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GAMIFYING EARLY MATH EDUCATION: AN INNOVATIVE AI GAME FOR CHILDREN

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ABSTRACT

Aim/Purpose	This paper aims to address the increasing demand for creative methods in childhood education by integrating technologies like artificial intelligence (AI) and game-based learning. To make arithmetic learning more interesting, the project focuses on creating an AI game and investigates its acceptability and efficacy.
Background	This study shows how traditional math education may be transformed by combining AI-driven tools with game-based learning to increase student engagement and enhance learning outcomes.
Methodology	The study included the development of a new AI math learning game and used qualitative feedback and quantitative analysis through pre-assessments and post-assessments to gauge the tool's efficacy.
Contribution	The study presents a new AI game for math learning and offers empirical support for the efficacy of the same.
Findings	Students' test scores increased by an average of 6.03 points (SD = 2.2), indicating a considerable improvement in their math abilities. Instructors noted that

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	the game successfully kept students' attention and enhanced their ability to concentrate on mathematical ideas.
Recommendations for Practitioners	Incorporating game-based learning tools into the curriculum and the use of AI are recommended to cater to diverse skill levels and learning speeds.
Recommendations for Researchers	Conducting studies to assess the long-term impact of AI-powered learning and the integration of game-based learning in higher education is recommended.
Impact on Society	The study throws light on the transformative potential of game-based learning and AI in modernizing traditional teaching methods. These tools can contribute to higher engagement and betterment in the learning experience for students.
Future Research	In the future, research toward expansion into subjects such as science and language arts and the incorporation of virtual and augmented reality can further enhance the learning experience.
Keywords	artificial intelligence, game-based learning, primary education, interactive learning, arithmetic learning

INTRODUCTION

The quick adoption of technology in daily life has had a big impact on how children approach learning. Children enjoy digital forms of recreation, especially games. This prospect presents a powerful opportunity to integrate modern, interactive approaches in early childhood education. Technology is becoming increasingly significant in education, and the integration of these modern approaches can not only foster creativity and critical thinking skills but also increase engagement and interest in learning.

Among the many areas of education, mathematics offers special chances for creativity. Traditional arithmetic education is uninspiring or too obscure for many children. This may make it more difficult to stay motivated and understand fundamental ideas. Digital game-based learning (DGBL) can be used in this situation to create games that are both immersive and engaging while having pedagogical value. This study looks into the development of immersive and pedagogically successful digital instructional games using artificial intelligence.

This study focuses on how an educational math game driven by artificial intelligence (AI) might enhance children's math education and examines its efficiency and acceptability among educators and learners in various school types. With multiple levels, the game can offer an engaging method of teaching basic mathematical principles. Through engaging gameplay, game-based learning combines research-based educational approaches with the ideas of game artificial intelligence to enhance children's arithmetic knowledge while maintaining their intrinsic drive. Building an opponent with artificial intelligence maintains the spirit of competition and boosts participation.

The study also investigates how children perceive these tools and what influences early schoolers' use of digital learning games. It aims to show how the fusion of AI and game-based learning may transform traditional teaching approaches. The game's design aims to enhance math knowledge while preserving intrinsic motivation by fusing AI concepts with research-based instructional strategies. The results of the study, which are backed up by an extensive poll, show how popular and successful the game is with teachers and students in a variety of educational settings. The game's usefulness and ability to sustain students' interest in mathematical ideas were also commended by teachers. This study highlights how educational games driven by AI will influence education in the future.

This paper is structured as follows. First, a review of existing literature on digital game-based learning (DGBL) and AI applications in education. This is followed by a methodology section, which provides a detailed description of the game mechanics and rules. The incorporation of mathematics

learning within the game is then discussed, along with a detailed section on the AI component of the game, which uses Min Max learning. Next, the user interface and level design are outlined. The survey component is also presented, including participants, questionnaire design, and qualitative and quantitative testing. This is followed by the results section, which presents the findings from both quantitative and qualitative evaluations, highlighting the improvements in arithmetic performance and the feedback received on the game. Finally, the paper concludes with recommendations for future research and practical implementation.

LITERATURE REVIEW

The integration of games in education has long been investigated as a way to improve student engagement, retention, and conceptual understanding in the classroom.

The pedagogical potential of games in education

According to research, digital brain games can help young learners enhance their cognitive and reasoning skills. Bottino et al. (2013) investigated the connection between children's academic achievement, digital mind games, and their capacity for thinking. According to the study, early interventions utilizing digital games with a logic component may improve children's ability to solve problems and, as a result, their academic performance. The LOGIVALI Test is used in an experiment with 60 elementary school students in Italy to evaluate their reasoning skills. The study investigates the distinct thinking skills that various student categories exhibit according to their academic performance levels (Bottino et al., 2013). Similarly, Qian and Clark (2016) conducted a meta-analysis of game-based learning (GBL). They concluded that well-designed educational games significantly outperform traditional instruction in fostering higher-order thinking skills, particularly in STEM fields.

Along with cognitive benefits, games also promote engagement through interactive and adaptive learning environments. Cabatuan (2019) developed Dismath, a gamified instructional tool for teaching propositional logic to computer engineering students. The study created an AI opponent using minimax tree search and alpha-beta pruning, drawing inspiration from the Damath board game and guaranteeing an engaging and difficult learning environment. The approach highlights how engaging and involved board games are as a way to improve learning. By fusing AI technology with strategic thinking, Dismath provides a novel method of teaching logic through gameplay that improves learning results in computer engineering education. Santoso and Supriana (2014) proposed games with turn-based strategy and incorporated reinforcement learning through Minimax algorithm. It uses dynamic scripting for specifying the game action.

Research conducted by Ke (2019) further supports game-based learning by demonstrating that adaptive game-based learning systems improve motivation and mastery in complex subjects like mathematics and programming. The study results indicated that the gaming group performed significantly better than the non-gaming control group in the math context problem-solving test.

Beyond traditional disciplines, games are being used more and more in a variety of educational fields. For example, to improve player decision-making, Padmanabhan et al. (2019) investigated the use of the TRON game as a learning tool by combining supervised learning and Voronoi heuristics. The study highlights the value of active learning strategies, which combine interactive, visual, and aural components to produce captivating learning environments. It highlights the trend toward offline learning that mimics online settings and promotes active learning strategies that include interactive, visual, and aural components. One useful method for enhancing these learning environments is gaming, especially the TRON game. Automating TRON, a complicated quadrilateral grid-based game with real-time dynamics, is challenging. To improve player strategies and decision-making in TRON, the study proposes using supervised learning and Voronoi heuristics to train bots. It also investigates the use of Voronoi heuristics to optimize player and bot motions, emphasizing strategic decision-making and gameplay prediction (Padmanabhan et al., 2019).

To improve the calibre of instructional simulations, Drageset et al. (2019) enhanced procedural level creation in the General Video Game AI (GVGAI) framework. Procedural content generation enables adaptive learning experiences by tailoring difficulty and content dynamically. The study creates adaptive learning settings by introducing a meta generator. It adjusts the random level-generating parameters based on AI play-testing. This meta generator improves the parameterized version of the random generator. To assess the quality of generated levels, the study proposes a composite fitness evaluation function based on AI play-testing. Comparisons with baselines for random and constructive generators in three GVGAI games (Butterflies, Freeway, and The Snowman) show that the meta generator performs on par with or better than the baselines. This suggests that it has the potential to improve level generation in the GVGAI framework. The study showed the importance of procedural content creation in guaranteeing scalability and diversity in educational game design.

More recently, work like Salta et al.'s (2021) highlights the benefits of cooperative AI contests like Geometry Friends, which replicate intricate physics-based settings that call for cooperative AI behaviors, situational awareness, and motion planning. The effects of these AI-driven tactics in an educational setting, however, are mostly unknown. Although Paduraru and Paduraru (2019) go one step further and use behavior trees and genetic algorithms to automate game difficulty management and behavior generation, little is known about how these methods can be directly applied to the development of cognitive skills and student learning progression.

Rather than concentrating only on optimal play, Zhao et al. (2020) investigated how intelligent agents might simulate human-like decision-making by striking a compromise between skill and style. This poses a crucial query: how can AI-powered games be modified to maximize learning retention and educational engagement in addition to providing entertainment? The potential for adaptive AI frameworks to adjust game difficulty based on player progress remains largely theoretical, with few concrete implementations in formal learning environments.

Researchers have also examined the relationship between gaming habits and academic performance. A study by Anderson and Dill (2000) found that excessive video game play correlated with lower GPAs among students. It is, however, necessary to understand the difference between passive recreational gaming and intelligently designed educational gaming frameworks. The potential of AI-enhanced learning games is truly vast and needs to be explored.

AI-driven learning strategies: minimax and beyond

Artificial intelligence has played a crucial role in enhancing the intelligence and adaptability of educational games. One of the most widely studied AI approaches in game-based learning is minimax search with alpha-beta pruning. Mozaffari et al. (2015) applied this technique in the Loop Trax board game, optimizing player strategies through hardware-based acceleration on an FPGA. The paper presents a hardware architecture for a Loop Trax board game solver. The design utilizes a minimax algorithm with alpha-beta pruning to optimize the player's gaming strategy. Key components of the architecture include the Minimax Controller, Path Analyzer, Win Predictor, and parallel memories for efficient data storage and analysis. The Altera DE2 platform was used to implement the design, which won Iran's 2nd National Digital System Design Contest, achieving a clock speed of 50MHz. For lowering data storage needs and streamlining game state judgments, the path-based memory approach is emphasized. The research presents a viable hardware solution for the Loop Trax game, highlighting performance, efficiency, and scalability

Similar to this, Maksim et al. (2020) showed how game AI approaches may be applied outside of standard video games by creating a software library for Tic-Tac-Toe that uses neural networks to improve AI decision-making. The study placed a particular focus on artificial intelligence in the game of Tic-Tac-Toe. The authors address the creation of a software library for building artificial neural networks. To arrange computations and carry out mathematical operations, the software library makes use of the NumPy library. For categorization and decision-making tasks in games like Tic-Tac-Toe,

the library has components for implementing the sigmoid activation function, the Rosenblatt perceptron, and artificial neurons.

Recent advancements have hybridized minimax with other techniques. Baier and Winands (2015) researched the hybridization of Monte-Carlo Tree Search (MCTS) with minimax in the context of sophisticated game-based decision-making, demonstrating that MCTS-minimax hybrids performed better than classic MCTS in strategic game situations such as Connect-4 and Breakthrough. This study demonstrates how AI-driven learning agents might improve game-based instructional tactics. The article shows experimental findings in the Connect-4 and Breakthrough domains and suggests three methods for integrating minimax with MCTS. In the test domains, the recently suggested MCTS versions with minimax integration fared better than the conventional MCTS. The study outlines potential avenues for further investigation to improve the performance of MCTS-minimax hybrids in diverse gaming contexts.

Hooshyar et al. (2018) introduced a data-driven PCG framework for educational games that adapts content dynamically based on learner profiles. Their study demonstrated that such adaptive systems not only enhance motivation but also support more effective knowledge acquisition by tailoring game difficulty and content structure to individual needs. This research aims to bridge these gaps by investigating how AI-driven, minimax-based game environments can enhance learning outcomes while maintaining engagement.

Besides that, Pop et al. (2020) extended the use of minimax in traffic modeling by employing Markovian processes to anticipate lane selections. The suggested method seeks to optimize lane selection based on intended destinations and related expenses by employing Markovian processes. The study emphasizes how difficult it is to predict driver behavior and how crucial it is to take into account a number of parameters, including desired destination, road network overcrowding, and interactions with other traffic participants. To illustrate the usefulness of the suggested strategy, a case study of a crossroads in Timişoara, Romania, is provided. The efficiency and efficacy of the suggested approach are demonstrated by the paper's comparison of the outcomes of the minimax strategy with those of other algorithms, such as Dijkstra's optimum algorithm. However, gaps remain in applying these AI techniques to pedagogically structured environments. The direct impact of such systems is understudied.

Research gap and need for this study

The importance of games in education, from skill acquisition to cognitive growth, has been well examined in the literature to date (Connolly et al., 2012). However, little is known about how game-based AI methods and adaptive learning settings interact. Digital brain games can improve problem-solving abilities (Wouters et al., 2013). There is limited research on how algorithmic decision-making – specifically, minimax-based AI systems – might be used for organized education. Similarly, there are limited studies that provide empirical support for the ways in which AI-driven game mechanics affect long-term learning results. This research aims to bridge these gaps by investigating how AI-driven, minimax-based game environments can enhance learning outcomes while maintaining engagement. By combining adaptive difficulty mechanisms, AI-driven player modeling, and procedural learning pathways, this study seeks to reframe the discussion around gaming and education, distinguishing passive from active AI-driven educational experiences and evaluating the effectiveness of AI-enhanced game mechanics in fostering critical thinking, decision-making, and strategy formulation.

METHOD

This study presents an AI-powered game with the goal of enhancing the learning experience of mathematics for students in primary education. To study its effectiveness and adoption, a mixed-methods approach has been adopted for evaluation. The research design incorporated both quantitative and

qualitative methods to provide a comprehensive understanding of the tool's impact on student learning outcomes, engagement, and satisfaction.

System Overview

The core of the project centered around developing an AI-powered educational game designed to make mathematical learning engaging and effective for children. This comprehensive system integrates advanced AI techniques, interactive gameplay mechanics, and intuitive user interfaces to create a transformative learning experience.

Game mechanics and structure

This AI-powered educational game combines mathematics and strategy on a 5×5 grid-based board. The objective is to gain control of the most tiles while reinforcing fundamental math skills. The players take turns placing numbered tiles. A tile's power is determined by its numerical value, and adjacent lower-value enemy tiles are captured upon placement.

1. Game board and tile placement

The game takes place on a 5×5 grid consisting of empty slots where players place tiles. Two players participate: AI (Red tiles) and Human (Green tiles). At each turn, a player gets a tile with a random numerical value between 0 and 15. Players take turns placing a tile on an empty grid slot. Once a tile is placed, it retains the player's colour unless captured by the opponent. Once captured, the colour of the tile is converted to the capturing player's colour.

2. Capturing mechanic: How to conquer tiles

Tile capturing is the game's key strategy. When a tile is placed, it checks all four adjacent tiles (left, right, top, bottom). If any adjacent opponent tile has a lower number, it is captured and converted into the current player's colour. If an adjacent tile has an equal or higher number, it remains unchanged.

> Example: The board has a Green "4" tile (Human Player) placed at (2,2). The AI places a Red "6" tile at (2,3), next to the "4". Since "6" is greater than "4", the Green "4" tile turns Red. This mechanic rewards strategic thinking – players must carefully place tiles to maximize control while preventing opponents from making strong moves.

3. Turn structure: How a round works

The player (human or AI) places a tile on an empty slot. Tile capturing occurs: Any weaker adjacent opponent tiles are converted. The turn passes to the other player. The process repeats until the board is full. The player with the greatest number of tiles at the end wins.

4. Winning the game

The game ends when the 5×5 grid is completely filled. The player who controls the majority of tiles is declared the winner. Each Red tile belongs to the AI. Each Green tile belongs to the human player. The player with the highest tile count wins. Capturing many tiles early on is important, but players must also think ahead to avoid losing tiles to higher-numbered placements later in the game.

5. Incorporating math learning

The game consists of six levels, where each level introduces a mathematical challenge before a tile can be placed. Players must correctly answer a question to unlock their move. Table 1 describes the level mechanics.

Table 1. Level mechanics

Level name	Math concept	Gameplay change
Greater Than	Compare two numbers, pick the larger one.	Surrounding tiles with a smaller numerical value will be captured.
Less Than	Compare two numbers, pick the smaller one.	Surrounding tiles with a greater numerical value will be captured.

Level name	Math concept	Gameplay change
Addition	Solve an addition problem before placing a tile.	The correct answer allows tile capture. Tiles with smaller numerical values will be captured.
Subtraction	Solve a subtraction problem.	The correct answer allows tile capture. Tiles with greater numerical value will be captured.
Multiplication	Solve a multiplication equation.	The correct answer allows tile capture. Tiles with smaller numerical values will be captured.
Division	Solve a division problem before making a move.	The correct answer allows tile capture. Tiles with greater numerical value will be captured.

Example in Level 3 (Addition):

- The player wants to place a tile with a numerical value of **15**. The player chooses a location having a surrounding red tile with value **4.** This scenario is shown in Figure 1.
- The game asks: **"What is 15 + 4?"** This case is shown in Figure 2.
- If the player answers **19 correctly**, they can proceed to place a tile. Surrounding tile will be captured. Similar process is repeated for other tiles with value less than 15. It is shown in Figure 3.
- If the answer is incorrect, they **lose the tile**.

This ensures that math practice is integrated into every move, reinforcing learning while keeping the game engaging.

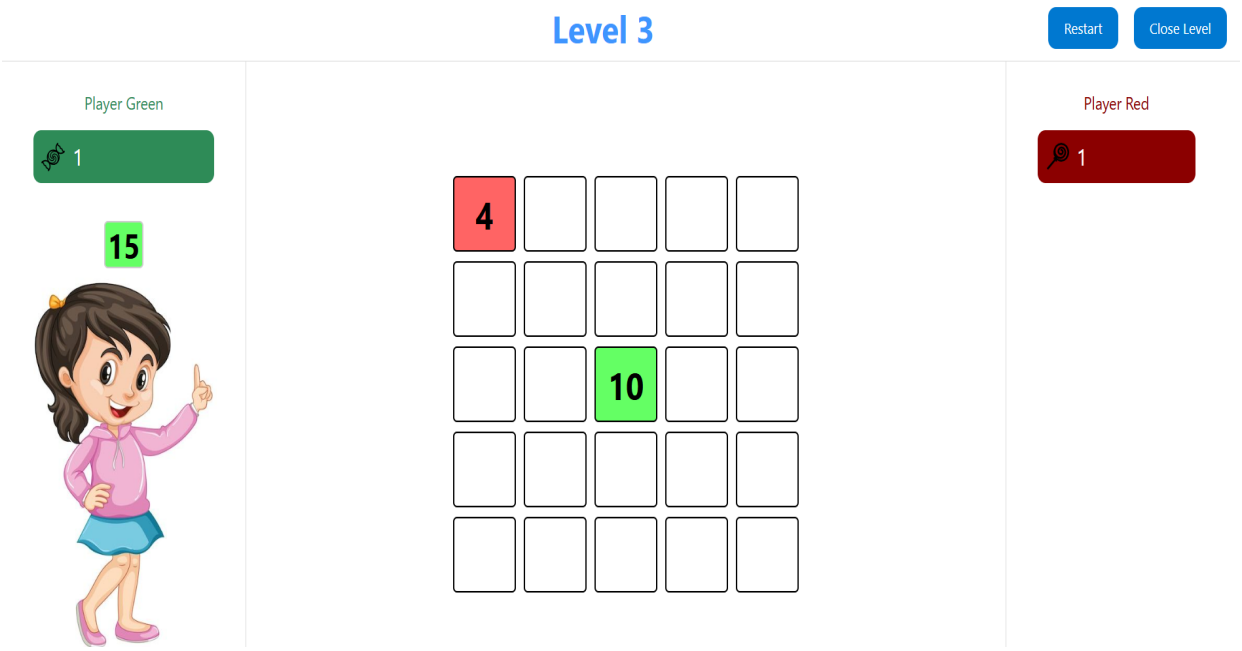

Figure 1. Player with current tile '15'

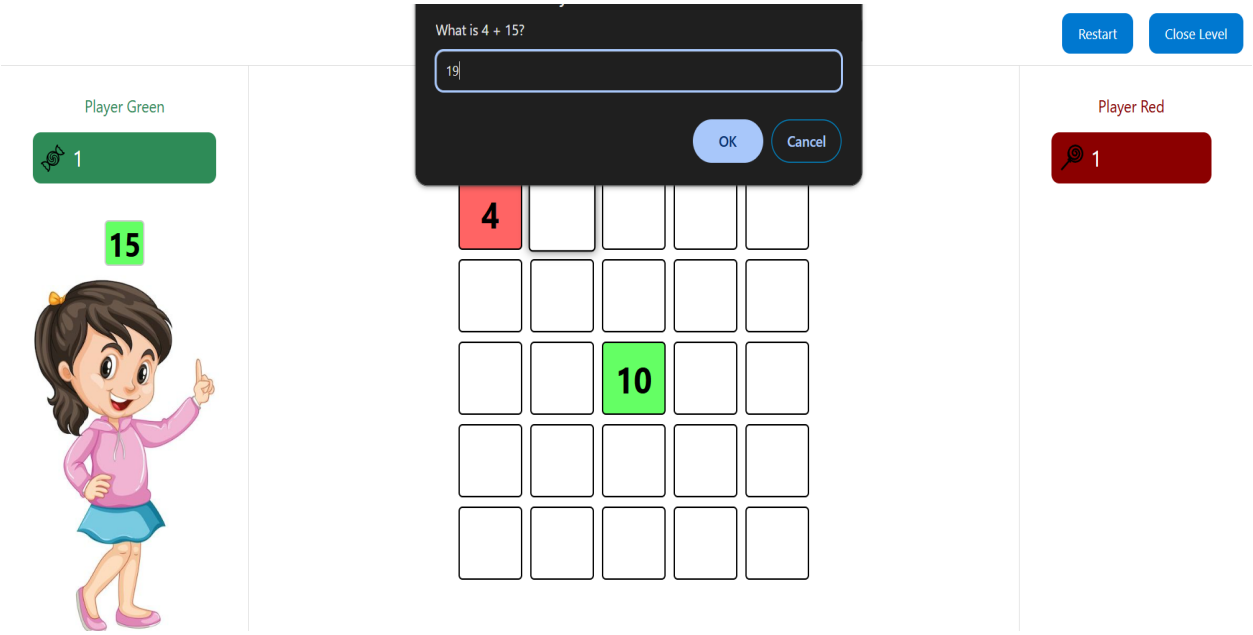

Figure 2. Addition problem given by system

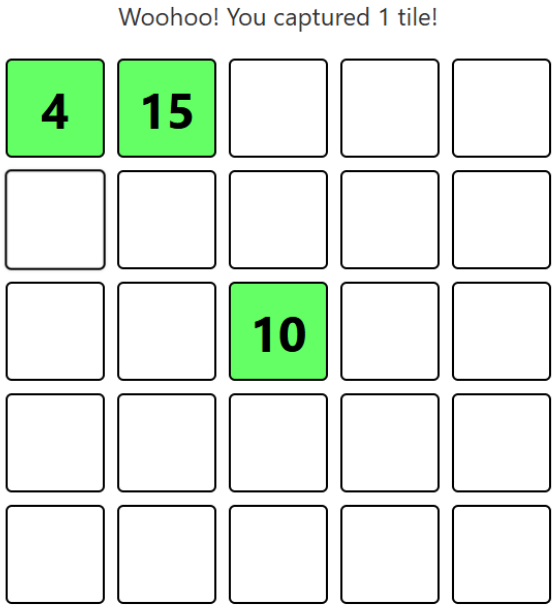

Figure 3. Opponent tile captured by player

AI-powered decision-making with minimax algorithm

The AI follows a structured search process, examining possible moves and their outcomes before selecting the most advantageous action. This is achieved using the minimax algorithm. The algorithm operates on the principle of minimizing the possible loss while maximizing potential gain. It systematically evaluates future moves, assuming that the AI plays optimally while the opponent also plays their best possible moves.

Minimax operates recursively, constructing a decision tree where each node represents a possible game state. It assumes:

- The AI (Maximizing Player) tries to maximize its score.
- The Opponent (Minimizing Player) tries to minimize the AI's score.

Typically, the algorithm explores all possible moves, evaluates the resulting board states at every turn, and backpropagates the best move to the AI's decision point. However, as the number of possibilities grows exponentially, an unrestricted minimax search becomes computationally infeasible.

Use of depth-limited minimax algorithm and pseudocode

With the help of the minimax algorithm, the AI opponent strategically selects moves to maximize its advantage while anticipating the player's best possible responses. Traditional minimax, however, is computationally expensive due to its exhaustive search across all possible moves. This challenge is soon discovered during the development stage, considering the grid size and the large number of possibilities. Traditional minimax proved to be extremely resource-intensive and time-intensive. As a solution, the algorithm is modified to employ depth limitation, allowing the AI to look ahead only a few moves.

1. **Depth Limitation:** Instead of exploring the entire decision tree, the AI searches up to a fixed depth of three levels, ensuring real-time gameplay without excessive computation.
2. **State Evaluation Heuristic:** Since minimax requires a way to assess non-terminal game states, a heuristic function assigns scores to board configurations, enabling the AI to make informed decisions. This game computes the difference in tile count as the primary evaluation metric.
3. **Move Simulation and Capture Logic:** The AI strategically places numbers on the board, assessing how placements influence tile captures based on the game's rules.

State evaluation and move selection

At each step, the AI evaluates board states based on the number of tiles controlled by each player. This implementation directly computes the difference in tile count as the primary evaluation metric.

1. **Tile Control Heuristic**
   The evaluation function simply counts the number of tiles controlled by each player. Given a board state, the AI scans through all tiles and assigns:
   - **+1** for each tile controlled by the AI ("red")
   - **-1** for each tile controlled by the human player ("green")

   The total score is then computed as:

   Score = (AI's tile count) - (Opponent's tile count)

   This straightforward metric ensures that the AI prioritizes moves that increase its own controlled tiles while reducing the opponent's presence on the board.
2. **Simulating Moves and Captures**
   When evaluating a move, the AI considers both direct placement and potential tile captures and places a tile in an available spot. If the placed tile has a higher number than adjacent opponent tiles, it captures them, converting them to AI-controlled tiles. Each captured tile increases the AI's score while reducing the opponent's score. This capturing mechanic is built into the simulation logic, where the AI checks each neighbouring tile and updates colours accordingly.
3. **Depth-Limited Lookahead**
   Instead of exploring the entire game tree (which would be computationally infeasible), the AI limits its search depth. At the maximum depth or if the board is full, the AI evaluates the state using the tile control heuristic described above. If the search depth is not yet reached,

the AI recursively simulates all possible moves, alternating between maximizing (AI's turn) and minimizing (opponent's turn).

4. **Move Selection Based on Minimax**
   The algorithm explores multiple possible moves and assigns a score to each. If it's the AI's turn (Maximizing Player), it selects the move with the highest score. If it's the opponent's turn (Minimizing Player), it selects the move with the lowest score.

Depth-limited minimax pseudocode

```
Function MINIMAX (board, depth, maxDepth, isMaximizing, currTileValue):
  // Evaluate the current board state
  scores = {"green": 0, "red": 0}
  For each tile in board:
    If tile is not empty:
      If tile is red:
        scores["red"] ++
      else:
        scored["green"]++
  // Base Case: Stop if maximum depth is reached or the board is full
  If depth == maxDepth OR All tiles are filled:
    Return scores["red"] - scores["green"]  // Return heuristic score
  If is Maximizing:  // AI's turn (Red)
    bestScore = -INFINITY
    bestMove = null
    // Loop through all available tiles
    For each empty tile in board:
      // Simulate AI placing a tile
      tempBoard = Copy(board)
      tempBoard[tile] = {number: currTileValue, color: "red"}
      // Simulate tile capture, neighbors are top, bottom left and right tiles
      For each neighbor in neighbors:
        If tempBoard[neighbor] is occupied AND tempBoard[neighbor].color is not "red" AND
          currTileValue > tempBoard[neighbor].number:
          tempBoard[neighbor].color = "red"  // Capture tile
      // Recursively evaluate the new board state
      score = MINIMAX(tempBoard, depth + 1, maxDepth, False, currTileValue)
      // Choose the best move for AI
      If score > bestScore:
        bestScore = score
        bestMove = tile
    // If at root level, return the best move instead of score
    If depth == 0:
      Return bestMove
    Return bestScore
```

```
Else:  // Player's turn (Green)
    bestScore = +INFINITY
    // Loop through all available tiles
    For each empty tile in board:
        // Simulate player placing a tile
        tempBoard = Copy(board)
        tempBoard[tile] = {number: currTileValue, color: "green"}
        // Simulate tile capture, neighbors are top, bottom left and right tiles
        For each neighbor in neighbors:
            If tempBoard[neighbor] is occupied AND tempBoard[neighbor].color is not "green"
AND
                currTileValue > tempBoard[neighbor].number:
                tempBoard[neighbor].color = "green"  // Capture tile
        // Recursively evaluate the new board state
        score = MINIMAX(tempBoard, depth + 1, maxDepth, True, currTileValue)
        // Choose the worst-case scenario to minimize AI's advantage
        If score < bestScore:
            bestScore = score
    Return bestScore
```

The AI does not simply pick random moves – it evaluates how many tiles it can control and prioritizes moves that increase its score. The capture mechanic is naturally embedded in the tile placement logic, ensuring that the AI strategically overtakes opponent tiles. The Depth-Limited Minimax approach ensures efficient decision-making while avoiding excessive computational load. This implementation, while relatively straightforward, results in strong, competitive AI behaviour that adapts dynamically based on the board conditions. Once all possible moves are evaluated, the AI selects the move with the highest expected gain.

React-based web application

Keeping in mind the need for compatibility across devices, the game was developed as a web application using React. React is a widely adopted JavaScript library for building user interfaces. React's component-based architecture allowed for modular and scalable development, while its efficient rendering capabilities ensured a responsive and dynamic experience. Figure 4 shows the gameplay experience.

Level design

The game features six distinct levels, each focusing on a fundamental mathematical concept. Each level was designed to align with educational standards, progressively increasing the level difficulty to maintain engagement and ensure skill development. Figure 5 shows the Web user interface showing Level Home.

Less Than Level: Players compare two numbers to identify the smaller value, supported by visual aids and interactive cues.

Greater Than Level: Similar to the less than level, this stage reinforces numerical comparisons by identifying the larger value.

Addition Level: Introduces basic arithmetic by challenging players to solve addition problems, building on prior concepts.

Subtraction Level: Demonstrates subtraction as the inverse of addition, encouraging players to calculate differences between numbers.

Multiplication Level: Introduces multiplication to strengthen understanding of products.

Division Level: Ends by presenting division as the opposite of multiplication, which tests players' ability to calculate quotients.

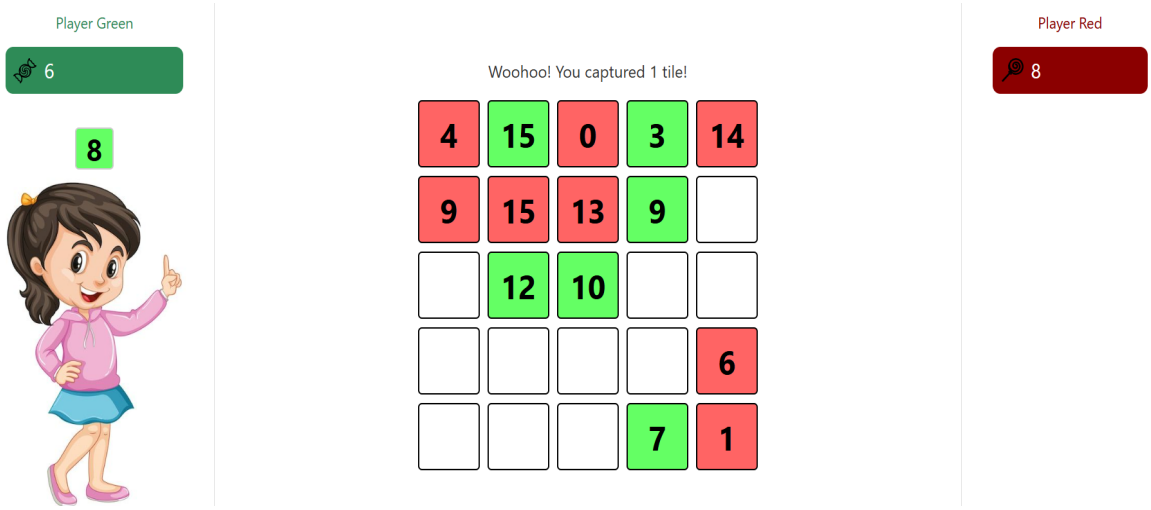

Figure 4. Gameplay experience

User interface and engagement

The user interface (UI) was designed with usability and engagement in mind. An immersive learning environment was produced with vibrant visuals, animations, and sound effects. Simple navigation made it easy for young learners to use the system. The user interface combines engaging games with instructional information and was especially designed to encourage continuous interest and motivation.

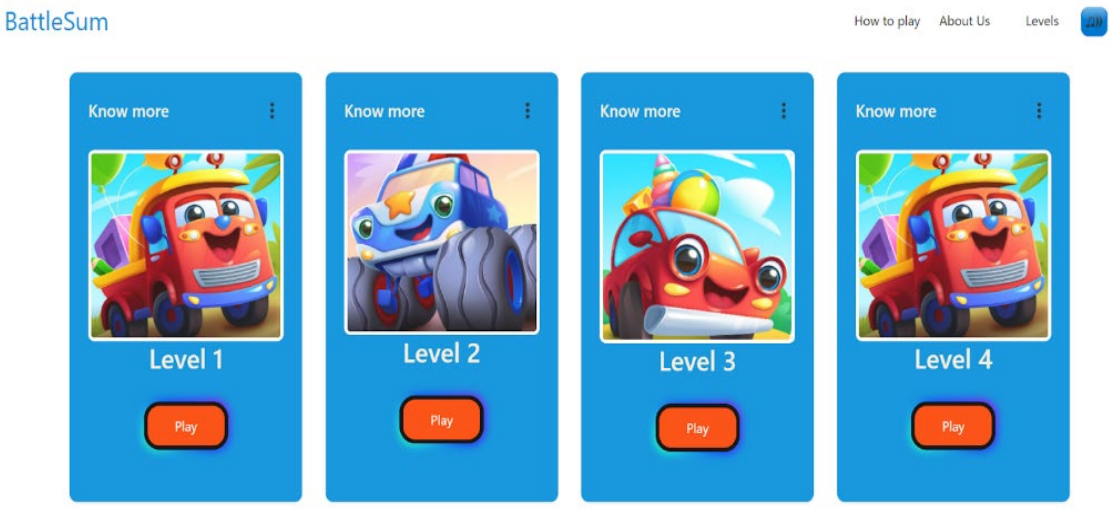

Figure 5. Levels and child-friendly UI

SURVEY

The study used a multifaceted way to assess the AI-powered math game's general reception, usability, and usefulness. Our study design comprised a thorough feedback survey to gather qualitative opinions from instructors and students, as well as pre-assessments and post-assessments to gauge quantitative gains in students' math proficiency. We were able to learn more about the game's impact as a consequence of this research.

In the first stage, elementary school pupils in Pune, India, participated in a survey. A thorough study was made possible by this mixed-methods approach, which included the collection of quantitative and qualitative data. Combining the two approaches allowed for a more thorough comprehension of the results, offering perspectives that would not have been possible with only quantitative data.

A questionnaire was employed to gather quantitative data, where students were asked to answer basic arithmetic questions. Following the survey, we engaged with the participants in discussions for qualitative analysis, allowing us to explore their opinions and experiences in greater detail. After this, our game was given to them to play for 15 days. After this time period, the test was conducted again.

This research methodology was employed based on the following research questions:

1. Can the AI-based game improve students' performance in arithmetic calculations?
2. What is the average improvement from Test 1 to Test 2, and how does it vary across schools?
3. How satisfied are the students and teachers with the game-based learning activity?

Participants

In this research study, primary section students were selected from a public, private, and a premium private education school. In addition to this, we consulted teachers from the school to understand the challenges faced by the students using traditional ways of learning.

A total of 157 students from three different schools providing public, private, and premium private education were selected for the survey. The general distribution was 53.8% male and 46.2% female. Figure 6 shows the gender distribution for the survey. Figure 7 presents the number of students selected from three types of schools: (1) private, (2) premium private, and (3) public. Figure 8 depicts a pie chart showing the school-type distribution.

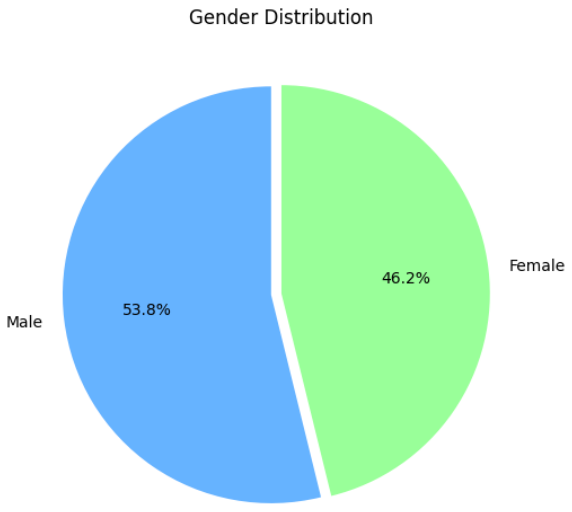

Figure 6. Gender distribution for survey

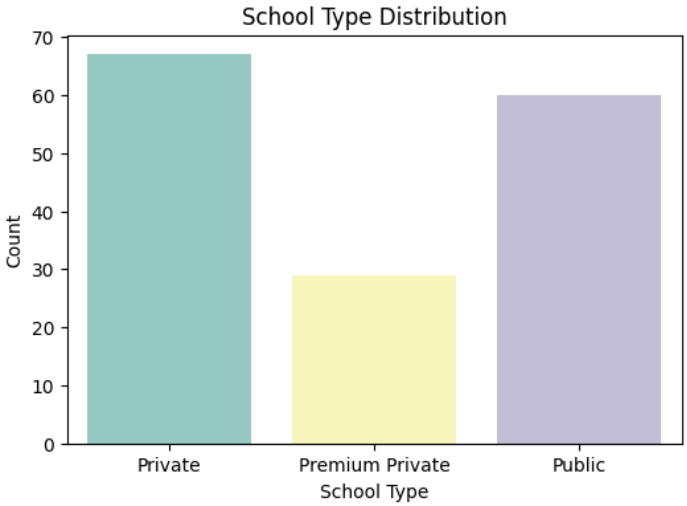

Figure 7. Count of students from different schools

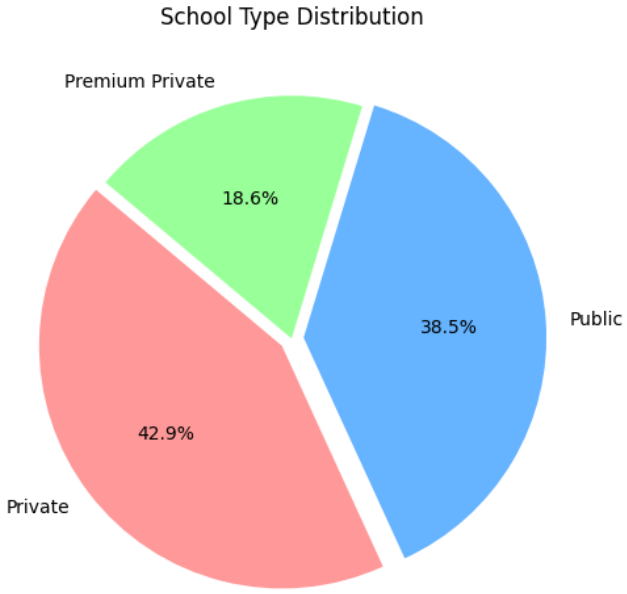

Figure 8. Distribution of students across different schools

Questionnaire design

A pre-assessment and post-assessment were conducted to evaluate the effectiveness of the AI game. Further, a questionnaire based on the Likert 5-point scale was provided to both students and teachers to evaluate the acceptance and satisfaction with the game.

Objective of the questionnaire:

The questionnaire was designed to evaluate the arithmetic proficiency of primary school students and to gain insights into their experiences with the educational arithmetic game. The primary goal was, first, to evaluate the students' arithmetic skills before and after interaction with the game; second, to collect qualitative feedback on their engagement and learning experiences with the game. The quantitative measures of mathematical skills and qualitative insights into the students' game interactions

provided a comprehensive understanding of the game's impact on learning outcomes and user experience.

Structure and format

Quantitative test

Students were asked to solve basic arithmetic problems, such as "What is 8 + 3?" with four possible answers to choose from. Similar arithmetic questions were asked after the students played the game, allowing for a direct comparison of their performance before and after using the game.

1. **Pre-Game Assessment:** This part focused on evaluating the students' initial arithmetic skills. It included basic arithmetic questions (e.g., addition, subtraction).
2. **Post-Game Assessment and Experience:** After the students played the game for five days, this section assessed any changes in their arithmetic skills and gathered feedback on their experiences with the game.

Qualitative test:

This questionnaire was based on the Likert 5-point scale. The game was evaluated for acceptance on the following four dimensions:

3. **Satisfaction**: Participants rated their overall experience with the game, reflecting how enjoyable and fulfilling they found the gameplay.
4. **Usability:** This metric measured how simple it was to use the game's features, comprehend its instructions, and navigate its UI.
5. **Engagement:** Participants were asked to rate the game's capacity to hold players' interest and attention across several sessions.
1. **Improvement:** After playing the game, participants' feedback on whether they felt they had made quantifiable progress in their math abilities was gathered.

Both teachers and students had the chance to share their opinions through the questionnaire, which yielded insightful information on the game's usability, acceptability, and effect on learning outcomes. The outcomes provide light on how well the game worked to create a stimulating and productive learning environment.

RESULTS AND DISCUSSION

This section presents the results acquired from the pre-assessment and post-assessment tests and satisfaction survey, as well as their implications concerning the research questions. The quantitative data from both pre- and post-game assessments were collected and statistically analyzed to evaluate the improvement in arithmetic skills. The qualitative data from the game experience section was analyzed to assess the acceptance and effectiveness from the students' and educators' perspectives. The findings are analyzed in the context of current educational traditions and game-based learning practices.

IMPROVEMENT IN ARITHMETIC PERFORMANCE (RQ1)

The first research question sought to determine whether the AI-powered game improved students' arithmetic performance. Analysis of the pre- and post-assessment scores indicated a statistically significant improvement across all groups. Figure 9 shows a comparison of average test scores in the pre-assessment and post-assessment across the schools. Table 2 shows the overall average test scores for pre- and post-assessment.

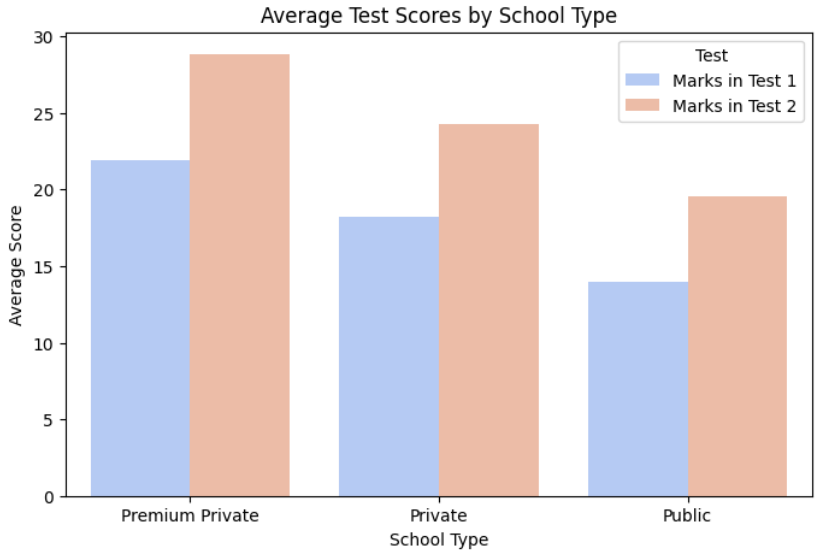

Figure 9. Average test scores across schools

Table 2. Pre-assessment and post-assessment results

	Mean	SD	Minimum	Median	Maximum	Range	Variance
Marks in Test 1	17.2	4.9	14.0	21.0	28.0	24.0	24.7
Marks in Test 2	23.3	5.4	19.75	28.0	30.0	22.0	29.7
Improvement	6.03	2.2	5.0	8.0	12.0	13.0	4.9

Descriptive statistics

The average score in Test 1 was 17.2 (SD = 4.9), while the average score in Test 2 increased to 23.3 (SD = 5.4). The mean improvement was calculated at 6.03 points (SD = 2.2), demonstrating a tangible enhancement in performance.

By school:

1. *Public Schools:* Students exhibited an average improvement of 5.61 points, indicating that even in resource-limited settings, the game was effective in fostering learning.
2. *Private Schools:* With an average improvement of 6.01 points, the game showed consistent results among students with moderate access to digital resources.
3. *Premium Private Schools:* Students from this category achieved the highest improvement of 6.93 points, likely reflecting their familiarity with technology and additional support systems.

The findings support the game's effectiveness in improving math abilities, showing steady gains in various learning contexts.

Average Improvement and Variations Across Schools (RQ2)

The second study question sought to measure and compare progress across various school types. The results imply that although the game worked for everyone, its effects differed according to contextual elements, including technological availability and past experience with digital technologies. Table 3 shows the test scores analysis for pre-assessment and post-assessment across different schools.

Table 3. Pre-assessment and post-assessment scores across schools

School	Mean test 1	Mean test 2	SD test 1	SD test 2	Avg improvement	Median improvement
Premium Private	21.89	28.82	2.05	1.79	6.93	7.0
Private	18.25	24.26	4.53	4.66	6.01	6.0
Public	13.95	19.56	4.13	4.69	5.61	6.0

Impact of school type

When comparing pupils from premium private schools to those attending public schools, the average improvement was noticeably greater. Better infrastructure, exposure to technology, and parental participation may be some of the reasons for this. Notably, though, children from public schools also showed remarkable improvements, highlighting the game's capacity to level the playing field.

Variance and range

The range of improvement scores was 13 points, with most students improving by 5-8 points. Variance analysis suggests that the game's adaptive difficulty played a critical role in catering to individual learning needs, ensuring progress for students at varying skill levels.

These findings align with prior research, which highlights that while access to resources can influence outcomes, well-designed educational interventions can significantly reduce achievement gaps.

Satisfaction with Game-Based Learning Activity (RQ3)

Four criteria were used in the acceptance survey to assess users' opinions of the game: improvement, usability, engagement, and satisfaction. The acceptability survey findings, as evaluated by instructors and students using a 5-point Likert scale, are shown in Table 4.

Table 4. Results of the acceptance survey

Metric	Students	Teachers
Mean satisfaction	3.8	4.2
SD satisfaction	0.5	0.3
Mean usability	4.0	4.2
SD usability	0.5	0.4
Mean engagement	4.1	4.1
SD engagement	0.5	0.4
Mean improvement	4.5	4.8
SD improvement	0.5	0.2

Overall satisfaction

With a mean score of 3.8 (SD = 0.5) for students and 4.2 (SD = 0.3) for instructors on a 5-point scale, both teachers and students expressed high levels of satisfaction. The game's capacity to make learning fun and less daunting was emphasized by qualitative comments.

Usability

Students gave the game's user-friendly design a mean usability score of 4.0, while educators gave it a score of 4.2. Students said the UI was simple and easy to use, and teachers especially liked how easy it was to incorporate the game into their lesson plans.

Engagement

With a mean score of 4.1 from both students and educators, engagement stood out as a noteworthy characteristic. Students cited the dynamic gameplay and competitive aspects as the main things that kept them interested. Teachers saw an increase in involvement and concentration, particularly from children who were often less involved in regular classroom settings.

Perceived improvement

Students and teachers gave the perceived improvement in math abilities a rating of 4.5 and 4.8, respectively. This confirms the efficacy of the game even more and is consistent with the objective performance statistics from the pre- and post-assessments.

The results of the poll support the idea that the game can improve student motivation and engagement in addition to academic success.

FUTURE SCOPE

It would be more beneficial for education if the game's curriculum covered a greater variety of mathematical subjects and levels of difficulty. Advanced subjects like calculus, algebra, and geometry could be included to appeal to older audiences and promote a deeper comprehension of mathematical concepts. Real-time multiplayer challenges and cooperative problem-solving exercises are features that might promote the development of communication and cooperation abilities. It might be beneficial to include the game in official educational settings if it were integrated with learning management systems or educational platforms.

Future studies might include more complicated gaming mechanisms to provide a more immersive and engaging experience. This might involve introducing new difficulties, riddles, or interactive features to improve problem-solving abilities and critical thinking. Using adaptive learning algorithms, the gameplay experience might be tailored to each player's competency level and learning rate. This would enable individualized material distribution and focused reinforcement of certain mathematical concepts, hence improving learning results.

In higher education, game-based learning might be expanded to teach more complex and challenging ideas. Additional cutting-edge technology, such as virtual reality and GenAI, can be included in the games.

CONCLUSION

This study highlights the enormous potential of incorporating AI-powered educational games into early learning to change the way core skills are taught. This study created an AI-powered math game that increased students' performance while also maintaining their interest and engagement over time. The pre-assessment and post-assessment findings revealed considerable improvements in student outcomes, demonstrating the tool's efficacy in improving mathematical skill development and knowledge.

The AI-powered educational game developed in this study can be viewed as a pedagogical evolution in primary mathematics instruction. By merging interactive gameplay with strategic AI decision-making, the tool shifts learning from passive memorization to active engagement. The use of depth-limited minimax AI, real-time problem-solving, and immediate feedback aligns with contemporary educational theories that prioritize learner agency, constructivist experiences, and adaptive scaffolding. The statistically significant improvement in arithmetic performance, coupled with high satisfaction ratings, suggests that AI can serve not only as a computational engine but also as an intelligent tutor. This convergence of AI and game-based learning demonstrates a meaningful advancement in how foundational skills can be taught, practiced, and mastered, offering a scalable, engaging, and effective alternative to traditional methods.

The feedback survey supported these findings by receiving good replies from both students and teachers, indicating the game's usability, satisfaction, and capacity to produce a more engaging and pleasurable learning experience. Students were highly motivated, and teachers commended the tool's congruence with educational aims and flexibility to different learning situations. The game was evaluated in three school types – public, private, and premium private – to provide insight into how digital technologies might help overcome educational gaps. The data demonstrated that, while all students benefited from the intervention, the degree of improvement varied according to their level of access and familiarity with technology.

This research fosters the effective and meaningful integration of artificial intelligence into education. The use of compelling images, sound effects, and intuitive UI design contributed to the game's overall success, demonstrating how aesthetics and functionality can work together to improve the learning experience. The game's effectiveness in making mathematics more interactive and enjoyable highlights the power of technology to alleviate low motivation and engagement.

While this study yields fruitful outcomes, it also opens the door to more investigation. As technology advances, including sophisticated AI techniques, such as reinforcement learning or tailored content delivery, may improve the efficacy of instructional games. This research urges educators and developers to continue investigating and embracing game-based learning's potential to improve education.

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