Beyond the Maze: How AI Personalizes Learning and Drives Engagement in Educational Games

Reno Yuri Camilleri and Vanessa Camilleri

University of Malta, Msida MSD 2080, Malta
reno-yuri.camilleri.20@um.edu.mt

Abstract. Games, especially serious ones, are widely adopted to enhance education. With advanced AI technologies and computational power, integrating AI to improve the game experience for users, especially in the education field, is becoming more widely applied. This study investigates the use of procedural content generation, LLMs and reinforcement learning in game design for user engagement. A feedback system using AI models is created and investigated in relation to user experience. This system will be assessed using specific indicators on a chosen serious game platform. This study merges education and engagement by creating an AI-powered game based on a maze-like environment and then evaluating it with a target group of users. Adapting game difficulty based on user performance aims to foster inclusion whilst maintaining some gamification elements driving competitiveness. Moreover, it introduces a review system where users can test their knowledge with custom-generated questions. The game itself offers teachers a seamless platform to transform quizzes into dynamic maze games. Through AI integration, teachers can effortlessly generate new wrong answers to shorten their workload and track student performance. Meanwhile, students can review their performance and reinforce their knowledge using AI-powered review exercises. Initial results of the first pilot study indicate that the use of AI in game creation can increase both learner and teacher engagement through a gamified approach to learning. This holds many implications that can be further evaluated and tested in diverse educational settings.

Keywords: Artificial Intelligence, Decision Making, Machine Learning, E-Learning, Gamification

1 Introduction

In recent years various academics such as K. Squire [1], D. Shaffer [2] and C. Steinkuehler [3] have published various studies on how Video Games can have a major impact on education. This study aims to evaluate the effectiveness of AI technologies on maintaining user engagement in games both from the perspective of the student as well as from that of the educator. While there are many educational games and gamified educational platforms on the market, this may not be enough to engage users in playing or learning. Studies have shown that this problem may also exist in games that are designed mostly for leisure purposes.

Raptr Inc. a company which tracked more than 23 million gaming sessions [4] declare that only 10% of users actually finish a game that they started. This is also backed by a study conducted by E. Bailey and K. Miyata [5] which found that the mean "completion rate" for a sample of 725 games was 14%. This study aims to investigate AI techniques that could be used to re-design a gamified platform and to evaluate whether AI is better at engaging and maintaining the user's attention.

AI plays a crucial role in education. Diverse applications have been investigated, from robots used to teach children routine tasks like spelling and pronunciation [6] to predictive analysis systems that predict a user's future performance based on their current and past behaviour to provide a better educational experience [6, 7]. This study evaluates the integration of AI techniques to offer a more tailored approach to meet students' needs more effectively.

1.1 Motivation

With the current advancements brought about by the fourth industrial revolution, the roles of teachers and students have drastically changed. Teachers now have a broader knowledge, including insights into how students learn, aided by AI-based learning portals [8] and students having gained more autonomy [8]. These advancements have made smart learning environments more popular, while education is becoming more student-centred. The use of games and gamification in education has been widely explored as tools to enhance learning experiences. Serious games are games designed for specific purposes to engage learners in goal-oriented tasks [8]. They have been successfully employed in various contexts, including science education, health professional education, and engineering training [8]. Furthermore, recently, serious games as well as gamified learning platforms have started using AI in components such as player modelling, natural language processing, and believable non-playing characters [9]. However, challenges exist in the actual implementation of these types of gamified learning environments. Most often, both teachers and students may not be sufficiently engaged with this environment to play repeatedly or for a specified duration. This study involves investigating how integrating specific AI elements can lead to enhanced engagement, both from the perspective of the teacher and from that of the student. Moreover, this study also aims to involve the teachers as co-creators of the gamified maze-game environment with characteristics that are tailored to individual player actions and needs [10].

The two research questions driving this study are:

RQ1: To what extent does the AI-powered feedback system using procedural content generation, LLMs, and reinforcement learning affect user engagement in the educational maze game, compared to a traditional static maze game?

RQ2:How does the AI system adapt the game difficulty to maintain a balance between challenge and inclusion for users with different learning paces?

A number of objectives have been identified to aid in the investigation of these research questions:

1. Recreate and improve the environment of a previously designed maze game that lacked AI features.
2. Design and implement AI models and techniques in a static maze game to allow for the personalisation of content displayed based on user attainments and past achievements.
3. Build a separate AI layer into the existing game architecture that can provide additional feedback on the learner's strengths and weaknesses and offer further personalised tests to aid the learner.
4. Design and create a simple UI to be used by teachers in creating different maze game versions and sharing these with their learners.
5. Compare a standard version of the maze game with an AI-driven version in terms of usability, engagement, and performance on problem-solving tests.

1.2 Document Structure

Chapter 2 will delve into the project's background, differentiating between serious and educational games as well as the technologies considered for the artificial intelligence algorithms. Chapter 3 will explore recent work in AI education and gamified environments. Chapter 4 will delve into the creation of the project, as well as discuss the design choices made. Chapter 5 will discuss the evaluation of results obtained, and lastly, Chapter 6 will serve as a conclusion.

2 Background Research

2.1 Serious and Educational Games

Games in educational settings are sometimes referred to as either serious games or educational games. In addition, educators have often experimented with gamified activities to hold students' attention.

At present, the academic community has not yet formed a unified definition for what is and what can be considered an educational game [11]. However, it is generally considered that an educational game can be defined as a computer software game that is both fun and educational and can skilfully integrate knowledge with games [11]. This splits educational games into two categories: games with the primary goal of education and games that offer educational aspects within the game. The former are all considered to be a subset of serious games. Whereas the latter can be implemented in all types of games, even those that have no real-world objective. For example, the Assassins' Creed games are primarily focused on action and game play, but the world of those games are built on actual historical data related to the time period the games take place in, and whenever a historic location or event is encountered in the game, the game gives you the ability to pause and read real-world facts on the location/event. This is done to such a good degree that there are even studies [12, 13] that attempt to use the game as a medium for teaching students.

A serious game on the other hand can be defined as a game designed for a specific purpose that engages learners in goal-oriented tasks and offers benefits such as interactivity and feedback [8, 14]. Furthermore, serious games can be used for various purposes, including education, health, recruitment, attitude change, and awareness raising [14]. Therefore, a serious game does not necessarily have to be an educational game, as education does not have to be the primary focus. Some studies that illustrate this include the use of serious games in a corporate environment [15] and serious games used in environmental awareness [16].

Various serious games and studies use a variety of different methods to measure engagement [17]. However, two very important aspects to analyse within serious games as defined by previous studies [17, 18] are the game aspect and the serious aspect. The game aspect refers to the game dynamics with the objective to analyse the users' level of enjoyment when playing the game, whereas the serious aspect refers to examining the user's attainment of knowledge, or skills targeted by the game. These aspects are both equally important as the goal of a serious game should be to give the user a certain benefit in a fun manner.

2.2 The Maze Game as a Foundation

The original "Maze Game" [10] that this study is based on is an educational web-based game that allows teachers to engage their class with an interactive quiz environment, it is similar to other quiz-like web games such as "Kahoot", "Quizizz" as well as "Quizalize" that offer gamified ways of tackling a classroom quiz.

The Maze Game was originally developed in 2022 as a project to create a maze-like educational game in Unity. The game worked by having a proper traditional maze-like structure, and the player while playing in first-person would traverse the maze. Each time the player would decide which path to turn towards, there would be text stating a question and two possible answers. The pathway with the correct answer would lead further towards the exit. The game was then further developed into a web game to allow for more accessibility. A UI also allowed teachers with no knowledge of the Unity engine to be able to insert their questions into the Maze Game.

Although the original maze game contained re-usable elements such as an accessible web page for teachers to create questions, as well as procedural content generation for questions and answers, its code-base needed to be redesigned for an adaptable format. In addition, the game's UI had to be redesigned in terms of its visual and audio presentation.

2.3 Reinforcement Learning

There are a number of different AI models that can be used in games to adapt to a user. These include Item Response Theory (IRT), Bayesian Knowledge Tracing (BKT) and Reinforcement Learning (RL). For the purpose of this study, RL was chosen as the ML model for content adaptability, changing content difficulty based on user performance.

In RL, an agent learns to make decisions based on interactions with the environment, and obtaining rewards from those interactions. RL is one of the most popular machine learning algorithms and has been used in various game genres and platforms such as backgammon [19, 20], checkers [19, 21] and Go [19, 22], robotic soccer [19, 23] as well as quiz environments similar to the maze game. The study by S. Liu [24] recommends the adoption of RL systems for educational games. RL was also chosen based on its popularity in video game design and development.

3 Literature Review

3.1 Emerging AI in Education

AI is changing education as we know it and will become a significant part of the future. F. Almedia [8] describes education 4.0 as the next step in education. Education 4.0 is a new educational paradigm designed to address the needs and potentialities of the fourth industrial revolution. Education 4.0 encourages students to learn through experimentation, and Almedia [8] states that this can be done through the inclusion of games, both in a classroom environment and through a remote environment.

A. Alam [25] agrees that AI is the future of education, delving deep into the practical applications of AI within education, both in assisting students and teachers [25, 6]. Alam states that AI tutors are necessary as there are too many students for instance, in English courses, as compared to teachers. As such teachers can not give personalised assistance to each student, whereas an intelligent system can. To back up his claim, he mentions "Duolingo," a multilingual learning platform that provides each user with personalised content to learn a language through a game-like structure. Alam mentions that students who used Duolingo as a platform managed to perform better on standardised exams as compared to students who did not [25].

3.2 Performance-Based Game Adaptivity

As a user progresses through any game environment, it is necessary for the game to adapt its difficulty to the user based on their different skills and on how capable they are at learning and adapting over time [19]. When it comes to changing game difficulty over time, there are two primary approaches which games tend to use: either a linear / non-adaptive approach where a game's difficulty either stays the same or linearly becomes harder over time irrespective of how the user is performing, or through an adaptive approach where the player's performance is analysed and the game adapts based on the performance [26, 19].

While using a non-adaptive approach is simpler than having to create AI algorithms that adapt to a user's performance, various studies [25–27] have shown that an adaptive approach is more effective at aiding a student in their education. In the first study on "employing adaptive learning and intelligent tutoring to virtual classrooms" [25], A. Alam states that students perform better and are more likely to remember what they learned when in an adaptive environment. Alam also states that Adaptive systems not only contribute to aiding students with their learning but also help teachers collect data on students' learning patterns and could even create the ideal learning route for each student based on their capabilities.

In the research experiment designed by S. Sampayo-Vargas [26] the same game was developed in two versions, one used a linear approach, while the other used a scaffolding adaptive-difficulty approach. The scaffolding adaptive approach worked by having a system where the user had to demonstrate mastering a particular level of content before a "scaffold" was removed and would move on to the next level. Similarly, if the student performed badly, a new "scaffold" would be put into place, lowering the student's current level. Results from the study [26] showed that the adaptive game group managed to obtain significantly better results than those in the incremental game.

T. Jagušt, investigated competitive, collaborative and adaptive gamification techniques in a mathematical setting [27]. In their experiment, they incorporated a game where a user had to solve mathematical questions to defeat a "virus-like" enemy. In their studies, one group of students learns in a typical classroom environment without making use of the game. In the second group, the students used the game as a learning environment. The personalised adaptive algorithm within the game would calculate how long it was taking each student to solve a problem, as well as if the student or virus was winning. The algorithm would then reduce the time by one second if the student was winning, or otherwise, it would give the student more time if the virus was winning. This meant that the students would always be kept on the edge of their limits. The results obtained from the experiment [27] showed an improvement in scores and overall performance for the gamified learning conditions as opposed to the regular classroom environment.

3.3 User Assessment and Feedback

Brusilvosky and Sosnovsky [29] in their study of individualised exercises mention that one way of exploiting post-quiz exercises for more effective learning is through the use of "parameterised questions and exercises.". Parameterised questions are question templates generated by the author, or for instance, a teacher. These templates are then used with varying parameters to create a massive bank of questions using only a few templates, which can then create a very large number of unique questions for each student to practice. This system works well as it could simplify the work done by the teacher, by using the initial quiz questions made by the teacher as the parameterised question templates. Since the main objective of post-quiz exercises is to provide students with a method of self-assessment and improvement, cheating is not an issue [29].

A recent study by W. S. Sayed [28] on an "Adaptive Personalised Platform for an Effective and Advanced Learning" utilised a Deep Q-Network Reinforcement Learning-based AI implementation using a rule-based decision-making strategy. In their work [28] they mentioned making use of an adaptive feedback system through hints, attempts, and feedback messages. This feedback system was shown to be quite effective. In a quiz-like environment, this could be implemented by giving the user a newly generated question with a hint of what the correct answer is, a retry system after getting a question wrong, as well as meaningful feedback explaining to the student what their mistake was.

4 Methodology

The creation of the maze game and the accompanying website were split into two sub-sections due to their complexity. The game was developed using the Unity Engine (Long Term Support - Version 2022.3.20f1). The website was developed using XAMPP (Version 3.3.0). XAMPP is a free and open-source web server package developed by Apache Friends and consists of both the Apache HTTP Server as well as MySQL and various other packages. For this project, only MySQL and Apache are used from the XAMPP package. Hypertext Markup Language (HTML), Cascading Style Sheets (CSS), JavaScript and Hypertext Preprocessor (PHP) are used for the website.

4.1 Usability Design

This game is intended to assist both teachers and students with having a simple yet effective system in place to create interactive quizzes in a gamified environment using elements of time, points, badges, and a leaderboard. While this study only defines one class of user within the program itself that has access to both the systems in place for students and for teachers, the needs of teachers as well as students are vastly different. As a result, the UML use case diagram shown in Figure 1 was used to compare and contrast the systems that will be in place for both parties.

Within the UML use case diagram, we will be considering the database and the Generative Pre-trained Transformer (GPT) 3.5 API as external entities. This project has its own login and sign-up system in place, and most of the application relies on the user being logged in to view and access the majority of the features. In addition to what can be seen in the diagram, there is also an error 404 page that is shown when a user tries accessing a page that does not exist.

Teachers: Upon logging in, teachers will primarily utilise the "My Maze" page to manage their mazes. This page enables them to view, create, edit, and delete mazes, as well as obtain access codes to share with students and monitor class performance.

To enhance the user experience for teachers, three mechanics will be implemented:

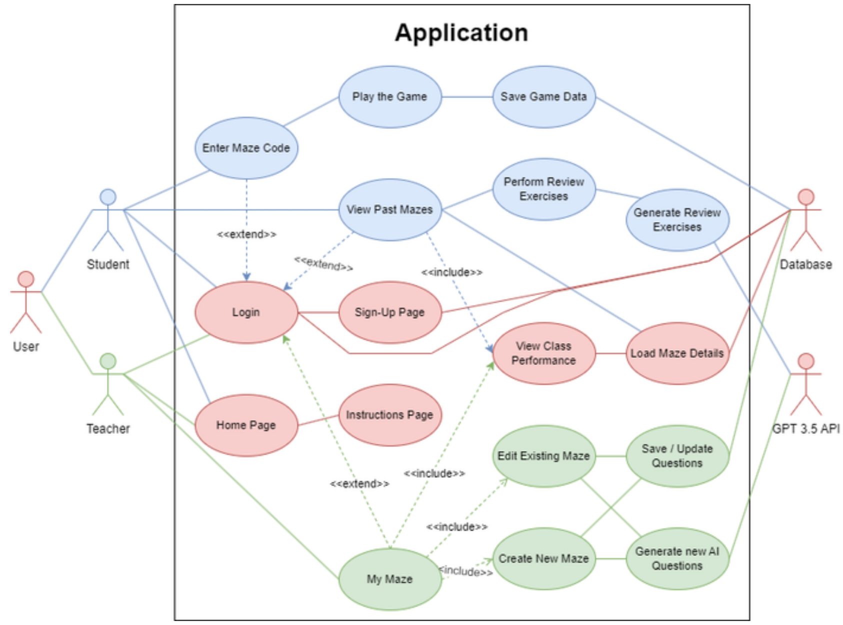


Fig. 1: Use Case Diagram of the System Design

1. Maze results, which will include student scores and badges highlighting performance, such as identifying the student with the fewest mistakes and the fastest student.
2. AI-generated additional wrong answers for each question will be available if the teacher enables AI, where based on the structure of wrong answers supplied by the teacher, new wrong answers will be generated to assist the teacher.
3. Post-quiz exercises, which will be entirely managed by AI, offer students a variety of review questions and relieve teachers of the task of creating numerous unique exercises.

Students: Upon logging in, students will primarily utilise the ”History” and ”Maze Game” pages. In the maze game, students input a code to access/replay the game multiple times, with attempts tracked on the class leaderboard. The History page allows students to review past maze attempts, including scores, rankings, questions, and answers, with graphs displaying performance over time.

AI systems are integrated into the maze game itself, adjusting difficulty based on student performance. AI is also used in review exercises to generate new questions and provide hints and explanations for correct and incorrect answers, enhancing individual learning.

4.2 Data Management and Storage Ethics

Data management procedures were put in place to safeguard any ethical concerns that could arise from this project. In terms of the collection of data within the game and website, the only data that is saved is the user's display name, username, and password. No identifying features regarding any user are present within the project, and care was taken to protect usernames and passwords. In addition to this, user-based evaluation tests were anonymised. The user's names were only collected via the consent forms, and these were only kept until the end of the study, and all data given apart from the results obtained was deleted.

4.3 Re-creating the Maze Game

As mentioned previously, the maze game was originally developed with the intent of having one question in combination with two answers: correct and incorrect. Due to the code base being built specifically to support that structure, a number of features needed to be adjusted or changed. Furthermore, the original version of the game lacked features such as tagging users who pick the wrong option, unoptimised procedural generation, and immediate procedural generation (which wouldn't allow the AI system to adapt continuously based on performance).

Prefabs: Question Rooms

The question rooms within the maze act as large rooms with a single entrance and multiple exits. The number of exits determines the number of possible answers a user has for a particular question given to them. For the adapted maze game, three different types of question rooms were implemented: one with 3 exit choices, one with 4 exit choices, and one with 5 exit choices. The AI will be making use of these 3 different choice rooms to adjust difficulty once implemented. In terms of design, a similar design was used to that of the original game, where each room is large and open and has a carpet leading to all the possible answers to make it simple for a user to notice the number of pathways. An invisible wall that can be passed through is placed in each question room close to the entrance. The wall, with the use of the "Questionroom_Tagger.cs" is in charge of detecting when a player collides with it, and in such an event, it is used by other scripts to perform various functions.

Pathways

Pathways act as corridors to move from one question room to another. They also serve the purpose of making the game feel like a proper maze. When it comes to the design of pathways, the game splits them into three categories, pathways facing the left, pathways facing the middle, and pathways facing the right. All three different pathway types are used to generate the maze without collisions. Just like question rooms, pathways feature a start and end point as well as an invisible user tagger. In addition to this, the Pathway prefabs also have an invisible part that can be passed through at the very entrance that features a text UI that showcases the answer placed on the pathway. Since the pathway will be aligned to the exits of the question rooms, the text will appear right in front of every exit.

Procedural Generation: The Procedural Generation within this game is controlled by a script titled "Maze_Generator.cs". Within the game, this script was attached to an empty game object called "GameManager". This script holds multiple public object references that need to be set by the developers, such as a reference to the Start Room game object within the scene, a reference to the Final Room prefab, a reference to the End Wall, a reference to the Time Controller script, as well as list references to the number of Question Rooms, Left Pathways, and Right Pathways available, as well as references to their actual prefabs. In addition, there is also a reference to the Centre Pathway.

For the first maze section generation, a "Begin()" function was implemented. It is important not to use Unity's built-in "Start()" function, as the procedural generation should not run immediately. The goal is to make the procedural generation a stand-alone script that is managed by an exterior script; in this game's case, it will be managed with a RL algorithm. The maze generation should only begin once the algorithm loads all the necessary data it needs to load, and is ready to launch the maze.

Removing Old Rooms

To improve user performance and avoid lag, the Maze Generator has a list of objects that contain all the items that need to be de-spawned. Each time a question room, corridor, or end wall is spawned, they are added to the list of objects, and each time a new question room is reached, the parent list is incremented. That way, once older rooms are closed off, the previous lists of objects (Excluding the current list of objects that would include the current question room and its corridors) would have the objects being references deleted.

Score Manager and Timer: The Score Manager is a script within the Game Manager game object that keeps track of the user's score and displays the score at the top-left of the screen. Apart from decreasing this score every second, this script also halves the current number of points the user has when the wrong answer is chosen. While other similar smart quiz games, like Kahoot, for instance, opt to give users zero points when the wrong answer is picked,.

The timer, on the other hand, keeps track of the amount of time a user has taken in the maze and displays it at the top of the screen. It is also in charge of tracking how much time the user spent per question.

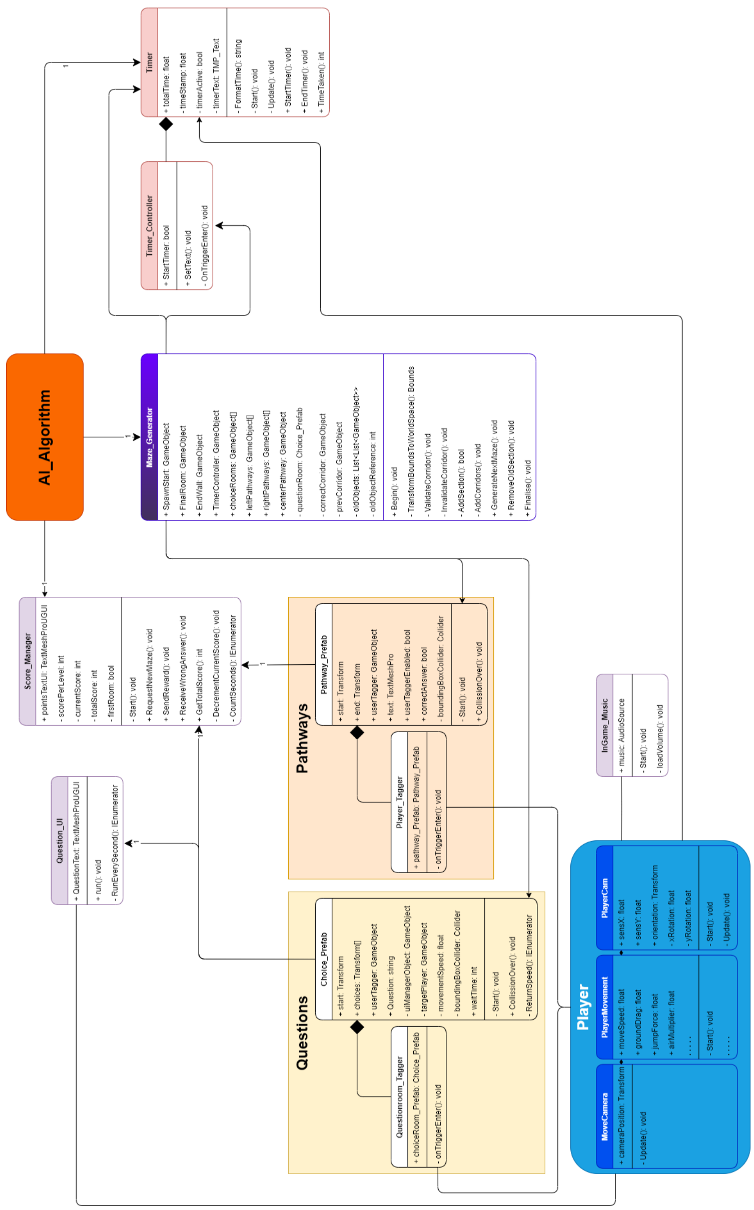


Fig. 2: UML Class Diagram of the System

4.4 Creating a new Website

This project aims to completely redesign and add more functionality to the website, allowing teachers an easier and more user-friendly experience to create mazes, adding a new level of AI to generate additional wrong answers to the maze, and providing users with review exercises, as well as giving users and teachers a way to view class performance in any given maze. Furthermore, while the website was made primarily for desktop and laptop users, this project makes use of dynamic sizes to ensure that each page is still easy to view and access on tablets and phones.

Maze Creator 'My Maze' Page: The My Maze page is split into two main aspects, which are the Maze list and the Maze Editor. When the page is opened, only the Maze List can be viewed expanded and in the centre, so that teachers can view their mazes, and copy the maze code or view statistics for a particular maze without needing to see the editor for no reason. Should the editor be required either by pressing "Create New" or "Edit Maze" on one of the mazes, the Maze Editor would create an empty maze format or open the respective maze.

When opening an existing maze, in addition to filling in all the values, the new AI-generated wrong answer is shown as an additional field. If "Use AI" is disabled then the new AI wrong answer is simply shown as "AI Disabled".

Once a new Maze is created or updated, a PHP script is run that either updates the list of questions or creates new ones. Depending on whether AI is enabled or not, the PHP script would also make a call to the OpenAI API to make use of GPT 3.5-Turbo to generate a new wrong answer, and that answer is saved in the database in addition to the other answers.

Maze Performance Page: The Maze Performance Page features the history of mazes that the user has done, to avoid cluttering the screen, the user's attempts are hidden and can only be viewed once a particular maze is selected, and an attempt is made. From the performance page, the user can view all the correct answers, the time it took them to answer the question, the points they made, and the number of mistakes they made, assuming they made a mistake. At the top of the page under "Overall Performance," the user can go to the Maze Statistics Page to view the class performance for a particular maze. Additionally, if AI is enabled, at the bottom of the page, the user can perform AI-powered review exercises (More info in the section "Building an AI Feedback Layer").

Maze Statistics Page: The Maze Statistics page features all the users that finished a particular maze, all placed in order of ranking from first to last place. The top 3 users have their colours set to Gold, Silver and Bronze respectively. In addition to this, the scores obtained by each user are shown as well as what attempts they currently have undergone. Badges achieved by users are also displayed here, the current badges available in the game are for the top 3 fastest players, and the top 3 players with the least mistakes. If two users are tied for a particular badge, they both obtain the same badge.

To stop users from accessing random Mazes they should not have access to, each maze has a unique code. A teacher should send this code to their students, and the students would insert the code inside this page. The code is then checked to see if it is valid or not; if it is invalid, an error will return; if it is valid, then the maze game with that particular code is loaded.

4.5 Integrating Reinforcement Learning

With the website and game now complete, this project has covered the first 2 objectives provided. Moving onto the 3rd objective outlined, in addition to the "GPT-3.5" algorithm mentioned in the "My Maze" section of the website, which offers teachers an easier experience to create more options in the serious game environment, another algorithm that is user-focused would be the RL algorithm.

The RL algorithm is implemented as the AI algorithm mentioned within Chapter 4.2 and manages the Maze Generation, starting/ending the game, loading questions obtained from the website database, saving wrong answers in a list, converting lists to a JSON string, and exporting player performance data back to the database.

The RL algorithm chosen for this project is a Q-Learning algorithm with an Epsilon Greedy strategy. Within this game, the Q-Learning algorithm uses 5 different states ("VeryLow", "Low", "Average", "High" and "VeryHigh") which represent the performance of a student, with 3 different actions (3, 4, 5) which represent the number of choices within a question room. The result of every state and action is the predicted score a user would gain from that instance. Using this predicted score, the AI estimates the median score a user would get by completing the maze and pushes each user to obtain that score. The QTable used by the algorithm is saved within the database as its own table. In addition to the questions of a maze being sent to the game, the QTable is also sent as a JSON string to the maze game and is loaded as a QTable dictionary within the game. As the user plays the game, the scores obtained are sent to the algorithm, which updates the QTable via a small learning rate, and at the end of the game the new QTable is sent back to the database. Using a very small learning rate set by the developer, the database's QTable is slightly pushed towards the new QTable. This is done as an additional method of updating the performance of the QTable.

4.6 Building an AI Feedback Layer

Moving onto objective 4 the AI feedback layer works using GPT 3.5 turbo, while its performance can be enhanced using the GPT 4 model, due to GPT 4 costing over 20 times more than the 3.5 turbo model (As of the writing of this thesis), it is not worth it from a financial standpoint to go for the GPT 4 model when the performance of the two is satisfactory with both versions of the model. The feedback layer works as follows, all the questions of a particular maze are loaded, a question is chosen at random, and then the GPT API. The Question parameter is replaced by the question that is chosen, while the difficulty is set to one of the following strings based on the current performance of the user: "an easier difficulty," "a slightly easier difficulty," "the same level in terms of difficulty" or "a slightly harder difficulty." While these may not necessarily be the best prompt for engineering the feedback layer, from a lot of testing, these prompts generally produce the best outcome. The resulting JSON response of the GPT API has always been in the right format, whereas answers are correct most of the time (there have been a few cases where the response returned was not correct). A JSON response by the API was also chosen to avoid making too many calls to the API, as more calls result in a higher expense for tokens and take more time to process.

The feedback layer also makes use of scaffolding, where if the user gets most questions correct, the difficulty increases, whereas if the user gets more questions incorrect, the difficulty decreases. The number of questions assigned to the user depends on the number of questions within the maze, but is never higher than 25. If a user desires, they may attempt review exercises multiple times. After each answer is chosen, the user receives an explanation as to why a particular answer is correct, and throughout the maze, the user may choose to click on a hint button to view a hint.

5 Evaluation

5.1 Literature Review of Game Evaluation Practices

T. Karsenti and S. Parent in their work [12] showed a variety of questions that they asked students to evaluate the effectiveness of their game both in terms of the fun aspect as well as the educational aspect which are the two primary aspects that need to be measured in serious games [17, 18]. A Video Game survey by Park University [30] was found whose questions were used to analyse the use of video games in the classroom environment. C. Ress has also provided a default survey [31] with basic questions that can be used to evaluate a game. Furthermore a survey by UPSKILLS [32] (An Erasmus+ strategic partnership for higher education) was found that specifically focused on studying information related to video games.

Due to the academic value and effectiveness of the sources mentioned above, for this project questions derived from those studies were adopted to provide the survey questions, care was also given to ensure that all questions followed our Ethics plan to ensure all students were notified on what their data would be used for, and care was given to ensure anonymity.

5.2 Student Feedback Evaluation

The Participants: For the initial pilot study, 13 students volunteered to participate in the evaluation of the maze game. One group of students was asked to play the AI version of the game, while the other group was asked to play the static version of the game. Both groups were given similar instructions and played a maze with the same mathematical questions, which were derived from standardised mathematics mental paper exam questions from the years 2020–2023. All students were of roughly the same age and are currently attending university-level courses.

It is important to note that the scope of this paper is not entirely in its evaluation, 13 participants were chosen using convenient sampling for a pilot evaluation. However, looking into future work which will be discussed later on, a large-scale evaluation, including both teachers and students would be ideal.

Instructions Given: In addition to playing the game, the students testing out the AI version of the game were asked to perform a round of review exercises. Both groups of students were then asked to fill out a survey to give feedback on what they experienced.

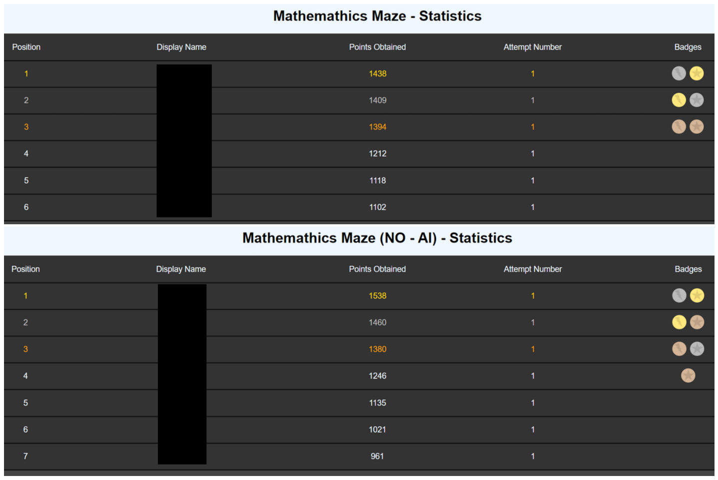
5.3 Reinforcement Learning Algorithm Evaluation

RL Algorithms are evaluated by their ability to either find a good policy or a good reward function [33, 34], this project aims for the latter. To find the optimal reward, there are two things to consider: What brings the agent closer or further to its objective? For example, Deepmind's AlphaStar utilised RL to master a game called Starcraft [35, 36], the project gave rewards for good decisions within the game, and removed points over time for being idle or making bad decisions [35, 36]. Similarly, this project aims to push users towards average performance, thus resulting in students with lower performance getting easier questions and students with higher performance getting harder questions. Similarly to the example, since other quiz-like games such as Kahoot and Quizizz have timed environments, points are reduced over time for taking too long to make a decision. The RL model then takes the points obtained from the user's performance to evaluate how good a particular decision is.

Since RL requires a large number of episodes to learn its performance, it is a common practice to have the RL model keep learning and improving itself over time [33, 34]. After each maze game, the results of the user's performance are sent back to the server, and the RL model is updated by a tiny learning rate to constantly improve itself and push itself towards the best performance.

5.4 Discussion of Results

From the results obtained from the game, the AI users exhibited scores ranging from 1438, the highest, to 1102, the lowest. This signifies a commendable point difference of 336 between the top and bottom performers. On the other hand, the non-AI users showcased scores ranging from 1538 as the highest to 961 as the lowest, resulting in a more substantial point gap of 577. This observation highlights the efficiency of the RL algorithm, which appears to be functioning as



Mathemathics Maze - Statistics

Position	Display Name	Points Obtained	Attempt Number	Badges
1	[redacted]	1438	1	
2		1409	1	
3		1394	1	
4		1212	1	
5		1118	1	
6		1102	1	

Mathemathics Maze (NO - AI) - Statistics

Position	Display Name	Points Obtained	Attempt Number	Badges
1	[redacted]	1538	1	
2		1460	1	
3		1380	1	
4		1246	1	
5		1135	1	
6		1021	1	
7		961	1	

Fig. 3: Performance of Students using the AI (Top) vs No AI (Bottom)

intended. Moreover, it suggests that the game is adeptly adjusting its difficulty based on user performance, thereby supporting a greater challenge for both high and low-performing students.

The survey results showed that all participants completed the maze game, and the majority of users have played quiz-like games in the past. Results show that 50% of both AI and non-AI users dedicate 16 or more hours per week to playing video games, reflecting a substantial interest in gaming activities among participants. No one found the controls for the game difficult.

AI-game users expressed a greater enjoyment of the game compared to their non-AI counterparts and expressed a higher likelihood of revisiting the game in the future. Moreover, more AI-game users remarked that the game possesses greater learning potential as compared to non-AI users. This might be due to the inclusion of review exercises as a means of reinforcing previously acquired knowledge and allowing users to be able to revise content at their own pace.

All participants agreed that games may act as a great medium for learning, with the majority considering the AI-powered game to be particularly good in this regard. Additionally, most users expressed a preference for a gamified or game-based learning environment over traditional classroom environments as a medium for learning. Lastly, the AI-game participants who had access to the review exercises, provided positive feedback regarding the review exercises, highlighting their efficiency in achieving learning outcomes.

(a) AI Survey (b) Non-AI Survey

Fig. 4: User survey - Enjoyment and Replay value

6 Conclusion

6.1 Challenges and Limitations

While RL algorithms can be very accurate in the long run, a large number of runs of a program are required before the algorithm achieves a fair accuracy. This makes the need to retrain the algorithm each time a major change is made to the game, a challenge.

One of the limitations of this study is the use of the GPT 3.5 API to create review questions. While in most cases the new questions generated are accurate, there have been several cases where the AI would give the wrong answer. For instance, within the test questions, the GPT API returned wrong answers when it came to calculating time-based mathematical questions. Throughout testing, it appears that swapping to the GPT 4.0 API provides better answers, but it comes at a significantly higher cost for tokens generated. In addition to this, the use of the GPT API in itself is also a limitation of the project. Since this is a paid service, the availability of this study to a wider audience would imply a financial cost each time they desire to perform review exercises.

6.2 Future Work

Following feedback obtained from the users who played the game, it is evident that enhancing accessibility features seems to be a factor that can be expanded on in the future to benefit the game's appeal and accessibility. One suggestion, in particular, was to incorporate a text-to-speech option to narrate both the question and potential answers within the game, to cater both to users with visual impairments and those that simply prefer audio-based interaction. Moreover, while the game was originally designed for devices that use keyboards, integrating touch-pad controls for tablet and smartphone users would allow more users to access the game, especially considering that tablets are also commonly used devices within schools.

Personalisation can also be added to the game in the future to improve user engagement and further immersion. However, implementing such features would result in ethical issues surrounding managing personal user data, which presents a challenge that extends beyond the current scope of the study's objectives. With that in mind, it would still be a good research point for future developments in user engagement.

In addition to this, while the sample size of 13 students was sufficient for this project, it is worth noting that the 13 students may not indicate the opinions of the broader student population. Expanding this study to feature a larger and more diverse group of students would provide a better understanding of the effectiveness of this study. Additionally, while the current study focused on a mathematics-themed maze, exploring alternative subjects such as science subjects or languages could potentially result in different results.

In conclusion, the exploration of adaptability is an area of study with limited research yet promising outcomes. As seen within the context of this project, the integration of a gamified environment with the use of adaptive AI has the potential to improve the educational sector. However, to harness the full potential of gamification and game elements, it is important for research efforts to delve deeper into understanding what drives user engagement in specific learning contexts.

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