit easier for the human player, the depth of the game tree searched by the algorithm is limited. This reduces the AI's look-ahead capacity and makes it less strategic than the hardest level. Plus, Emma's move choices are not always optimal. The variable "*move probability*", set to a value of 0.7, introduces a degree of randomness in Emma's decisions. If a random number between 0 and 1 is less than "*move probability*", Emma makes the optimal move. If the random number is greater, Emma makes a random move. This means there is a 70% chance that Emma would make the optimal move and a 30% chance she would make a random move, which adds an element of unpredictability to the game.

Chris (Advanced): In the "advanced" level, the AI character "Chris" utilizes the full power of the Minimax algorithm. Chris's moves are entirely strategic and are decided by the Minimax algorithm without the limitations imposed on Emma. This means that Chris always selects the move with the highest chance of winning. The strategy assumes the human player also plays optimally. The advanced level is the most challenging and is designed for players who have mastered the game rules and basic strategies and are ready for a tougher challenge. The difficulty at this level lies in the AI's ability to look ahead and plan its moves strategically. This difficulty level forces the human player to think more critically about their own moves. Given Chris's advanced strategic capabilities, the human player would never be able to beat Chris, the best possible outcome for the human player would be a tie. It should be clarified that the interface and AI character's function have been designed via Jupyter Notebook and Python programming.

C. *Data Collection*

The study was a part of a larger initiative at a public K-8 school located in a mid-sized city in the Northeast USA, involving five different projects, each with the objective of introducing AI concepts to students in an engaging exhibition [34][35]. The students participating in this project were 1st, 6th, 7th, and 8th graders, totaling 56 students. At the onset of the project, the students were quickly introduced to the objectives and details via a trifold poster presentation lasting 1-2 minutes. Following this brief introduction, they proceeded to play the game. After their gameplay experience, the students filled out a post-assessment survey. This sequential order was deliberately chosen to ensure that the students' responses were informed by their firsthand experience with the AI game. The primary goal of the post-assessment was to gather insights into the students' perceptions of the game and to assess their grasp of AI concepts as influenced by this interactive encounter. All procedures and interactions were carried out with the approval of the Institutional Review Board (IRB) to ensure ethical considerations.

D. *Observations*

The post-assessment survey collected basic participant information, including name and grade level, along with four open-ended questions asked by the observer after the game. If participants were unable to write like the 1st graders, the observer recorded their responses. Older graders wrote their answers directly on the paper. The responses on the post-assessment survey helped to "*identify the AI character they liked the most*", "*Who is the mid-level AI character*", and "*whether they enjoyed playing more with a friend or a computer*". In the following, we took out some observations from each group specifically.

1st Graders (8 Participants): The younger students struggled more with distinguishing between different AI characters and the difficulty levels. Some perceived AI opponents to be more challenging than human opponents. Notably, these students showed a fondness for "Olivia," likely due to a higher win rate. The preference correlates with their level of challenge and success.

6th Graders (16 Participants): This group showed a robust understanding and recognition of the different difficulty levels in the AI characters, which affirms the project's effectiveness. This group's feedback highlighted that they learned to understand AI moves and "Chris" was identified as the most challenging AI opponent, whereas "Olivia" was deemed the easiest.

7th Graders (12 Participants): Some students from this grade perceived the AI's decision-making capabilities as superior to human intelligence, with comments highlighting the AI's perceived intellectual superiority. This indicates the effectiveness of the AI's decision-making algorithm in presenting a challenging opponent.

8th Graders (20 Participants): These students demonstrated good recognition of the different difficulty levels and AI characters. They could easily identify "Olivia" as the easiest and "Chris" as the hardest level. Despite their skill, they showed a preference for playing against human opponents and believed that humans offer more challenging and strategic gameplay.

An interesting observation across different grades was the varied perception of AI's intelligence and capabilities. While some students considered the AI opponent to be smarter than a human player, others preferred the challenge and strategic depth offered by human opponents. This variation in perception and preference highlights the importance of offering diverse difficulty levels and character traits in AI design to cater to a wide range of player skills and interests.

IV. Strategy Analysis

Our analysis went beyond evaluating students' understanding of AI concepts. The investigation focused on strategic gameplay behaviors observed in both AI opponents and human players. To perform this analysis, we utilized a combination of image processing techniques and spatial data interpretation. It should be noted that due to the lack of screen recorders data, the strategy analysis was conducted specifically for the 1st grade group with 8 participants. This consideration allowed us to understand the foundational strategies and perceptions they held towards AI. This was largely due to the availability of screen recording data for this particular group, which provided an invaluable resource for accurately tracking and assessing game play strategies. To add this, it is important to state that the names provided in this paper are pseudonyms. This measure was taken to ensure confidentiality and align with ethical research practices.

A. *Movement Tracking*

We made use of the labelImg technique, a graphical image annotation tool that enabled us to precisely track and document each move made by the players during the game. Through this technique, we could create bounding boxes around the individual spaces on the Tic-Tac-Toe grid where the players (AI and human) made their moves. The process involved marking the specific locations of each move on the screen. Each marked location or move was assigned a sequential number. Odd numbers represented the children's moves as they were the beginner, and even numbers represented the AI's moves. This sequential labeling helped to differentiate between the moves of the AI and the human players. The bounding box method or labelImg, more than simply marking the moves, allowed us to collect all interaction data about the game play strategies. By identifying the boundaries of each box (which corresponded to a move made on the Tic-Tac-Toe grid), we could pinpoint exactly where each player made their moves as depicted in Fig. 5. This approach facilitated an in-depth analysis of the strategic choices made by each player during the game. In our examination of the game play strategies, we observed a discernible differentiation in AI and human approaches. The AI's moves, dictated by the specific algorithm it was built upon, tended to follow a logical and consistent pattern, maximizing its chances of winning or drawing the game. The children's strategies were not always as systematic or consistent. Their choices were influenced by their understanding of the game rules, their ability to plan and think ahead, and their ability to learn from previous moves. Some children exhibited a clear understanding of the game mechanics and were able to employ strategic moves, while others played more randomly, possibly due to a less comprehensive understanding of the game's strategies.

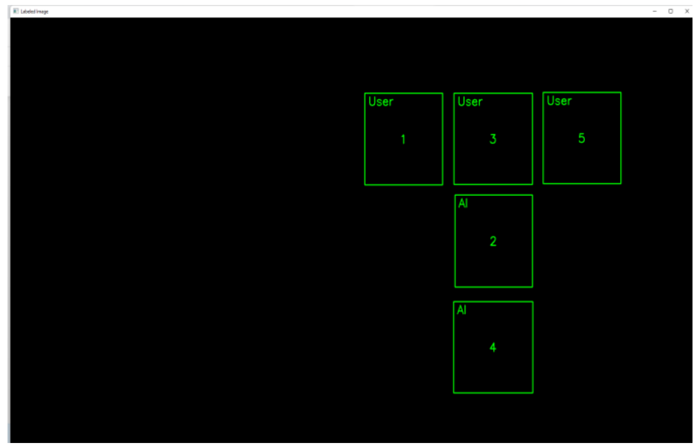

Fig. 5: Annotated example of Tic-Tac-Toe player and AI gameplay strategies using LabelImg. The green bounding boxes represent individual moves, with odd sequences (1, 3, 5) for the children's (User) moves and even sequences (2, 4) for the AI's moves.

B. *Spatial Distribution of Moves*

According to Fig. 6 in the following, the distribution of moves during game play in the 1st grade group reveals a clear preference for specific squares on the board, notably those in the first row's left and middle sections. Concretely, these favored squares may be perceived as providing a strategic edge, or children may be mimicking successful moves from their AI opponents. Alternatively, visual or spatial cues in the game design might guide the children's choices, or the simplicity and natural appeal of these positions could align with young players' cognitive preferences. This intricate pattern provides valuable insights into the decision-making processes of young players. The analysis reflects a blend of strategic understanding, observational learning, design responsiveness, and cognitive adaptation within an AI-mediated gaming environment. Interestingly, we observed that participants from other grade levels also tended to favor these specific squares when starting the game. However, due to data limitations, we can only confirm this pattern for 1st-grade students with certainty.

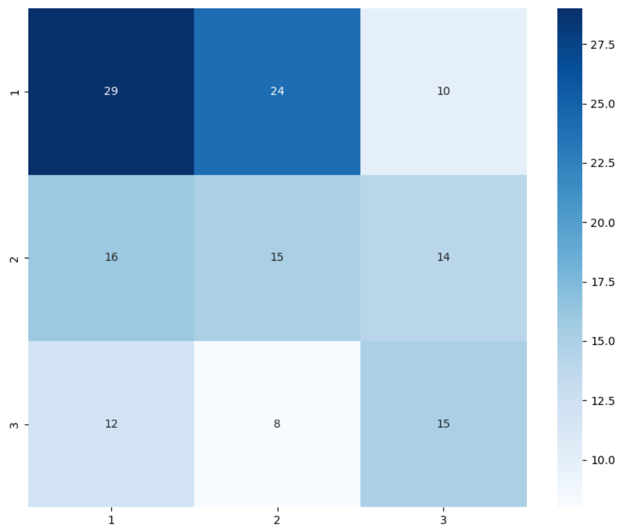

Fig. 6: Distribution of moves by 1st graders showing a preference for the Tic-Tac-Toe board's top-left and center squares. This pattern suggests a strategic inclination or mimicry of successful AI strategies, potentially influenced by visual cues or cognitive biases towards certain positions.

C. *Performance Analysis*

We chose to examine the performance of one of the 1st-grade participants, Caleb (pseudonyms name), throughout his gameplay. The reason for this focus on Caleb was twofold: Firstly, he was one of the few participants who engaged with all AI opponents, unlike many others who did not face off against every AI character. Secondly, by concentrating on a single participant's interactions across the entire spectrum of AI opponents, we aimed to glean more detailed insights into how a young candidate would adapt and respond to varying AI strategies. Caleb's trials encompassed five distinct interactions against all of AI opponents. His performance has been meticulously recorded and analyzed, with each trial outcome being assigned a specific value: winning = 1, losing = 0, and tie = 2. This analysis provided a structured case study of learning progression. Caleb’s engagement with all AI opponents offered a clear view of strategy adaptation in a young player. These results are visually represented in Fig. 7 below.

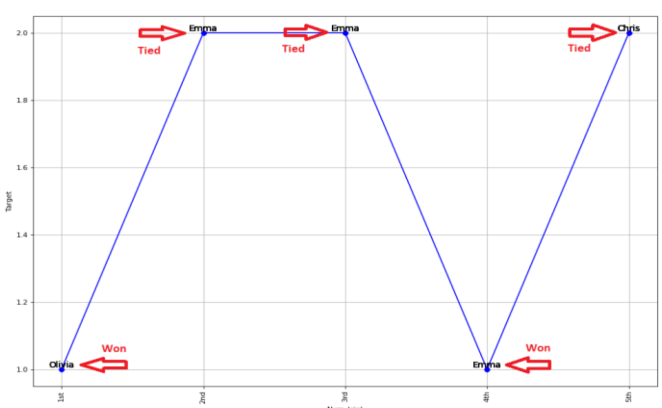

Fig. 7: Caleb's performance shows an initial win against the least complex AI and ends in a strategic tie with the most advanced AI and the progression represents adaptability and learning through increasing game difficulty.

Trial 1: Caleb started strong with a win against Olivia. The result reflects an immediate grasp of the game's mechanics and demonstrates an ability to capitalize on the AI's lack of strategic play.

Trials 2 & 3: Caleb faced Emma, a more challenging opponent. Both trials ended in ties. The results suggest a well-matched strategy against Emma's medium difficulty level.

Trial 4: Against a repeated AI opponent; Emma, another win was achieved by Caleb in the third effort. This trial indicates consistency in Caleb's approach and possibly a refinement of strategy based on his previous experience with Emma.

Trial 5: Against Chris, the hardest AI opponent. Caleb managed a tie which showed a maintained level of performance. This may reflect a deeper understanding of the game and an ability to adapt to the higher complexity presented by Chris's strategic play.

Technically, Caleb's game play across five trials offered a revealing insight into a child's learning and adaptation process in an AI-enriched environment. Beginning with a win, followed by two ties, and another win, his performance demonstrated a resilience and an ability to adjust to different AI opponents. His consistent results, devoid of any losses, hinted at a continuous refinement of strategy and possibly an understanding of the AI's behavioral patterns within the game. His experience illustrated how AI-based games empower strategic thinking. The interaction also built a broader awareness of AI functions. Through engaging with various AI characters, Caleb's game play served as an interactive journey. The experience highlighted adaptation, collaboration, and intuitive learning within an AI-driven educational framework.

V. Result & Discussion

In the broader exhibition, the Tic-Tac-Toe AI game project stood out as one of the most engaging activities. This AI game remained distinct even among other innovative exhibits. ChemAIstry, for instance, was an interactive software tool which allowed students to learn about lab safety through machine learning [36]. They would select objects deemed safe for a chemistry lab and train the model to classify items, thus directly engaging with the concept of AI learning and classification. The Ask Me Anything (AMA) booth featured a ChatGPT-powered chatbot limited to discussing child-friendly topics such as Astronomy and Sneakers [37]. Its design provided students to witness the capabilities of AI in understanding and maintaining topic-specific dialogues. And the AI for Self-Driving Car simulation provided an experiential understanding of how AI can be used for societal benefits, such as in autonomous vehicles. Students explored the ethical implications of AI through role-playing. They learned the importance of diverse data in training AI models. Each of these exhibits shared the common thread of interactive learning, but the Tic-Tac-Toe AI game project was particularly noted for its balance of education and entertainment. It resonated with its target audience and provided a hands-on approach to understanding AI. The comprehensive analysis of Tic-Tac-Toe AI project illuminated its potent effectiveness in achieving its pedagogical objectives. The amassed data, encompassing post-assessment responses and a nuanced strategy analysis, furnished significant insights into students' perceptions and comprehension of AI principles. The results revealed that the game engaged students effectively and enabled them to discern and differentiate AI characters based on their respective difficulty levels. Among the AI characters, Chris was identified as the most popular and challenging adversary. The study's strategy analysis further showed the students' decision-making processes, pinpointing a consistent inclination for particular squares on the game board. During the testing phase, insights into the children's interaction with the system became especially pronounced. They displayed a plethora of strategies to outsmart the AI opponents. While some began with seemingly random decisions, a deeper familiarity with the AI characters led them to fine-tune their approaches. For instance, they mastered the art of leveraging Olivia's unpredictable moves and adeptly responded to Emma's more reactive strategy. However, the matches against Chris were especially challenging. The students had to plan several moves in advance due to its forward-thinking gameplay. Interestingly, some students took the strategies they had cultivated against Chris and attempted to apply them, perhaps unnecessarily, when facing Olivia and Emma. This might have stemmed from their eagerness to proclaim a win, the fervor to shout "I won!" or "Chris is unbeatable!" was palpable. A competitive spirit thrived among the students. They were motivated by outplaying the AI. Demonstrating their skills to peers also encouraged them to assert superiority in the gaming arena. This competitive drive was further outlined by the post-assessment survey results. An overarching sentiment emerged: many students expressed a preference to challenge their friends rather than the AI. This inclination could potentially be attributed to their inherent desire for competition and to prove their mettle against familiar adversaries. Given that Chris (the AI opponent) is unbeatable, a tie against Chris is considered as a success, akin to a win. It is worth noting that the accuracy of the decision model for the 1st grade group reached an overall score of 66%. The following TABLE I. represents the success rate for 1st graders.

TABLE I. 1ST GRADER'S SUCCESS RATE AGAINST THE AI OPPONENTS

Username	*Num of Prompts*	*Olivia (Easy)*	*Emma (Medium)*	*Chris (Advanced)*
David	8	69%	29%	N/A
Ethan	5	100%	N/A	71%
William	6	N/A	17%	N/A
Michael	2	100%	N/A	N/A
Mason	4	100%	100%	62.5%
Caleb	5	100%	29%	100%
Jacob	3	75%	N/A	N/A
James	10	100%	N/A	N/A

We have compiled TABLE II. which provides predictions of the next prompt by the decision tree model. To prevent the top Tic-Tac-Toe player from being identified by gender, we assigned pseudonyms to all players. This approach maintained a uniform gender identity across the board.

TABLE II. DECISION TREE PREDICTIONS FOR THE AI'S NEXT PROMPT

Username	*Olivia (Easy)*	*Emma (Medium)*	*Chris (Advanced)*	*Accuracy*
David	Win	Win	Unable to Predict	61%
Ethan	Tie	Unable to Predict	Tie	69%
William	Unable to Predict	Lose	Unable to Predict	45%
Michael	Win	Unable to Predict	Unable to Predict	100%
Mason	Tie	Tie	Tie	50%
Caleb	Tie	Tie	Tie	57%
Jacob	Win	Win	Unable to Predict	40%
James	Win	Unable to Predict	Unable to Predict	100%

VI. CONCLUSION

Valuable insights were gleaned into children's learning trajectories and interactions with AI. Although certain limitations must be acknowledged. The availability of only one recorded screen restricted an in-depth analysis of the children's decision-making processes, while the small sample size N = 56 students) and the confinement of the study to a single educational institution, may have impacted the generalize ability of the findings. Future studies may benefit from a broader data collection, including screen recordings of all participants, a more extensive sample size, and the inclusion of diverse educational settings. These improvements would enrich a comprehensive understanding of the effectiveness of AI-based games in teaching AI concepts to children.

VII. ACKNOWLEDGEMENT

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