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A GRAPH-BASED APPROACH FOR ADAPTIVE SERIOUS GAMES

Nidhi G. Patel
Rowan University

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By

Nidhi G. Patel

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Thesis Chair: Ying (Gina) Tang, Ph.D., Professor and Undergraduate Chair, Department of Electrical and Computer Engineering

Committee Members:
Ben Wu, Ph.D., Assistant Professor, Department of Electrical and Computer Engineering
Cheng Zhu, Ph.D., Assistant Professor, Department of Civil and Environmental Engineering

Dedication

My thesis is dedicated to God, mom and dad, and Advisor Dr. Ying (Gina) Tang.

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Abstract

Nidhi G. Patel
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Ying Tang, Ph.D.
Master of Science in Electrical and Computer Engineering

Traditional education systems are based on the one-size-fits-all approach, which lacks personalization, engagement, and flexibility necessary to meet the diverse needs and learning styles of students. This encouraged researchers to focus on exploring automated, personalized instructional systems to enhance students' learning experiences. Motivated by this remark, this thesis proposes a personalized instructional system using a graph method to enhance a player's learning process by preventing frustration and avoiding a monotonous experience. Our system uses a directional graph, called an action graph, for representing solutions to in-game problems based on possible player actions. Through our proposed algorithm, a serious game integrated with our system would both detect player errors and provide personalized assistance to direct a player in the direction of a correct solution. To verify system performance, this research presents comparison testing on a group of students engaging in the game both with and without AI. Students who played the AI-assisted game showed an average 20% decrease in time needed and an average 58% decrease in actions taken to complete the game.

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Chapter 1

Introduction

Video games are a vital part of society and are considered a remarkable form of entertainment with their different genres [1]. A player can choose from puzzles to first-person shooters, casual to hardcore, novels to action films, PlayStation to PC, etc. [2]. It provides the aspects of reality where it gives the player a choice based on abilities and aspirations. Therefore, they enhance the player's immersion in the game and contribute to his desire to play [1]. Every day new games are coming out in the market as freeware or very low-cost games with high features. Computer games are considered the most popular entertainment medium throughout the world. In the last few years, video games have also begun to be more than just fun. Now scientists and tech companies are exploring how games can be used as teaching tools and play a crucial role to make learning interesting. [3].

With recent technological advancements, this field of education has evolved into various new concepts, formats, and functions that support learning more effectively and efficiently like educational games [17]. Educational games give us more knowledge to learn through designed educational tasks to achieve new goals and objectives for learning. Many types of educational games are developed for students to learn the importance of the environment, mathematical formulas, engineering approaches, increase general knowledge, etc. [5]. As educational games can provide students with a more engaging and effective learning experience, while also helping teachers to better understand and support student learning, becoming very popular and favored in recent years. By combining entertainment with education, these games can help students stay engaged and focused on the material, while also promoting active learning and problem-solving skills. Additionally, educational games can be used to meet the needs of different learning styles and abilities, making education more accessible to all students. However, the learning style needs to be effective and accessible to all types of students.

A number of recent reports make it clear that the classic one-size-fits-all teaching method is not universally effective given the wide range of preferred learning styles and personality traits found in students. The traditional one-size-fits-all teaching method doesn't work because if we have 100 students in the class, each student is different, and they have different styles of learning. In traditional education systems, students often receive limited feedback, which can limit their understanding of the material and limit their ability to improve. Sometimes it is also inflexible, making it difficult for students to adjust the pace or content of their learning to suit their individual needs. Traditional education approaches are often slow to respond to changes in the needs of each student with unique and distinctive adapting capabilities. Overall, it is very difficult to personalize learning by considering a student's individual needs and learning styles.

Technology has revolutionized the way we learn and teach. In light of these observations, technology has progressed, and innovative systems have been developed to assist both tutors and students, such as online tutorials. Today, teachers and students have access to a vast array of online resources that make education more interactive, engaging, and effective. One of the most popular forms of technology-based learning is through online tutorials and videos.

Online tutorials and videos are two powerful tools that teachers and students can use to enhance their learning experience. Whether you are a teacher looking to enhance your lessons or a student looking to supplement your learning, technology is present to help. While online tutorials and videos have many benefits, they lack interaction and feedback. Online tutorials and videos may not take into account individual learning styles or pace, and they may not provide the level of customization that some students need. Thus, the other is educational games. Which is a perfect blend of fun and learning. It keeps students engaged and entertained and also tracks their progress and improvement. This offers an enjoyable and interactive way to develop new skills and knowledge.

The game-based learning strategy is an instructional method that incorporates educational content and learning principles into video games with the goal of engaging learners and amplifying the functioning of the brain [5]. Also, they inspire children to learn new things, develop their skills, and build an emotional connection to learn the subject more closely with real-world scenarios. Educational game-based learning is incorporated with the purpose of education, quality of skill, creative awareness, and enhancement of the brain by applying knowledge which helps to give a completely new form of learning [5].

However, it is necessary to develop fascinating educational games to keep the students engaged throughout the entire duration of the game. If the game is poor strategically, delivered with less informative and productive ideas, then it could leave the players feeling ineffective. As a result, they will end up frustrated and give up on tasks due to lack of motivation and attentiveness. Games created on theoretical tutorials and puzzles might become tedious at some point. Children do not like to read a manual to play a game, but a short movie or a video can capture their attention to play instead of reading the written manual [4]. This approach can be frustrating if implemented improperly, or if the student lacks prior knowledge or motivation will just get them nowhere. Instead, they may feel defeated and give up on tasks [38], [39]. According to a recent study, personalization has the potential to unlock the full potential of educational games as an effective teaching tool. It enhances a student's confidence, self-efficacy, and a positive, enjoyable learning experience. By incorporating personalization elements opens the doors of individualized learning goals, personalized feedback, and adaptable difficulty levels which effectively meet the diverse needs and abilities of students.

Although educational games help to make learning interesting, it is very essential to data collection and players' behavior to make it adaptive [4]. Games are an exceptional platform for personalized learning based on test data and players' gameplay which reflects students' learning experience. By integrating pedagogical content into a virtual environment, both students and educators are provided with a solid structure for contextual learning. Additionally, easy access to student data through such virtual environments provides a wide range of opportunities to understand what truly happens when students are stuck on a problem. Collecting data during gameplay allows for a more in-depth analysis and makes improvements. researchers and analysts can gain a better understanding of player behavior and decision-making processes. Based on that wide range of student data, accurate and relevant scaffolding and support can then be easily offered [32], [33], [35].

Generally, games are simply designed in a way that gives the generalized or a specific hint that developers build previously for a player when they need help in a similar type of situation. Additionally, the environment of the learning games inclines to simply present problems and feedback and they do not attempt to engage with learners to complete the activity to check whether they are facing any problems while gameplay or not [1]. In reality, when learners do not get personalized help when stuck in a situation, they get frustrated and eventually give up on the task. Providing tailored feedback during gameplay after tracking the player's flow of action enhances performance and motivation which leads to optimal decision-making. Educational games often take place best when the learner is taking part in an insightful problem-solving process.

With this remark, this thesis develops a graph-based heuristic approach to guide the design of an adaptive serious game. In particular, this thesis makes the following contributions: We provide a graph-based framework by which solutions to in-game problems from educational serious games can be represented. Using this framework, we develop a graph search algorithm to both detect errors in a player's in-game actions and to provide assistance to a player when needed, guiding them toward the correct solution. Finally, we test the proposed system through a case study in which we compare student opinions and in-game performance on a game with and without the proposed system.

1.1 Motivation

These days, artificial intelligence driven personalized games are widely making an impact in the gaming industry. Where the AI automatically adapts the behavior of the player in the environment, derives strategies which increase the entertainment values and capture players' attention [1]. The motivation behind proposing personalized adaptive games is to increase students' motivation, engagement, productivity and provide them with an enjoyable gaming experience tailored to their individual preferences, behavior, and playstyle. This delivers memorable and enjoyable experiences which also help to enhance their communication skills and collaboration abilities that lead to compete better in real-world scenarios.

Based on these observations, in this research we used a real-time game called Algae city which is developed for secondary school students. Algae City is an educational game that imparts information on algae and spreads awareness for the environment. We tasted our proposed system on Algae City's one of the modules called Pipe Game. The proposed algorithm is designed to both detect errors in a player's in-game actions and provide assistance to a player when needed, guiding them toward the correct solution. This system is invented with constant engagement with the player during gameplay, recognizes his gameplay behavior, and provides a timely, personalized, and cognitive framework. We are using a heuristic graph-based approach to accompany the learner's strategy and provide help in the form of hints when required during his gameplay after crossing the performance scale score of time, movements, and error in the solution. The feature of receiving personalizing feedback in the game boosts player's confidence, increasing motivation to reach the correct solution.

1.2 Significance of Research

The purpose of Artificial Intelligence (AI) in games is to convey a realistic gaming experience for players. It gives real-time immersive pragmatic exposure on virtual platforms along with fascinating design and concept. It achieves success by enhancing the player's interest and satisfaction to meet their imagination of games [1].

There are divergent ways in which Artificial Intelligence, machine learning, and game development are piled up through each other [2]. The fact of the authentic world is that AI keeps on being habitual to bringing life into computer games currently being developed and designed with the intention to study the player's pattern in order to improve their experience and strategy to adapt to difficulties along with requirements to deliver the best game. Virtual Reality, Augmented Reality and Machine Learning algorithms are considered the present and future of the gaming industry. The hike of Artificial Intelligence is a very beneficial and important steppingstone, by creating games that are way more smart, entertaining, interactive, and delightful to play by delivering a real-time simulation experience. Some of the traditional developers believe in standard AI techniques (traditional AI) such as Machine learning, Neural networks, Fuzzy logic, and designing games using CPU [6]. However, modern AI gives credence to Deep Learning, Deep Neural Networks, Bayesian Statistics, and Reinforcement learning and takes more advantage of the graphical representation of games.

This study was conducted with the motive of creating an interactive, immersive, and personalized experience with the directional graph algorithm in a serious game. A preliminary assessment was performed on a group of students engaging in the game with AI and without AI the comparison of results has been derived including performance criteria (time, movements, and errors). The results of the study revealed positive feedback from students toward learning after using the adaptive educational game with personalized help to correct and guide them to the correct solution if needed. The proposed system was built gradually, with each parameter designed by considering students.

1.3 Thesis Objectives and Outline

The objectives of this thesis are:

1. Create an AI-based system for educational games that students can play repeatedly and get the best advantage of learning without getting monotonous and tedious experiences.
2. Generate an assisted system using a machine learning algorithm like a directional graph called action graph to detect a player's in-game error using solution graph and assist them by showing the correct solution (as hints) when the player needs assistance. Giving hints boost player's confidence and encourage them to make progress in the game. It will collect real-time data by observing the player's gameplay and make decisions accordingly.
3. Compare the result of the game played with the AI segment and without the AI segment .

The thesis comprises in five parts, as follows:

Chapter 2 is a literature review on different areas of the study along with machine learning concepts and approaches taken by various games are discussed in this section. A detailed study has been conducted on educational games, their behaviors, importance of Adaptive mechanisms in educational games and their personalization followed by an overview of directed graphs and how it is used in this system. This chapter will help readers to visualize the functionality of algorithms.

Chapter 3 explains the Action-graph based Heuristic approach for adaptation followed with action graph and heuristic algorithms. Heuristic algorithm comprises action graph searching mechanism and player assistance and solution checking mechanism.

Detailed case study has been derived including the overview of algae city game and implementation of adaptation in the game with personalized hints. Each step of the proposed algorithm followed by architecture and pseudo-code for the algorithm has broken down.

In Chapter 4, we perform a preliminary assessment on a group of students engaging in the game with AI segment and without AI segment, the results have been derived based on their performances considering time, movements, and errors. This also contains the comparison of results based on collected data and surveys taken from the students.

Chapter 5 discusses the conclusion of the research along with quantitative evaluation. A brief discussion of future scope of improvements is also covered by this section.

Chapter 2

Literature Review

This chapter contains a complete review of all the literature aspects that are relevant to the work presented in this thesis. Research indicates that the average time a person spends playing video games, during a regular school day is two hours. In recent years, video games have become increasingly popular among people of all ages. With the advancements in technology, video games have evolved from simple arcade games to highly sophisticated and immersive experiences that can be played on a variety of platforms including consoles, PCs, and mobile devices. One of the reasons for the popularity of video games is that they offer a form of entertainment that is highly interactive and engaging. Players can immerse themselves in a variety of virtual worlds, explore new environments, and interact with characters and other players in real-time. It is widely agreed by most people that video games incorporate motivational and immersive features that may be used in the learning process [13].

As video games continue to gain popularity in modern society, the educational sector has recognized their potential and has begun to develop educational games as a means of engaging and teaching students in an interactive and immersive way. The usage of fun and entertainment factors that games encompass, makes the educational process more enjoyable.

2.1 Educational Games

Educational games are different from commercial video games on the grounds of the primary objective, which is learning, or assisting the students to learn while commercial games aim for entertainment. Experimental findings have stated that educational games are great tools that promote learning skills [12].

There is a wide range of games available today that can be used for educational purposes. These games are designed to make learning fun and engaging, allowing students to learn new concepts and skills in an interactive and enjoyable way. From math and science to history and language arts, there are games available for every subject, age group, and learning level. Whether played in the classroom or at home, educational games can help students develop critical thinking, problem-solving, and decision-making skills while having fun.

In the initial state, most commercial games adapt Artificial intelligence and machine learning techniques to reach the next level in the gaming industry. When educational games followed the same tread that helped the learning system to adapt more and helped to understand the students [12]. Furthermore, Machine learning and AI are being increasingly used in educational games to provide personalized learning experiences for students. These technologies can analyze data on a student's learning progress, preferences, and strengths and weaknesses to tailor the game to their individual needs. This results in a more engaging and effective learning experience for the student. AI-powered games can also provide immediate feedback to students, helping them to correct mistakes and learn from their errors [12]. Educational games are designed to help students to enhance communication, creativity, collaboration abilities, and visual skills which escalate learning along with fun [12].

2.1.1 Prominence of Educational Games

A well-built educational game is the fusion of learning objectives with an educational module including a commercial game's fun, attractive features, and ambiance [13]. Educational games are built with the purpose of motivating students to self-learn to obtain problem-solving skills.

It is very difficult to get the student's attention, where all students in the group have different personalities, inconsistent learning techniques also poles apart with adapting abilities and preferences [4]. Games sometimes become competitive platforms for players who look forward to getting to the top, earning rewards, and expect an intoxicating experience. Due to the popularity of video games in today's generation, it proved that it is a favorable experience by combining education with the game, helping educators to deliver their concepts easily compared to the standard learning method [1].

Research states that students easily remember the game character where they defeat the opponent and what type of reward they got during gameplay. Research states that it is easier to convey the purpose of a learning module using games either picturized or video-based tutorials than a written manual [12]. Students would not get any learning information if the source is not interesting enough to learn. That is where educational games play a role by helping them to adapt their learning and skills to compete in a real-world scenario with help of the implicit learning process. It has gained a lot of attention as they have proven to be an effective learning tool for engaging and motivating students [12].

2.2 Adaptive Games

Over the past years, artificial intelligence took place in many industries. AI is a consultancy of concepts like machine learning and Neural networks which give the industry a perspective to drive towards success [9]. In the gaming industry, AI brought up many techniques where systems mimic the design, and elements of human behavior and behave accordingly to increase the entertainment value of the game. Artificial intelligence-trained machines are capable of performing many tasks such as solving various problems, learning behavior, and match more like a human does. AlphaGo (One of the most successful games in AI) is known to defeat one of the top human Go players, because of its complexity and multiple layers of strategic thinking [9].

Artificial intelligence mimics human intelligence where it explores applied strategies in the game. It understands the in-game behavior and comprises with a decision-making algorithm which defines the behavior of the character in the game [11]. It performs all the necessary tasks like creating challenges based on the player's strategy and determining the pattern followed by a player in the complex environment of two-player or third-party games. A successful educational Game AI is where it can predict the unpredicted behavior of the student, fulfill the purpose of the learning module, and deliver entertaining games.

The artificial intelligence mechanism learns the player's behavior during his gameplay and makes the strategy to deliver an adaptive experience to the player. A major drawback of non-adaptive AI is that players can not engage with the game, and they give up on the level and the developer couldn't recognize that. Non-adaptive games have several drawbacks, including not understanding the player's behaviors and not being able to find the player's weaknesses, so as a result, the player becomes vulnerable and quits the game. The adaptive mechanism allows developers to adapt the game process and assist to understand user behavior. Using the AI mechanism developers can learn user moves and react accordingly based on their actions in the environment. Developers can change the strategy and help the player if the player needs in-game assistance.

There are many commercial games available designed in a way that AI makes the game more challenging and interesting [11]. One of the key aspects of game-based learning is that each player receives immediate feedback on their performance, with suggestions on how they can improve. Game-based learning has shifted focus from learning with lectures and written tasks to learning with games and it has become an indispensable part of modern education [11].

To extend serious games, adaptive serious games adjust aspects of the game based on observations of or input from the player. The end goal of this adaptability is to maximize one or more aspects of the player's experience, with games typically focusing on user engagement or learning efficiency. For example, an educational serious game might determine a player's areas of difficulty with specific content and provide support in those areas. Alternatively, a game might adjust difficulty to maintain a balance and prevent the player from becoming frustrated. When compared to other adaptive educational technologies, adaptive serious games excel in terms of data mining, implementation, and user engagement. By the nature of these games, any information about the player's actions or the game environment is readily available to the developer, making it easy to gather and utilize that information. These games also allow for high flexibility in terms of what game worlds can be created and what content can be represented to the player. A serious game might extend a dull math lesson into a more interesting fantasy world while still delivering the same content to the player.

Finally, adaptive games allow for more goal-based learning. Players can be more motivated to complete a lesson when they see a score number increasing, or some resulting effect of their actions in a virtual game world. Although most approaches described above demonstrate proficiency in improving student learning, they also are often very specific to the domain of choice, limiting potential applications in other serious games. But, all serious games generally share a similar structure, in which students must perform sequential decision-making processes in order to find the right solution to a presented problem. This system offers to achieve correct sequences of actions to arrive at a goal with less effort and error detection technique.

2.2.1 Adaptive Mechanism in Educational Games

Educational games help students to develop various skills like critical thinking, creativity, and problem-solving skills with knowledge attainment. It is very essential at some point to know that educational games are useful, students make the best use of them, and games fulfill the purpose.

Game AI helps developers to make games intriguing and give an enjoyable experience to the player [12]. Educational games give the synergistic experience of challenging levels, well-orders problems, and several other key principles to deliver an effective educational strategy. A learning educational system requires a learning environment for students to engage with. It provides players with both goal-based features, simulations of real-world problems, and goal-focused motivations. Learning game AI gives students the scenario where they can engage in the problem-solving process and enhance their learning [17]. These types of adaptive educational games have been strongly proven beneficial in assessing students, providing a personalized system that can support and guide students along their respective learning paths [17].

With the help of AI, these games are able to adapt the individual needs of each student, providing a personalized learning experience. By analyzing data on the student's performance, the game can adjust the difficulty level, content, and feedback to better match their learning style and abilities. This leads to increased engagement, motivation, and learning outcomes. Traditional educational games have limitations in that they often have a fixed structure and content and are not able to adapt to the individual needs of each student. Based on this the research is aimed at creating more effective and efficient learning tools that can help students of all ages and backgrounds reach their full potential.

One of the key benefits of educational games that use machine learning is their ability to understand and analyze player behavior. These games can collect data on how a student interacts with the game, including their choices, responses, and time spent on different tasks. This data can be used to create a profile of the student's learning style and preferences, enabling the game to adapt and customize the learning experience to better meet their needs. By understanding player behavior, educational games can help educators and parents identify areas where a student may need extra support or guidance, leading to more targeted and effective learning outcomes.

2.3 Existing Methods for Adaptive Game

In this section, we will explore some of the existing methods for adaptive games, including rule-based systems, machine learning approaches, and player modeling techniques. These games use various methods to adjust the gameplay, such as changing the difficulty level, modifying the game environment, or providing customized feedback. We will examine the advantages and limitations of each method and discuss how they can be used to create a more engaging and satisfying gaming experience.

Several educational game engines focus on the aspect of game development themselves to assist game developers and teachers in creating educational games. Like the video-based, AI approach taken by the “Modular Educational Game system” [12], which suggests a video for students’ mistakes in class [12]. Where the student-based model adapts the student’s behavior and suggests the video when the student makes a mistake in the game. Also, teachers can update the database based on students’ real-time scores and AI suggests a suitable video to students on the ground of statistics. Sometimes, watching long and crowded videos does not prove useful for students. Surveys indicate that most students do not prefer to watch such videos [12].

Modifying or generating new environments is a common approach used by adaptive methods in serious games to utilize the game environment. For example, Gombolay *et al.*, (2019), proposed a method for generating sequences of tutorials from test results, applying hidden Markov models to generate sequences automatically [11]. One approach by Mitsis *et al.*, (2020), even focused on dynamically generating the behavior of in-game characters, targeting behavior that would further enhance a player’s learning using genetic algorithms [12]. Even when not modifying content directly, games can instead provide hints to players. For example, González-González *et al.*, (2019) proposed a system that observed the action history of players to adaptively recommend future exercises [13], [44].

A vivid example of such integration can be found in the ITS developed by Squirrel AI [13], [14], where each student is recommended a unique learning path in the knowledge graph according to his own ability assessment in real time [15], [16]. It is noted that the games used in Squirrel AI are not connected with the ITS in the learning content wise, rather they serve as an incentive to students for their engagement [18].

A perusal of current literature provides a number of works that take advantages of serious games for adaptive learning systems. For example, one work from Papadimitriou *et al.*, (2019) presented a fuzzy logic-based approach to dynamically adjust quiz questions and game content based on a player's performance in an escape room game written in HTML [8], [44].

Likewise, this paper, Georgila et al., (2019) also used computational intelligence to optimize a tutoring system within a serious game [21]. In particular, they designed a reinforcement learning agent to select actions (what tutoring assistance to provide) based on player data variables, such as player performance. Using prior game data, their system was able to learn and implement a new policy for what tutoring to provide to which players within the game [43].

One method of content adaptation focuses on dynamically populating game content into learning scenarios. Approach by Hussaan *et al.*, (2011) focused instead on generating educational scenarios tailored to players based on a detailed player profile that was populated prior to game intervention. It also considers the player's history of interactions with the system. The learning scenarios differ in terms of selective concepts that the student hasn't mastered and a set of in-game resources to cover that domain knowledge [43]. Takahashi *et al.*, (2018), meanwhile, focused more on a social aspect of serious games by dynamically selecting dialogue for characters in the game to create more human-like conversations and statements to say to the player [10], [44].

Outside of learning styles, Volkmar et al., (2019) proposed an adaptive game that tailors in-game achievements to different types of players [15]. Their methodology focused more on tailoring in-game challenges to a player's preferred play style using a player taxonomy method called BrainHex [16] to classify players based on their game playing preferences; for example, players who prefer exploring or risk-taking. In testing, they found that players were willing to expend more effort for objectives that fit their preferred style of play [43].

In some implementations , unsupervised learning methods can be used to improve existing methods based on newly collected student data. Machine learning allows these methods to automatically extract the player's pattern based on the player's actions. Bermudez et al., (2020) used data mining in a game based learning environment to extract patterns from players' actions, based on which the game's in-game tutoring logic was updated. In this way, their player model is defined as patterns of player actions into which new players can be matched. Their method used PrefixSpan [17], a data mining algorithm, to locate ordered patterns in lists of student actions that they could leverage to create a more personalized and supportive game experience [43].

"The Scope of Adaptive Digital Games for Education" [13]. Player has a choice of which tasks they attempt next, each leading along a slightly different part of the storyline. Rather than having every task available to the player from the start, it is available based on the completion of other tasks [13]. AI also determines what can be the next level based on the player's score, the game AI will decide when to offer the hard, moderate, or easy level [13]. In this, Game AI makes sure that the player does not repeatedly get hard levels if he's not able to compete for that on the ground of the current state in the game. When the game is developed for a learning purpose, AI determines the next level's difficulty based on the player's current knowledge level [13]. That can be in the form of question answers, puzzles, or scores. A simple example of this dynamic difficulty adjustment might be to change the number of opponents the player is faced with within the next stage, in relation to how quickly they dispatched with the opponents in the current stage [13]. This type of adaptation is done already in games like Sandbox games, Grand Theft, where players would otherwise be performing unguided exploration. Players have a choice of which tasks they attempt next, each leading along with a slightly different approach and goals [13].

Similar to the above approach Grappiolo et al., (2011) implemented a method where it uses data-based modeling methods to predict a player's future score in a game. It creates a system to train conflict resolution, where an artificial neural network is trained on the past data to predict what score a player would get on the next level [22]. This prediction guides the generation of the next level game, attempting to maximize the improvements in a score that a player would get on a subsequent level [43].

Khabbaz et al. [25] demonstrate a fuzzy logic method for computing a quantified performance level from players based on their in-game performance, while Massoud et al. [26] instead proposed to focus on predicting a user's future score with fuzzy logic, using the player's in-game performance. Bayesian networks, too, offer developers an opportunity to estimate a user's skill level using probabilistic relationships determined by a game's developer as demonstrated by Rossol et al [42].

Bellotti et al. (2009) proposed adaptation method allows experts to enter new content based on the difficulty, entertainment, length into the game. In their method, when game authors specify learning objectives of their game, expert personalized content based on the creator's objective. Reinforcement learning and genetic computation methods were compared. Where the genetic computation method iteratively generates scenarios while attempting to maximize a fitness function, which in this case is based on how well the chosen tasks fit the learning objectives. The reinforcement learning approach instead selects the next task at every juncture rather than generating the entire scenario [43].

"Simple arithmetic lessons through an adaptive snake game" [14]. In this research, the snake game has the features where Q/A sessions are performed to give a boost to players to advance in their game and answering questions correctly will accelerate play while answering incorrectly could have consequences of either failing to advance or possibly even being moved in reverse [14]. Given the technologies to adapt both the functionality of the game engine and the content assets available, the concept of a fully adaptive game seems more feasible. The system would also require a way to decide what to adapt, when to adapt it and how to adapt it, and some data to base those decisions on. Things got distinct when it comes to the educational game where the objective is not only having fun but in addition to fulfilling the learning purpose [14]. In these techniques and approaches taken by developers they are not retrieving the performance during the game play. In this what happened when player not able to move forward because he's getting wrong answers he will quit, there's no one who will help him during game play.

"kNN-based Adaptive Virtual Reality Game System" [4]. The paper presents an adaptive VR game framework based on kNN classification. The system monitors the player's in-game behavior, collects a corpus of his actions to systematically assess his domain knowledge and potential difficulties, and responsively provides explicit support.

An empirical evaluation demonstrates that the kNN-based game system accurately predicts players' domain knowledge levels on which it offers differentiated instructions to guide them to solve the problem. This system could be improved by determining the user's skill level and providing relevant feedback. Having a static quiz-based model pulled from the database to solve the problem, instead of answering the questions, could ask the player to solve the problem, so the user can feel more like activity and less like a test.

Tahai et al., (2019) and Lara-Álvarez et al., (2018) made a system to support voice-based emotion recognition. Their goal was to assist players to focus, if they need to skip the level, the system skips the level to add more positive emotions in players. Trigano (2018) proposed a general-purpose emotion-driven player modeling approach for adaptive serious games [29]. They offered a generic architecture for adaptive serious games with the goal of measuring, accounting for, and adapting to player emotion in real time. From these functions, their system determined and adapted to a player's emotional state in real time [43].

Another significant attribute contained in the game is a running timer. The timer is an additional adaptive characteristic as the difficulty level of the game determines its speed. In beginner mode, the timer runs slowly, and students could think more about the correct answer. In the intermediate level, Timer runs a little faster than beginner level and students have to respond within the given timer, in advance level timer will reach its highest speed [12].

2.4 Graphs and Educational Games

The use of graphics in games has revolutionized the gaming industry and transformed the way we interact with digital media. Games are a graphic method, utilizing graphics and visual representations to convey information and engage players. With the advent of powerful graphics engines and game development tools, games have become more immersive and visually stunning, with realistic environments and detailed character models.

Graphs are a common tool used in many systems to represent data and visualize relationships between different entities. For example, a graph can be used to represent the relationship between different historical events, or to visualize the steps involved in a complex scientific process. In computer science, graphs are often used to represent networks, such as social networks, transportation networks, or communication networks. Graphs can be used to model complex systems and processes, such as traffic flow or supply chain management, and can help identify patterns and trends in data.

Games also use a discrete event approach, meaning that specific actions and events occur at predetermined points in the game, giving the player a sense of control and agency within the game world.

Graphs can also be used in machine learning and AI to analyze and classify data, or to optimize processes such as recommendation engines or search algorithms. The use of graphs in educational games can enhance the learning experience by making complex concepts more accessible, helps to track progress and provides feedback to help students improve their understanding. Overall, directed graphs can be a powerful tool for enhancing educational games and improving learning outcomes.

One type of graph is directed graph, which is particularly effective in representing causal relationships between different variables and concepts. directed graph provide a clear and interpretable representation of the underlying structure of the problem. This can help learners understand the logic behind the game and the reasoning required to solve it. In our research we are using directed graph technique to create personalized learning paths based on the learner's previous interactions and progress, making the game adaptive and responsive to individual needs.

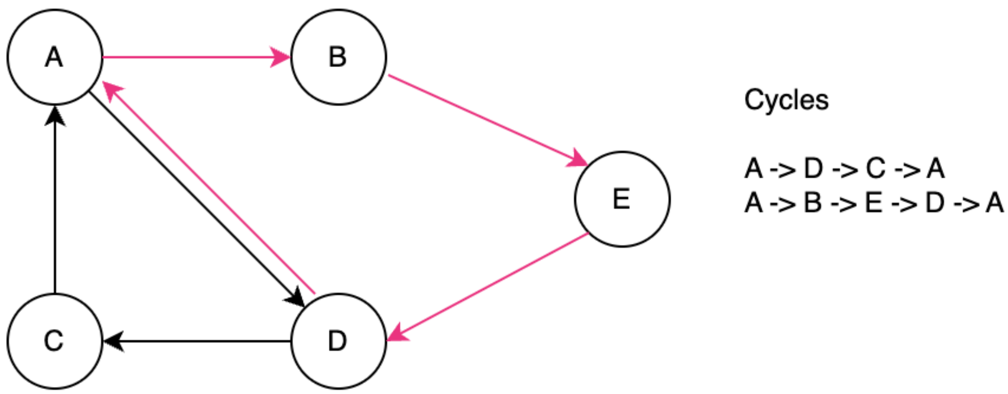
2.4.1 Literature Review on Directed Graph

Directed graphs are often used in serious games to present the possible states of the game and transition between these states. Directed graphs provide a roadmap for the student to follow as they progress through the game. The use of directed graphs can also help to identify knowledge gaps or areas where the student may need additional support, allowing for targeted and personalized learning experiences. Additionally, directed graphs can be used in game design to create branching storylines or complex decision-making scenarios, adding depth and complexity to the game.

In this study, A Directed graph is called an action graph where all vertices/ nodes are connected through all edges, and all edges are directed from one vertex to another. The graph is defined as a set of edges subordinated to a pathological structure. The nodes in the graph are defined not only as the boundary points of the edges but also as the point at which two or more edges join [41]. The nodes represent the states of the game, and the directed edges represent the actions that the player can take to transition from one state to another. As shown in the figure below A, B, C, D and E are Vertexes. where all vertexes are connected through edges. The edge with arrows shows the direction of the cycle . Action graph allows multiple connections with the same source and target vertices.

Figure 1

A Simple Directed Graph



Overall, graph-based representation provides a convenient way to model the structure of the game, and it allows for easy modification and manipulation of the game's rules. Directed graphs have various forms based on their distinct types. A directed graph which have no multiple edges is called a simple directed graph. A complete graph in which each pair of vertices is joined by a symmetric pair of directed arcs called a complete directed graph. A directed graph having no symmetric pair of directed edges is called an oriented graph. Directed graph differs from the undirected graph where all edges are unordered and not directed.

In our proposed system, we develop a graph-based heuristic approach to guide the design of an adaptive serious game. This directed graph is defined as the solution graph, representing all acceptable sequences of actions that lead to a solution. Using this framework, in the following chapter we develop a graph search algorithm to both detect errors in a player’s in-game actions and to provide assistance to a player when needed, guiding them toward the correct solution.

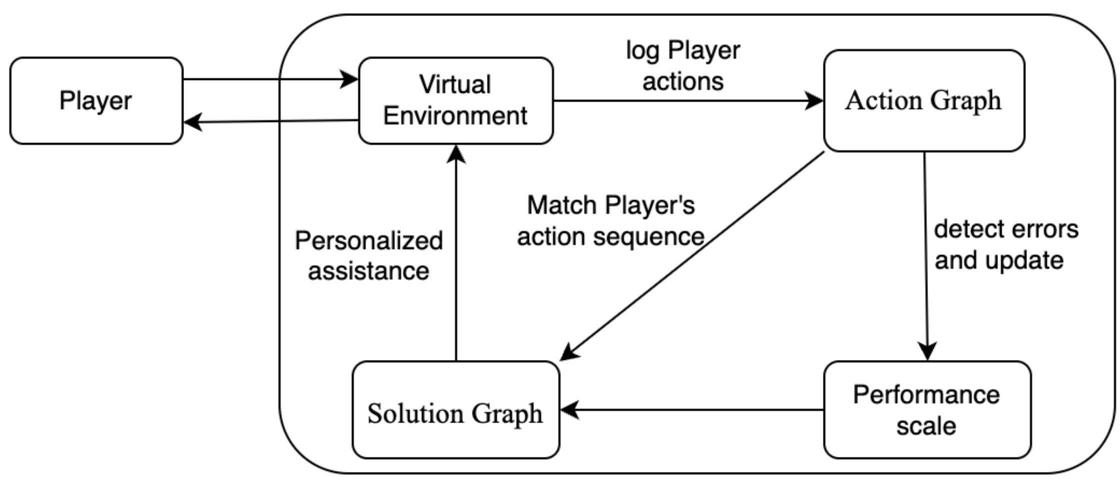
Chapter 3

Methodology

The process of learning is a very complex cognitive task that requires a lot of effort and motivation from learners. Research indicates that the more students are aware of their learning process, the more they can control their goals, dispositions, and attention, which helps them to become successful learners. Students often find educational games boring and unappealing due to the lack of personalized games assistance. The dropout rate is high, especially when it's for children. When a learner plays the very same game frequently it becomes monotonous and tedious. Students could not get the learning out and ended up only getting frustration and disappointment.

Figure 2

Player Modelling in Serious Games



The above diagram depicts the adaptation module of our personalized system. Action Graph, Performance scale and solution graph are key components of this algorithm. As players go through this process, the game server logs all player's actions to analyze player performance and game effectiveness. This data collection is a crucial element of this system. The system detect the errors based on the player's actions by comparing them through a solution graph.

3.1 Action-Graph Based Heuristic Approach for Adaptation

As players are engaged in a serious game to solve a problem, they usually associate sequences of actions with game scenarios, creating a "best" decision at any given moment that leads to a specific destination/objective. Each action can impact the path by leading them to the destination or diverting from that. Usually, in games, we can derive multiple solutions which can lead to the ultimate destination. For a given problem, an action graph can be built beforehand by a domain expert to represent all possible action sequences that lead to the destination/objective. As players learn to play the game, their actions are logged as an action model. When superimposing the action model on top of the solution graph, it is easy to compare the player action sequence with the action graph and recognize the differences. Such diagnosis allows the system to easily spot the wrong actions players take and provide appropriate guidance to correct the player. In this way, the players can more easily grasp the problem presented to them and reach the objective quicker.

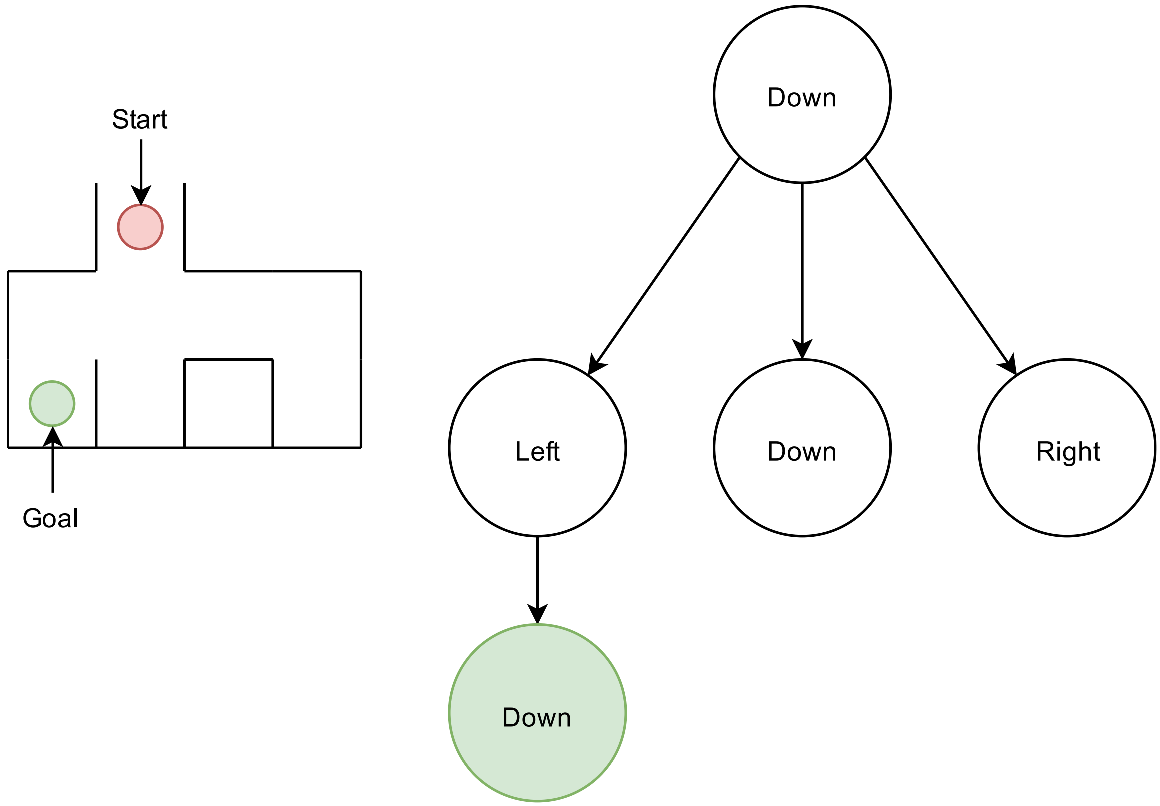
Following this line of thinking, this section presents the solution-action tree structure first through Action-graph. The heuristic algorithm for error detection and personalized guidance is then presented in section 3.3. The detailed case study has been derived including the overview of the algae city game and implementation of adaptation in the game with personalized hints in section 3.4. Each step of the proposed algorithm followed by architecture and pseudo-code for algorithm has broken down.

3.2 Action Graph

Action Graph is a directed graph structure, that represents all possible solutions students could give to a game problem. The below example of a simple maze diagram, a student could move Up, Down, Left, or Right. And on the right side shows the action graph of the maze. Where each node in the graph shows the single action. The possible list of actions could be as follow which student can take. First action could only be to move down, for the second action student could move Left, Down, right. But only Left lead to a solution. So, in this case if student move Right, system will traverse the graph and mark that as an error. With the action graph we can check if student is still on the track to get a solution or not.

Figure 3

Illustration of Directed Graph – Action Graph



To represent and search the possible solution space within a serious game, we propose representing the space of possible solutions as an action graph. An action graph is a rooted tree data structure where each node represents a single action that a player could take within a given serious game. In this way, such a graph can be formally defined as $G = (N, E)$, where N is a set of nodes and E is a set of directionally connected edges:

- $N = \{n_1, n_2, \ldots, n_j\}$ The set of nodes that comprise the action graph. The single root node from which all directional connections originate is defined as $n_1 \in N$.

- $E = \{e_1, e_2, \dots, e_j\}$ The set of directional edges, each of which connects from some source node $n_s \in N$ to some destination node $n_d \in N$.
- $f_p(e)$ is a function that, given an edge $e \in E$, returns the source node from which the given edge originates, also known as the parent node.
- $f_c(e)$ is a function that, given an edge $e \in E$, returns the destination node to which the given edge travels, also known as the child node.
- $C(n_i) = \bigcup \left\{ n \in N \middle| \exists e \in E : n_i = f_p(e), n = f_c(e) \right\}$ is a function that, for a given node $n_i \in N$, returns a set of all nodes $n \in N$ that are child nodes of n_i.
- $L = \bigcup \left\{ n \in N \middle| \nexists e \in E : n = f_p(e) \right\}$ is the set of all leaf nodes $n \in N$, defined as all nodes that do not have edges originating from them.

The action graph for a specified game is defined in such a way that following any sequence of in-game actions from the root node to a leaf node will result in a complete, correct solution applied to the relevant in-game problem. Thus, by extension, any unique sequence of nodes that starts at n_1 and traverses to a leaf node represents a unique solution to the given in-game problem.

3.3 Heuristic Algorithm

With the action graph described above, we seek to implement error detection, adaptive student guidance, and solution checking all through one combined algorithm. The proposed algorithm uses a list of actions that a student has taken in a game, traversing the graph to both check that the student is still on track toward a solution and, in the case of an error, providing assistance to push the student in the direction of the "nearest" solution. This approach is formalized in Algorithm 1.

Algorithm 1 then returns a flag if the player has made an error and returns the list of actions the player must take to move from their current state to the nearest solution. To fully integrate this low-level algorithm into the system and provide personalized student assistance, we also must consider the player's overall performance. If we provide hints and assistance on every single error a player makes, they have little opportunity to learn on their own. Thus, we consider a performance score.

Algorithm 1: Action graph searching

Inputs: Action graph for target in-game problem, G
Ordered list of player actions, P, where $p[i]$ represents the *i*-th element of P and $p[1]$ is the first action associated with the root node, $n_1 \in N$, n_i represents the player's current node position.

1: **Initialize** $n = n_1 \in N$
$error = false$

2: **For** $i = 2, i = i + 1, i < |P|$ **do:**
- a. **If** $p[i] \in C(n)$ **do**:
  - i. $n =$ the node $\in C(n)$ that represents $p[i]$
- **b. Else if** $p[i] \notin C(n)$ **do:**
  - i. $error = true$
  - **ii. Break**
- **c. End if**

3: **End for**

4: Starting from parent node of $n_i \in N$, **depth first search** to find the shortest path to a leaf node.

5: Parse shortest path into action list P^*, which is the list of actions the player must take to reach the nearest solution.

6: **Return** $error$ and P^*

The performance score is a numerical indicator of a student's performance in the game, with higher values indicating more negative performance. The specific method for computing performance score depends on the implementation, though typically, the score would be derived from performance-indicating variables such as number of incorrect answers, time taken to make a move, number of past errors, or other relevant values. Finally, Algorithm 2 shows the top-level method for solution checking and providing assistance.

Algorithm 2: Player assistance and solution checking

Inputs: Action graph for target in-game problem, G
Player's prior performance score, ω
Minimum performance threshold, ω_{min}

1: **Initialize** player action list $P = \emptyset$ and $\omega = 0$
2: **While** problem is not solved **do:**
  a. **If** P is updated from the system **do:**
    i. Receive list of player actions P from system
    ii. Call **Algorithm 1** with G and P as inputs to get $error$ and P^*
    iii. Compute new ω using errors and other player data
    iv. **If** $\omega \geq \omega_{min}$ do:
      1. Use P^* to provide hints to the player.
    v. **End if**
  b. **End if**
3: **End while**

3.4 Overview of Algae City Water Purification Game

To better visualize the educational impact of our proposed method, this section presents a case study from an in-classroom implementation of our proposed action graph model. To measure system effectiveness, we implemented our proposed system and algorithms into a game called Algae City, and specifically into the Water Purification module. In this section, its briefly overviews Algae City and the Water Purification module.

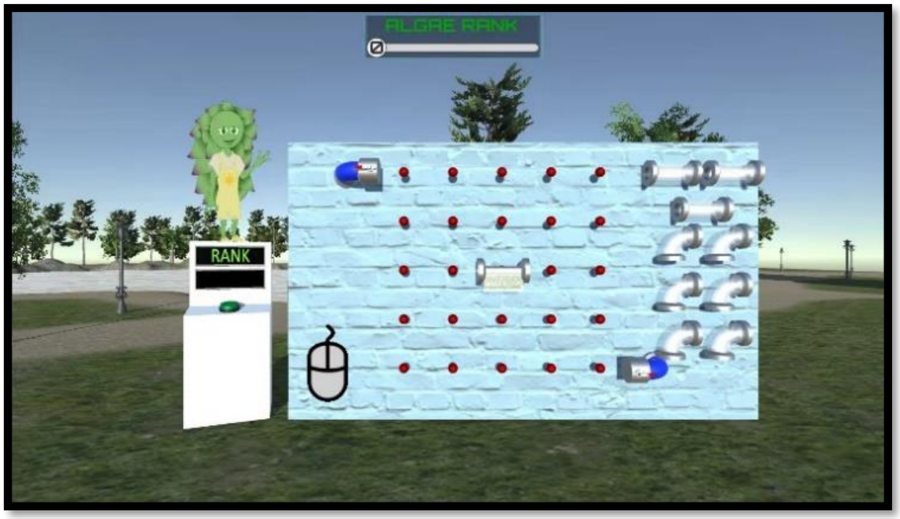
Algae City is an interactive educational game built in the Unity engine that focuses on educating students in various applications for algae. The game is designed for middle school students (age 11-13). While most students in the target audience will be aware of algae as a common photosynthetic organism, the game focuses on educating them in less common and more significant applications for algae. Algae City does so by prompting students to explore algae as an environmentally friendly solution to problems such as pollution, energy generation, vehicle fueling, and skin cosmetics. Specifically, the game is composed of 4 modules: water purification, algae reactors, algae fuel, and algae mart, each of which deliver different contents pertaining to the overall purpose of the game (Refence Dr Jahan's paper). Fully combined, Algae City is a very good platform to enhance students' individual learning processes and improve their problem-solving skills.

Figure 4

Water Purification Introduction Scene

Figure 5

Pipe Challenge Scene



To exemplify the adaptation process in serious games using the proposed graph-based approach and demonstrate its performance, the Water Purification module is used in the case study. The puzzle game posits players at a polluted lake in a city park and challenges them to implement a simple but effective solution. The players are then asked to choose proper pipe components from a given list and form a pipe through one or multiple algae scrubber(s) to clean the water. The tasks get more challenging as the types of pipe segmentations and the quantities of them per type increase. Table 1 provides an example list of pipe segmentations for the beginning level of the game. Fig. 1 is the solution-action graph of *Water Purification.*

The goals of the game are:

- Achieve a high rank. Rank is based on the number of pipes and algae scrubber's player use.

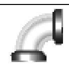
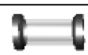
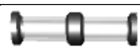
- Be efficient with pipe placement. Try to use fewer pipes and all the algae scrubbers to score better.
- Configure algae scrubbers correctly. Algae Scrubbers can be changed to deal with nuclear waste by right-clicking on them.

3.4.1 Case Study – Algae City Game

In our case study, we implemented the proposed system and adaptive support process into the water purification module. In the water purification module, students control a character in a virtual city park environment, where they immediately see a polluted lake. A cartoonish in-game character then prompts players to solve the lake pollution using algae, as shown in Fig. 1(a). Players are then tasked to solve a simple puzzle by placing pipe components from a given selection into a grid, shown in Fig. 1(b). The full problem to solve is to connect the input valve (left) to the algae scrubber (middle) and then to the output valve (right). As players solve levels of this game, the task is made more difficult through increasing grid size, different choices of pipe segments, additional algae scrubbers, and obstacles in the grid preventing pipe placement. Table 1 provides the full list of pipe segments that students use to solve the in-game problems. Taking the list of possible pipe segments, we can then derive an action graph for the first level of the pipe game, as shown in Figure 2.

Table 1

List of Pipes Segmentserso

Pipe	Pipe name	Acronym	Quantity of Pipes
	Elbow Pipe	Elb	2
	Elbow- Elbow Pipe	ElbElb	2
	Elbow-Straight Pipe	ElbStr	4
	Elbow-Elbow Curve Pipe	ElbElb C.	1
	Straight Pipe	Str	1
	Straight-Straight Pipe	StrStr	2

To provide learning assistance and problem-solving experience, Algae city collects data as input for Performance Scale criteria (time, errors, movements) throughout the game to adapt player's actions. Data collection during gameplay is a common approach to measuring the behavior of adaptive game. The performance scale logs all inputs from students and records them for classification. Collected data from students will help to adapt the criteria. Performance criteria update over time, as more players play the game. The threshold value ($THRv$) is a combination of errors, movements, and time. Threshold value ascertains when to give the instruction to the player based on their need.

1. Time: When students take significantly longer than average to pass the level, it indicates that they either lack time management or focus or are running into difficulties solving the level. As the student plays through various parts of the game, time

measurements for problem-solving steps are constantly recorded. Time for each connecting pipe (in direction to get a solution), as a real number measuring the total duration in seconds taken to play.

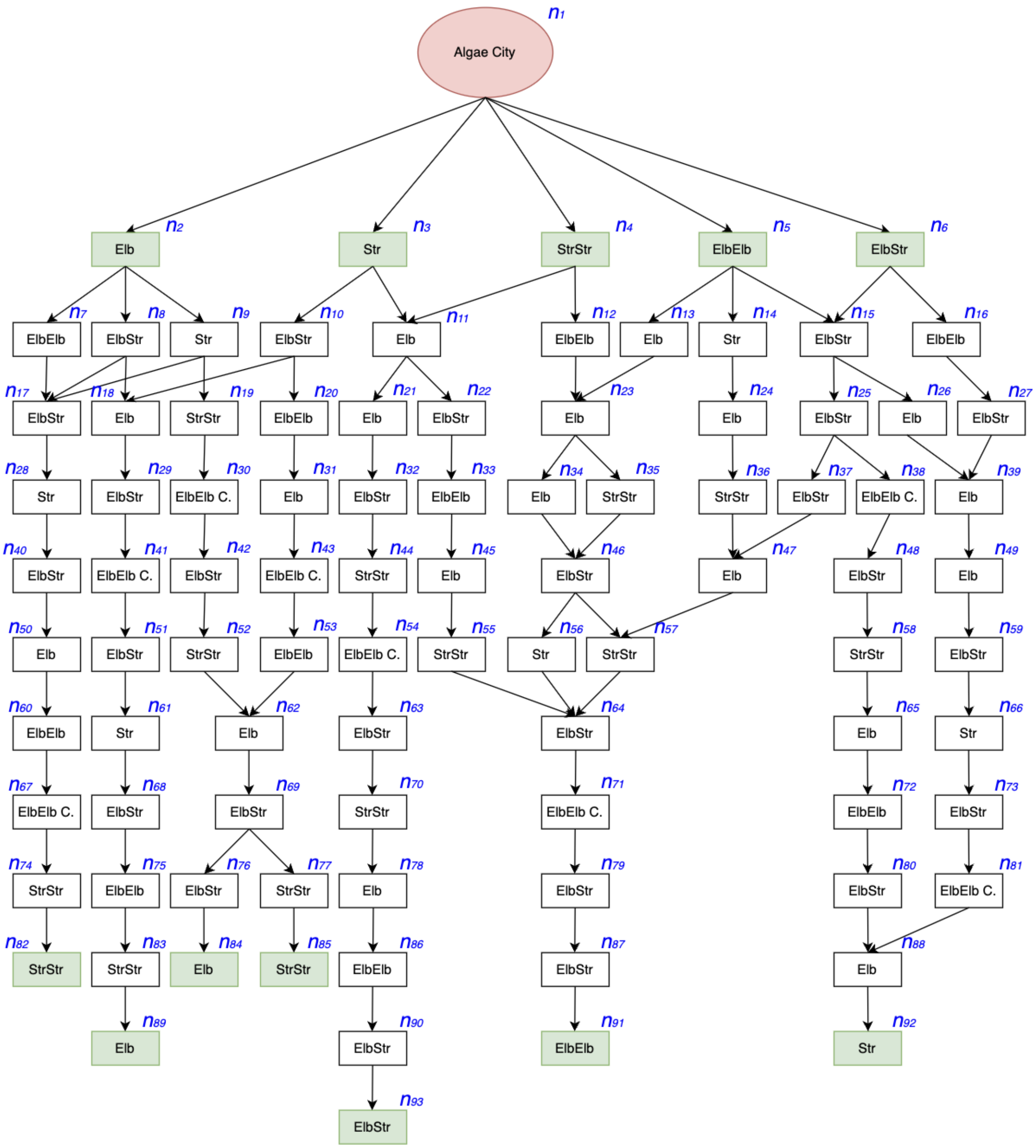
2. Errors: In addition to recording students' actions as they connect the pipes, the action graph algorithm detects the errors. Whenever students attempt to connect the pipe, the value will increase by 1, if the algorithm detects the error in placement.

3. Movements: The Performance Scale tracks the player's movements in the game. A player's total number of mouse movements (pipe clicked) while playing with pipes gets recorded in the log file to determine the movement of the player. The student's movements will help to predict his state of mind and ability to solve the level.

Note that, the purpose of this adaptive game is not to anticipate immediate help to students, because human tutors (teachers) let students do most of the work in overcoming impasses, and don't stop them right away, the algorithm lets them play until they reach the threshold value, when they surpass the threshold value, the algorithm provides instruction that leads them to a productive solution path and improves learning performance. When student surpass the Threshold value ($THRv$), action-graph searching algorithm traverse to detect the errors, also predict both the most suitable hint and the player's next possible actions if algorithm determine student is not on the track.

Figure 6

The Action Graph of Water Purification Representing All Possible Solutions to the Problem Based on What Pipes are Placed in What Order



As shown in Fig. 6, a new player is initialized with node n_1 as their starting position with no prior actions taken. The space of possible solutions in the game level is then shown over the rest of the action graph with $N = \{n_1, n_2, \dots, n_{93}\}$. When starting, it can be seen in Fig. 6 that all possible actions lead to possible solutions with the exception of the elbow-elbow curve pipe. Taking an example list of player actions, P:

$$P = [Elb, Str, StrStr, Elb, ElbElb]$$

The algorithm would then traverse nodes $n_1 \rightarrow n_2 \rightarrow n_9 \rightarrow n_{19}$ before finding that no child nodes of n_{19} have the Elb action. In this situation, the system would then enable the error flag and stop traversing the graph. Algorithm 2 would then return a $true$ error flag and a path to the nearest solution, P^*:

$$P^* = [n_{30}, n_{42}, n_{52}, n_{62}, n_{69}, n_{76}, n_{84}]$$

The provided path would then be used to inform our integrated hint system. However, since this is the student's first error, they would likely not be provided immediate assistance. Similar to a human tutor, the goal of the system is to give students space to solve issues and overcome impasses through their own effort and learning processes. As such, the game does not provide immediate assistance but rather waits until the player's performance score exceeds a certain threshold.

Algae City collects student data as they play including number of movements, time taken to move, and number of errors, combining them to derive the performance score. When a student's performance score exceeds a certain threshold, Algorithm 2 will actually begin to provide assistance to the player using P^*. Say, for example, the student from the earlier example continues to play through and produces the following sequence of actions:

$$P = [Elb, Str, StrStr, ElbElb\ C., ElbStr, StrStr, ElbStr]$$

The system would then traverse from $n_1 \rightarrow n_2 \rightarrow \cdots \rightarrow n_{52}$ before encountering another error and enabling the error flag. Like before, P^* is returned, this time as follows:

$$P^* = [n_{62}, n_{69}, n_{76}, n_{84}]$$

This time, the student's performance score exceeds the threshold due to the additional error. The student would then be provided a hint that recommends they explore the action represented by n_{62}, which is to place an elbow pipe in their solution. And while the pipe game is a specific case of this issue, many such problems in educational serious games can be decomposed into simple sequences of actions, making the system very flexible for many games and problems.

This game is centered on secondary school children. Rather than directly giving them an answer, the algorithm provides hints. The hints are purposefully not straightforward, giving students a puzzle-style clue instead of a direct hint. The hints are presented as follows:

- **Elbow Pipe:** use a single pipe which could be the joint for 90 degrees.

- **Elbow- Elbow Pipe:** use the pipe which consumes 2 spots and a combination of Elbow and Elbow pipes.

- **Elbow-Straight Pipe:** use the pipe which consumes 2 spots, and a combination of Elbow and Straight pipe.

- **Elbow-Elbow Curve Pipe:** use the pipe which is combination of two Elbow pipe in a shape of semi-circle.

- **Straight Pipe:** use a single pipe that can connect in the same direction.

- **Straight-Straight Pipe:** use the pipe which consumes 2 spots and combination of two Pipes which cannot band.

Chapter 4

Results and Comparisons

In this chapter, we summarize the information presented in this thesis along with survey, results and comparison of students played AI-assisted game and non-AI game. First, in order to provide some context to the discussions, would like to revisit some foundational topics. Primary objective of this thesis is to create the adaptive environment for students where the system observes the gameplay, detect payer's in-game errors and provide hints as assistance if needed. The algorithm is developed using directed graph which calls Action graph. The case study is performed on educational game called Algae city pipe game.

With previously obtained data that has already been derived and annotated by a human expert, the action graph derived which represents all acceptable sequences of actions that arrive at a solution. As new training data is obtained from experimentation and testing of the game, the model can be rapidly updated, and the model will continuously improve. With larger amounts of data and increased reliability of data as testing and experimentation continues, the model will become more stable, and the predictions of the tree will become more accurate [42].

As previously stated, the three components of the data (time, error, and movements) are collected from students as they play the game. This data is represented by various measures such as how much time a student is consuming to solve that level, how many errors student made during his attempt, and how many movements he made during the process of reaching the destination. If other features are identified during testing and studies of the system, they can and will easily be added into the overall process.

When student cross the performance scale limit system provides the hint which helps students to play game with more enthusiastically without getting bored and having monotonous experience. Hints were also erected in a creative way where students must think inventive way and involved in a learning process to solve it. Algae city game purpose was to adapting game elements and putting them in a way to serve educational needs, allow the development of educational games which may engage learners to discover more knowledge and to obtain new skills that encompass problem solving skills.

AI techniques have been used in this games-based learning to improve players' engagement and learning outcomes. Hence, games deal intelligently with issues for learning purposes and make the player entertained and enlightened at the same time. In this context, we conduct a survey where students play game with AI and playing without AI and they find out playing game with hints helps their learning, keep them engaging and more entertaining, where hints itself is challenging and interesting.

It is important to mention that despite of the impact of adding an intelligent side in games, there are a limited number of intelligent games with learning purposes. Numerous AI techniques are involved in games which makes the modification of the game more flexible, that improving the game and adding some functions helps to enhance the student's experience.

In, the experimentation proves benefits of the AI based learning system in attracting students and shows the facility of using it as well as its impact in increasing student's problem-solving skills.

4.1 Experimental Assessment of Research

The experimental assessment was conducted using two versions of Algae City: 1) Game played without the learning guidance (Game-A: Control Game), and 2) Game played with the learning guidance (Game-B: Experimental). Our comparison case study used a focus group of 14 students to compare the educational effectiveness of our serious game. The 14 students were randomly split between Game A, the control group without adaptive guidance, and Game B, the experimental group with adaptive guidance. All 14 students that participated in the case study had similar educational standing in terms of GPA. The game included all necessary instructions, as well as several parts and subgames for them to acquire knowledge about algae. Students were also challenged to finish the game and achieve a high score in the various components.

As the students played through Algae City's water purification module, we recorded the time taken and the number of actions required for them to complete, and errors they made in the pipe puzzle game. Specifically, we evaluate if our assisted game (Game-B) with hints helps boost students' engagement, or otherwise enhance their experience and keeps them entertained. With our evaluation goals in mind, a focus group of seven students was gathered for the experiment. The data collection process for assessment started with introducing the game to the group and having each of them play the game individually at their own pace. Recorded values are shown in Table 2.

From Table 2, it can be observed that the experimental group using Game B showed overall faster and more efficient completion of the pipe game. On average, students who used Game B completed the game in 38 actions, compared to 52 actions from students using Game A. Comparatively a smaller number of actions shows that Group 2 reached to destination in less efforts compared to group A. All students who take more actions clearly need more time as shown in the table. Additionally, students in the experimental group completed the game in 259 seconds, on average, compared to 317 seconds for the control group. Fig. 3 visualizes this data to further show the impact on completion time and actions taken. Table also shows how many hints were used by students of Group B to lead them towards their solution.

The proposed system provides automated educational hints and guidance to students as they play. The reduction in time and actions needed for players to complete the game demonstrates positive initial results for the system's ability to impact players' educational experiences. When students get help tailored to their need it can eliminate the tedious and monotonous experience of educational game.

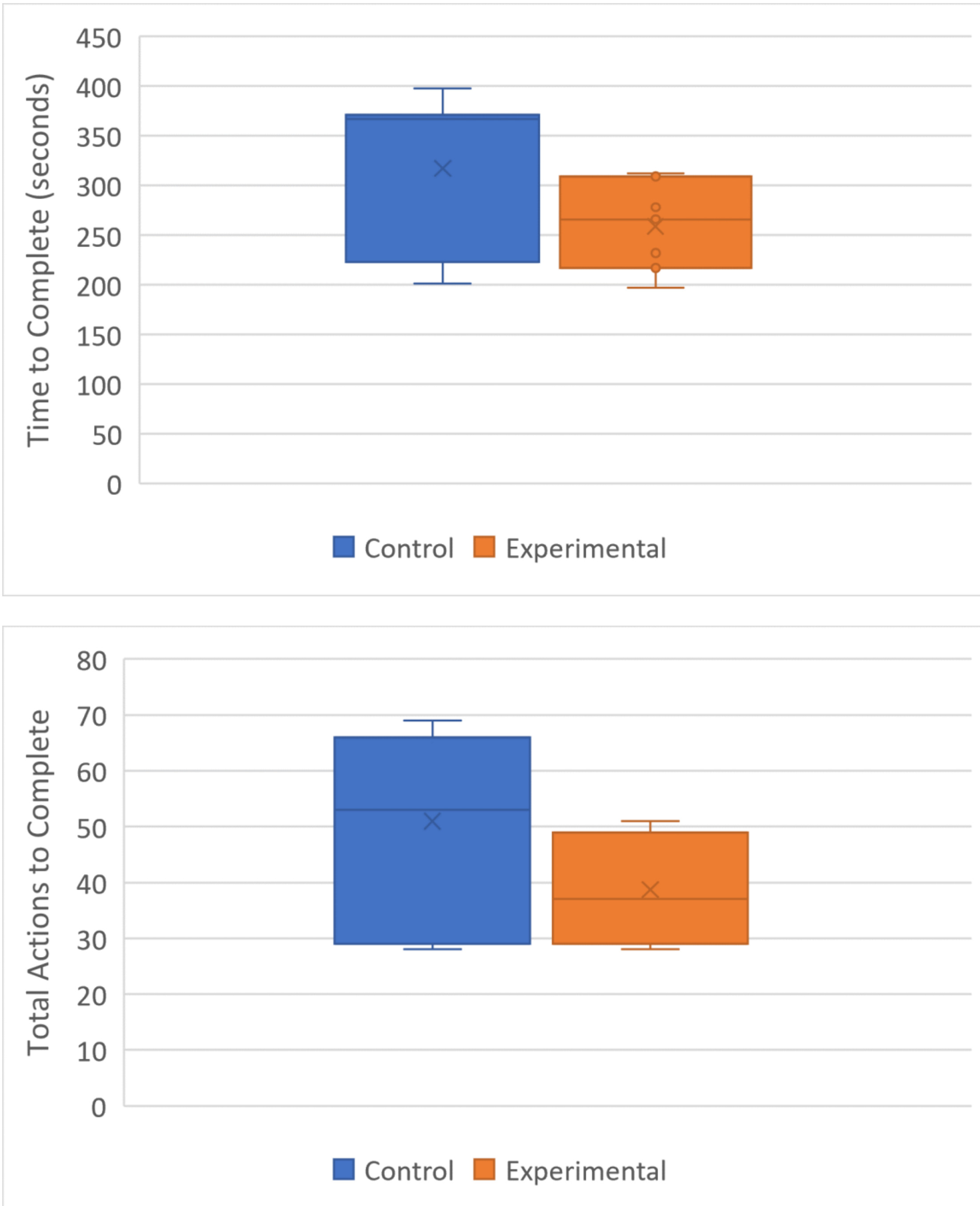
Table 2

Data Collected from Students in the Control (Game A) And Experimental (Game B) Groups

Game A (Control)			Game B (Experimental)		
Player	**Time (s)**	**Movements**	**Time (s)**	**Movements**	**# Hints**
1	371	66	266	49	2
2	398	69	312	51	3
3	201	28	197	29	1
4	289	49	232	33	2
5	371	63	309	44	3
6	367	53	278	37	2
7	223	29	217	28	1
Avg	*317*	*51*	*259*	*39*	*2*

Figure 7

Comparison Between Experimental Control Groups in (A) Time Taken; and (B) Actions Taken



4.2 Survey

To get a better understanding of how the learning assisted adaptive game impacted students, the survey was conducted where students were given a set of questions to rate their experience on a scale from 1 to 10. Survey was conducted to know the impact of AI assisted game and to know the scope of improvements. Students were also allowed to write down the general comments if they have any in the comment section at the bottom of the survey. The questions were as follow:

1: Rate your gameplay experience.

2: Rate your experience playing the game with learning guidance.

3: Rate your experience playing the game without learning guidance.

4: How much were hints the relevant to the game?

5: Rate your opinion of learning guidance to make game more interesting and enhance your playing experience.

Fig. 4 shows the results of the survey. As shown, the majority of students found the game with learning to be a better overall experience. The survey results states that adaptive approach helped to boost students' experiences. According to the survey, game played using AI segment resulted positive above than average.

The purpose of this hint-based AI module is not to give the direct solution to the students and make the things easy for them. We wanted students to be challenged and get the knowledge of the algae, that is the main purpose of developing this game. Students stated that giving hints based on performance is a very useful feature. It's an interesting game. While we were conducting survey, the students reported dealing with a variety of emotions while playing. They expressed feeling challenged, happiness, and motivated.

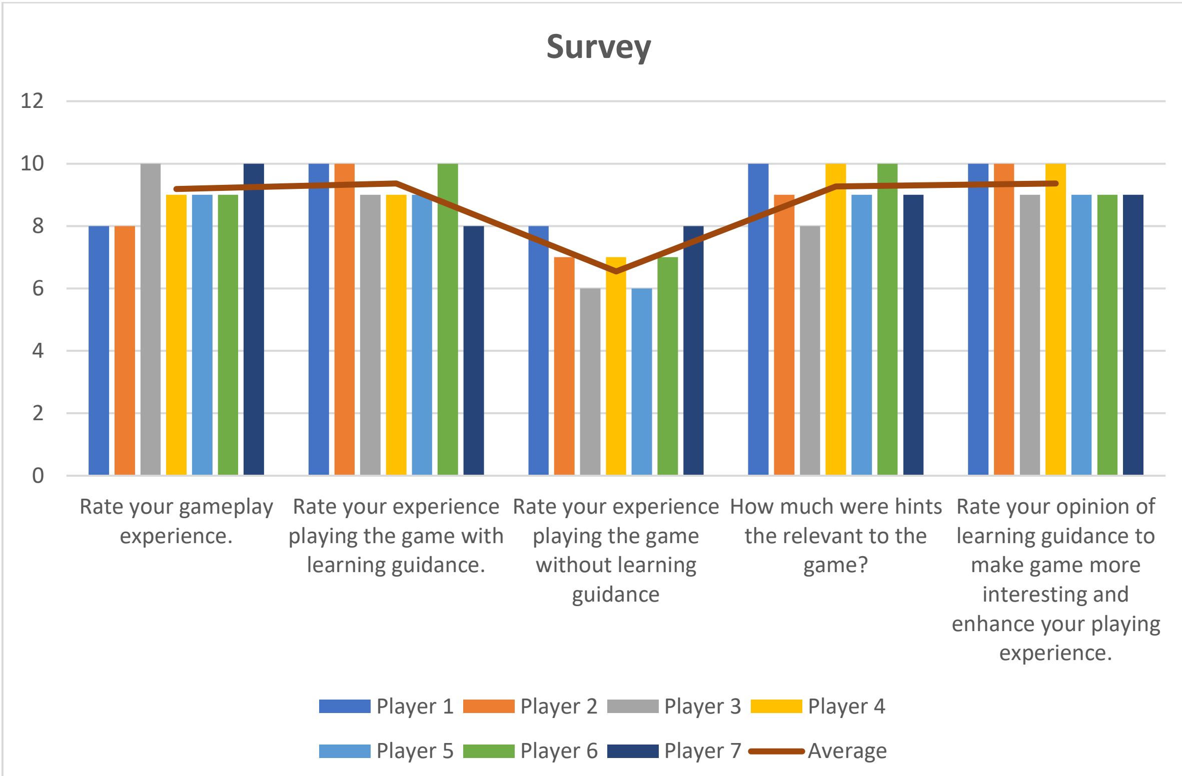
When children are feeling challenged, they could mainly be connected to the adaptivity of the game as it provides them the difficult tasks and goals to achieve. To crack the hints also have to think what pipe is this and with given pipes how to connect start node and end node using the algae purifiers. Overcoming these tasks made students feel happy, confident as they learned to tackle different problems of the game by solving them using the help of hints created by game adaptivity.

Accordingly, children expressed feeling confident several times during the survey where they have to us fewer hints compare to other students, and that makes them happy as they solve the levels by themselves. Students also expressed that thinking were experienced during the game play (I solved this issue by thinking a lot. Sometimes problem happens because we they have limited pipe and have to connect ends by using both algae purifiers.) and it was also perceived as a learning gain (The game gives more ability to think. And how to make strategies to get high scores. I also used hints; it helped a lot).

Besides, all children enjoyed the cognitive challenge the game provided them with, claiming to have enjoyed the difficulty and the possibility to compete with oneself and get the high scores by solving the levels by cracking hints. Students also stated that this game have so many different features overall which give the complete gaming experience on learning perspective with knowledge of algae. Also offer feasible and motivating learning experiences to them. What’s more, all children believed that this game is suitable for using at school.

Figure 8

Survey Collected from a Group of Students After Their Experience



4.3 Adaptation of the System's Approach

The graph-based approach can be applied to any serious game provided that the developers are able to create an appropriate action graph. When varying the learning context of serious games, the educational performance is ultimately up to the design of hints and the design of the game itself. The proposed system is designed to augment a player's experience with personalized guidance toward a solution. The actual form of that guidance and the problem presented in the game would vary the performance of the system. However, given an appropriate action graph, the system is always able to provide the player with hints toward a solution, and as such, it is expected that the player would always reach a solution faster than in an unguided system.

The chosen learner model, as well, could impact the system's educational effectiveness. Our performance scale model accounted for several aspects of a player's performance (such as time taken, number of errors made and number of actions/movements requires to complete the game) to determine if the player needed assistance. Depending on the context of other serious games, other variables may need to be accounted for to achieve comparable educational effectiveness. In general, it is key to provide the system with a solid metric of student performance to make informed decisions on when to provide assistance and when to allow the player to self-learn. Given such a metric, the system should then always be able to leverage the action graph at appropriate times to guide a player toward a correct solution.

Chapter 5

Conclusion

5.1 Summary of Research

Our purpose of the adaptive game is to offer students timely feedback tailored to their needs. We presented an online adaptive clustering algorithm in a decision tree framework, which has an adaptive tree and a code formation layer. The code formation layer stores the representative codes of the clusters, and the tree adapts the separating hyperplanes between the clusters. The cluster memberships of a sample depend on the tree parameters which are adapted in the online mode depending on the stored codes. We defined a global objective function analogous to that of soft means and showed that the control parameter (exponent) regulates the number of clusters (as opposed to c-means where the number of clusters is always fixed). In the online adaptation process, we never freeze the learning and therefore the model is able to adapt to the input distribution of the data. In addition to online adaptive learning of the sample groups, the tree produces a hierarchical representation of the clustering by minimizing a global objective function as opposed to the existing hierarchical clustering algorithms where an objective function is optimized locally at every level. We have demonstrated the effectiveness of the model for performing class discovery in the unsupervised mode on certain datasets.

5.2 Quantitative Evaluation

This research is conducted to evaluate the effectiveness of a new AI based personalized approach for improving student performance and enhancing their learning experience. The research hypothesis is that this proposed system will result in a significant improvement in student performance and is intuitive for developers. Students who played the AI-assisted game showed an average 20% decrease in time needed and an average 58% decrease in actions taken to complete the game. The system under consideration offers automated educational hints and support to students while they play. The decrease in the time taken and actions performed by the players to finish the game shows favorable early outcomes for the system's capacity to influence the students' educational experiences. It can be concluded that the proposed approach is effective in improving student performance compared to the non-AI module.

5.3 Scope of Future Work

This study provided an understanding of how secondary school students approach educational games adapted with AI and without AI. The results from this study have shown that moving forward, students will benefit from this experiment. This game will provide students with a unique and customized learning experience, based on their individual needs . Personalized gaming systems that are tailored to individual players can greatly increase player engagement and satisfaction. Proposed system will help students by providing an experience that is constantly evolving and challenging, reducing the likelihood of players becoming bored and moving on to other games.

In the future, this system will experiment with a wider range of games and conduct surveys to gather more data. This additional data collected from both types of games will enhance the system's accuracy. With more data being collected on player behavior and preferences, it will give us the opportunity to better analyze player data to create more targeted and effective personalization. In the days ahead, the game will acquire more adaptability so it can continuously adapt student’s progress and ensure they are always challenged and learning at the right level. It can also adjust the difficulty of the levels based on the student's performance. By continually adjusting the game experience to match the player's skill level and preferences, this study will facilitate to improve player retention. By adding the facial recognition technique into this research, we can make learning more engaging and enjoyable for students, which helps to know when a student is getting frustrated, feeling stuck or getting bored.

Future work will continue focusing on increasing motivation and interest in the subject by making learning more engaging and enjoyable for students. Interactive and dynamic nature of this personalized game can help students better understand the information they have learned. Overall, the future of personalized gaming experiences is full of exciting opportunities that have the potential to greatly enhance the gaming industry.

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