M102CEM – Individual Project

ARTIFICIAL INTELLIGENCE EDUCATION USING VIDEO GAMES

Eduard R. Georgiev

MSc Computer Science

School of Computing, Engineering and Mathematics, Coventry University, United Kingdom

Author	**Student ID**
Eduard Rumen Georgiev	8240390
Module Leader	Dr Rochelle Sassman
1st Supervisor	Dr Jianbing Ma
2nd Supervisor	Dr Jacek Lewandowski

Author e-mail address: e.r.georgiev@gmail.com (E. R. Georgiev)

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First Name:	Eduard
Last Name:	Georgiev
Student ID number	8240390
Ethics Application Number	P70383
1st Supervisor Name	JianBing Ma
2nd Supervisor Name	Jacek Lewandowski

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ABSTRACT

Developing a video game that implements an artificial intelligence is a challenging task, but this research project manages to do that and more, such as gathering data on how users react to the developed video game, how they feel about it and how well they value each element in regard to the educational value it provided. As such, this paper attempts to understand how an interactive video game developed specifically with educational purposes can be used to entertain, and at the same time educate with its interactive nature on the topic of artificial intelligence, specifically neural networks and genetic algorithms. The video game implements well-researched design patterns which, together with other game elements, help the user experience education in a new way, a way which allows him to learn in multiple learning methods, one or more of which are likely to suit his needs.

The achieved results show on which areas educational game developers should focus, how the players prefer to interact with different elements of the game and the way they respond to them. Furthermore, conclusions are made about attempts to keep the attention of the user for longer and what is the result if certain key elements are skipped. Based on the achievements and the result analysis, proposals are made on how future work can improve on what this project has achieved, which proposals are key towards developing software that is meant to be understood by many players of different backgrounds and interests.

Keywords: Artificial Intelligence, AI, Education, Computer Games, Games

JEL Classification: I20, L82, O33, Y40

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1. INTRODUCTION

Artificial intelligence (AI) is intelligence demonstrated by machines, which is attempting to replicate the intelligence of a human being. With the ever-growing advancements in technology, AI is becoming more widely used, increasing in relevancy in almost every professional field. Furthermore, its growth is expected to be rapid and ever-accelerating, mainly because of recursive self-improvement (Yudkowsky 2008). AI is able to automate even jobs that depend on human intelligence, recently becoming more accurate even at tasks such as image recognition (Manyika 2017). Frey and Osborne (2013) estimated that 47 percent of total employment in the US is at risk of computerisation.

With many professional positions at a risk of global automation, many people will start losing their jobs, which is often their main source of income and stability. New generations will no longer be able to ignore the topic of AI in just about any professional sphere as more and more jobs become dependent on such knowledge. Traditional methods of studying artificial intelligence include mainly theory and research, which can be dull and uninteresting for people that prefer to see their knowledge put to use as soon as they acquire it, especially the younger or unfamiliar crowd that would lack the needed attention span to delve into the immense books on AI.

1.1 Objectives

This project aims to research and develop a solution that would provide an entertaining and interactive way to educate people with little knowledge on the topic of AI and then identify how it was received and how well it performed at its task. Existing research papers will be analysed to better understand the topic of AI in gaming, AI education and different AI technologies. A demonstrative product will be developed using Unity Game Engine and the programming language C#, which product will be the result of the research analysis performed. The product will be made available to a focus group of 30 people, which will then be questioned on how educational and captivating they found it to be. Project objectives are as follows:

a) Analyse existing research
b) Develop a software solution
c) Perform tests using a focus group
d) Create a questionnaire and analyse results
e) Draw conclusions

1.2 Background

Basic knowledge on the topic of computers and gaming will be sufficient to gain an adequate understanding of the reasoning, analysis and conclusions that this research project has drawn. Familiarity with artificial intelligence articles and theory will complement the ability of the reader to delve deeper into the way that this project is implemented and understand the logic behind it.

The gaming and the automation industry can benefit from this research, as it can help answer questions about target audience, recruitment, product development and employee education. Furthermore, this paper will provide methods of implementation and design that can be crucial towards creating a popular product.

Gaming communities that are seeking a new, education and innovative product will be interested in what this project has to deliver.

1.3 Terms

2D – Two-dimensional.

AI – Artificial Intelligence. Specifies a type of software that is designed to make decisions based on simulated brain neurons, mimicking human intelligence.

Cross-Platform – Software that is adapted to or is able to produce software for multiple platforms. For example, the Unity 5 game engine can produce games for both Android mobile phones and Windows desktop computers.

Game Engine – A software tool that aid the development of video games.

GUI – Graphical User Interface. Like UI, but the interface elements are graphical.

Triple-A or AAA – Used to classify video games with high development budgets and levels of promotion.

UI – User Interface. Specifies the array of interface elements that the player uses to interact with a given software.

1.4 Overview

A multitude of topics will be included in this paper, split into different sections and reviewed separately:

a) Literature Review
   Analysis on research from credible, contemporary and peer-reviewed papers that observe learning techniques, game engines and their features, game design patterns, AI technologies in the spheres of gaming and education and good user interface practices.
b) Method
   Description on what was done in order to answer the research question, and what methods the researcher used to gather and analyse information. Discussion about the overall requirements, product and survey testing and project management is also included and summarised. Research project implementation is discussed in detail, in order to allow future researchers to recreate this work and verify the results, as such, the information written is in greater detail, which may require knowledge on the related topics.
c) Results
   Presentation and analysis of the results from the survey described in the method part of this paper. Conclusions are drawn on what was done to answer the research question and how it can help researchers, developers and companies.
d) Discussion
   Discussion on research project achievements, deficiencies, problems, issues, ways of solving listed issues and how things could have been done differently.
e) Critical Review
   Discussion on used methods, learned lessons, quality assurance and risk analysis.
f) Conclusion
   Brief statement on how the results and analysis have answered questions stated in the introduction.
g) References
   A collection of references that are used to credit authors throughout this paperwork.
h) Appendices
   Mandatory documents and raw data tables.

2. Literature Review

Games come in a myriad of varieties, including popular games like Football, Chess and Volleyball. Video games are a rather recent implementation, starting from the very first Pong game made on an oscilloscope. They have gained an immense exposure over the last years, developing to be a massive part of the entertainment industry. This research paper will focus on creating a two-dimensional video game that can be used to educate students on the topic of AI in an interactive way.

The following topics will be researched and analysed:

a) Learning
b) Game Engine
c) Unity 5
d) AI Design
e) UI Design
f) Game Design

2.1 Learning

Understanding how people learn best and how to present information in a way that is fit for most users is crucial towards completing the project and providing a successful solution that can expand upon currently available research.

A properly-established and thoroughly reviewed paper by Felder and Silverman (1988) observes several different styles of learning models, focusing on engineering students, which is ideal for this research as Artificial Intelligence is often part of or comprises entire engineering courses. They conclude that learning style mismatch accounts for professional frustration and a loss of many potential excellent engineers. The learning styles are as follows:

a) Sensing and Intuitive
b) Visual and Auditory
c) Inductive and Deductive
d) Active and Reflective
e) Sequential and Global

Sensing and Intuitive

Learning through sensing involves using human sensory information to observe and gather data, while intuitive relates to learning using speculation and imagination (Felder and Silverman, 1988). Engineering courses, including those that target topics like Artificial Intelligence, tend to favour intuitive learners as information is transmitted using lectures and books Often times the reader would have to imagine and construct different concepts in his mind, while speculating about information that is scarce or relies on previous knowledge that the reader might lack. This is an issue that can be covered using video games, as they can present information in a way that both sensing and intuitive types will be able to understand equally well.

Visual and Auditory

Felder and Silverman (1988) state that visual learners remember best by looking at pictures, animations, charts, demonstrations, while auditory learners may not remember what they have seen but would rather excel in remembering details about conversations and verbal explanations. Personal computers, especially laptops, almost always come and rely on an integrated display and a set of speakers to present visual and auditory information to the user. Using these assets, a video game can stimulate both senses at the same time, maximising the learning potential and appealing to all types of players.

Inductive and Deductive

Induction refers to a reasoning that is based on using observations to discover laws and theories, while deduction deduces consequences based on governing rules (Felder and Silverman, 1988). A video game can easily appeal to inductive learners, as it introduces the player to an environment that is unknown and difficult to solve, which would require the player to try, fail and improve in order to make progress. Further consequences can be deducted using previously established rules and laws.

Active and Reflective

Active learners use experimentation and testing in order to understand better, while reflective learners are more oriented towards theory, observation, examination (Felder and Silverman, 1988). While video games can tend to reflective learners using certain written tips and methods, they are more suited to benefit active learners, as the player is often encouraged to experiment and then only then analyse.

Sequential and Global

Material that is logically ordered in a progression can be easily understood by sequential learners, while students who are global learners may not understand logical progression, but rather learn in “fits and starts” (Felder and Silverman, 1988). Most contemporary games offer a better experience for sequential learners, as they present a linear tutorial, which must be followed from start to finish, mastering simple and advanced techniques. This can be adapted to suit global learner, too, by adding the option to skip the tutorial. This will allow the player to learn concepts of any complexity at any time during the game or when required to do so in order to advance certain levels. To avoid strict level advancement requirements that may restrict global learners, a good level design must always implement more than a single solution or technique.

Most often people tend to favour one set of learning styles over the other (Felder and Silverman, 1988). With the power of video games, the user can be taught in a style specific to his own preferred way of learning. This project improves upon traditional learning ways by combining multiple learning styles, using assets that most engineering students already possess, like a personal computer.

Identifying player learning style can be performed using certain formal tests and quizzes that are already in use in some schools, as noted by Pritchard (2013), which is clearly based on and influenced by previous studies on the subject. This study will offer only a simple form of self-identification using a questionnaire due to limited time and resources, which identification would be used to provide a basic understanding of the styles that the project mostly appealed to. Furthermore, some recent studies have been able to find only minimal evidence supporting learning styles (Pashler et al. 2008), often contradicting as results seem to vary. Going into further detail without sufficient supporting research data on learning styles may be unwise. Interpreting the relation between player learning style correlation with game representation will be left for the questionnaire and for the reader to decide for himself.

2.2 Game Engine

Many modern games have their own custom-built game engines that allow for quick, relatively easy and intuitive gameplay programming, which would otherwise be very bulky, unorganised and inefficient. A game engine is, at its core, is an optimised set of tools that aids game development. It is oriented towards reuse and often supports scripting languages like C#, JavaScript, Python. Some game engines include their own language, like the Havok engine adapted by Blizzard to process "Galaxy" script in order to enable efficient mod creation and enhance the game development experience. It is important that a game engine is chosen in the beginning of this project.

There are many game engines available. The following are not only free to use for non-commercial projects but are also very popular and some of them are well established:

a) Unreal Engine
b) Unity
c) Godot Engine
d) Construct 2
e) Amazon Lumberyard

Unreal Engine

Unreal Engine, developed by Epic Games, is a game engine that presents some of the best tools and feature sets in the industry, including shader creation, graphical user interface (GUI) creation and logic programming called "Kismet" (Gregory 2014). It is free to use for non-commercial projects and it is a good starting point, but Unreal Engine has been designed for the creation of three-dimensional first-person shooters like Unreal Tournament. This is not ideal for the development of a two-dimensional game. Furthermore, it is most often recommended for teams, rather than a single developer, hobbyist or a student. Due to time and resource limitations, Unreal Engine cannot be considered a viable option.

Unity

Unity is a cross-platform game engine, which has a primary goal to ease development, make assets available for independent developers and provide a powerful set of tools for video game preview, analysis and optimisation (Gregory 2014). It supports scripting in C# and provides support for character animation, AI and network connection. Unity is often recommended for big and small teams alike, as it is very efficient at creating both three-dimensional and two-dimensional games.

Godot Engine

Comparably simple to use multi-platform game engine that allows users to create games with ease (Godot 2018). While the engine provides an intuitive environment, which is great for beginners and small projects, it is very young in its development, so much that the community is small, there are just a few assets available and there is just a small library of plugins that can support game production.

Godot supports C#, but it is not yet fully implemented and rather at the experimental stage. Instead, it uses a custom-made programming language that is simple, but it would require time to learn and adapt to. It is important to note that Godot does not support Artificial Intelligence at its current stage.

Construct 2

Construct 2 is an HTML5 game creator designed for 2D games, which allows developers to create games without any programming (Scirra 2018). With its incredibly simple to use interface, it can allow anyone to create a video game. Furthermore, it has an integrated speech-recognition system that can be useful for the purposes of this research paper. The community of Construct 2 is well established, which would assist with problem solving. Unfortunately, the only language that the engine support is JavaScript, which is used to make plugins in order to extend the features of the engine. Time restraints and uncertain plugin availability make the engine undesirable for the purposes of this research project.

Amazon Lumberyard

A highly customisable and free game engine created by Amazon that provides cross-platform development features (Amazon 2018). Similar to Unreal Engine, Amazon Lumberyard is marketed as a Triple-A game engine, which is not what this project is aimed at. Upon further inspection, Amazon Lumberyard proves to be inefficient in the creation of 2D games, as it is designed for 3D gameplay and offers relatively low performance and productivity when tasked with the creation of a 2D game.

Craighead, Burke and Murphy (2008) compare Unity against other development platforms and conclude that the main advantages of Unity are the documentation, community, environmental editor, physics and rendering engines, multi-platform distribution and low cost, defining the Unity engine to have high fidelity. The study focuses on a game mode that is irrelevant to this study, but conclusions apply generally to Unity, further reinforced by another study made by Petridis et al. (2010), which states that Unity lacks support for some network protocols, but offers great multiplatform distribution, technical support and accessibility. For this project, network connectivity will not be an issue, as the software developed will be single-player. However, Petridis et al. (2010) notes that Unity has one of the lowest composability factors of all engines, which defines both the ability of the engine to reuse content created within the engine, and its capability to use data from proprietary sources. It would seem that the study reduces the composability score of Unity based on its available developer tools, but it is important to note that the study is a bit outdated in that regard, as a substantial amount of third-party and official tools have emerged in the Unity asset store, with a considerable portion of those applying to two-dimensional graphics. As such, this project will use Unity Personal version 2018.1.3, which is best suited and recommended for hobbyists and students.

2.3 Game Design

The features of a video game, such as plot, graphics, sounds effects, controls and similar are all part of the game design and are often called “gameplay”. When implemented correctly, a video game can be easy to understand and enjoyable to play.

Immersion is a gameplay element that serves a purpose to keep the player engaged with the digital world that the game presents. Realism is an important tool when gameplay developers want to make their game more immersive. Imaginative immersion is a term that describes story elements that make one feel for or identify with a game character (Ermi and Mäyrä 2005). Similarly, challenge-based immersion is based on achievements using mental or motor skills, while sensory immersion represents audio-visual execution of games (Ermi and Mäyrä 2005). Ermi and Mäyrä (2005) created a gameplay model, which helped them compare popular game titles like "World of Warcraft" and "Half-Life 2". Their conclusions indicate that games that implement all three types of immersion in a balanced manner score the highest and prove to be the most popular, while games that may score amazing results in a single immersion type but lack in the other two would prove to score lower and be less popular. Games with an average score are treated as casual, which would benefit users that prefer not to spend time engaging with a game but rather prefer to unwind and relax. The study from Ermi and Mäyrä (2005) is limited in a sense of result analysis and conclusions are brief, further research on the topic is needed to better understand human gameplay preferences.

In order to promote effective learning, the gameplay must encourage elements that logically require the skills that the player needs to obtain, a good example of this being a game that is about locating treasures on the map, requiring math skills to plot XY coordinates, as otherwise the user will tend to lose interest (Ke 2008). Such a technique can be implemented into this study by making the player perform tasks that require knowledge of AI to improve the AI. The study from Ke (2008) warns that adding such elements to the game may disrupt the state of engagement, since the player would, in a sense, leave the game world while solving the problem. Therefore, this project will aim to create a world that incorporates learning mechanisms as closely related to the game as possible with an emphasis on immersion. Ke (2008) falls short in the fact that it uses only a small focus group of students, but it identifies its own downfalls and performs an in-depth analysis on the results to the best of its ability.

Rewarding gameplay is essential for keeping user attention, especially when combined with software that is designed to educate the player on a complex topic. Realistic sounds effects are often used to give the player a sense of reward, which are further enhanced by randomisation and almost always accompanied by a visual reward system (Harrigan et al. 2010). Creating a rewarding environment would stimulate the player to further explore the game. In the case of this project, this would allow the user to receive further education on the targeted topic, as he will be enthusiastic to proceed to the next level. To increase difficulty and skill requirements with each level, gameplay designers often implement a levelling system, where the player is granted a certain amount of points to increase the capabilities of his character, which in itself can be seen as a reward. Bonus rounds can be implemented into the game that reward good performance, increasing player enjoyment. Competition is also an important factor that would motivate players to achieve higher scores (Harrigan et al. 2010). The study proposes infinite progression and ever-increasing difficulty as a way to keep the user entertained, but this would not be applicable to players that prefer the mental enjoyment of finishing a game rather than playing it forever, which would result in a feeling for lack of completion and possible future avoidance of similar games.

2.4 Artificial Intelligence

Artificial Intelligence is one of the newest fields in science and engineering, encompassing a variety of subfields such as writing poetry or driving a car. There are six main disciplines of AI (Russel and Norvig 2016):

a) Natural Language Processing – Verbal communication.
b) Knowledge Representation – Storage of information.
c) Automated Reasoning – Draw new conclusions using stored information.
d) Machine Learning - Adapt to new circumstances, detect and extrapolate patterns
e) Computer Vision – Perceive objects.
f) Robotics – Manipulate objects.

Arthur Samuel defines machine learning as a field of study that gives computers the ability to learn without being explicitly programmed, similar to spam filters of today, which learn to differentiate spam email by using user-provided examples (Geron 2017). While spam email is a simple example, it offers a good analogy that reveals the foundations of the subject. Due to the vast nature of these disciplines and the limitations of this project, this research will focus only on machine learning, more specifically: genetic algorithms and neural networks. Furthermore, Unity game engine has recently added native machine learning support (Unity Technologies 2018).

Galway, Charles and Black (2008) conclude that machine learning, when used in digital games, while encouraging innovative approaches, faces several setbacks such as the need for constraint and guidance over the learning process. These are the two skills that this project will aim to teach to the player, at the same time providing educational knowledge on the topic of AI that would serve the user to further improve gameplay control and ability to affect game outcome. One of the emerging trends, related to this project, is called reinforcement learning, where the system only receives an indication whether an action is correct or not (Jordan and Mitchell 2015), in the case of this research paper, the indication would be based on how well the AI performed at a given task.

Genetic Algorithms

Genetic algorithms attempt to simulate natural evolution, by creating and using structures called "genomes", which structures contain variables called "alleles". Alleles are often generated values that are often modified, swapped, or removed in order to improve the performance of the system, sometimes in a rather random manner that follows a certain algorithm, often prioritising genomes and alleles that have helped the system perform better at a given task. This allows the AI to better itself with each iteration, ideally becoming optimal at solving incredibly complex tasks that can baffle even great human minds.

Genetic algorithms in AI as described in Schwab (2009), are a technique that relies on evolutionary science to advance and provide solutions, with three basic stages:

a) Initialisation

   Genetic algorithms begin their process of evolution based on a somewhat arbitrary starting set of potential solutions (Schwab 2009). Such an initialisation can be setup with the beginning of the game, allowing the player to start his adventure without the need for complex knowledge and deep understanding.

b) Evaluation

   Each of the starting solutions is subjected to evaluation using a specially designed fitness function that returns a number which represents its overall performance (Schwab 2009). During evaluation is where the player will have the ability to make choices as to where, why, how and which methods to use in order to progress further.

c) Generation

   After evaluation is done, a selected number of the solutions are selected for breeding using crossover, mutation (genetic variation) or elitism (using only the most fit) (Schwab 2009). The user could be able to choose a generation method in order to understand how it reflects on his genetic algorithm.

If not scaled correctly, the fitness function may result in a stagnation that does not allow the algorithm to progress further (Schwab 2009). There are three methods of fitness number scaling:

a) Sigma truncation

   As seen in Schwab (2009), the sigma truncation results in a non-negative number, with $\hat{F}$ being the average fitness, c being a multiplier and sigma being the population standard deviation, forming the following equation: $F' = F - (\hat{F} - c * sigma)$ (Schwab 2009) . This equation will be implemented in the code of this project in order to successfully process fitness numbers using sigma truncation.

b) Rank scaling

   Each fitness score is assigned a rank based on other fitness scores in the population of solutions, often resulting in a genetic algorithm that takes a long time to converge (Schwab 2009). Such a rank-based system may be the easiest way to introduce the player to fitness numbers and scaling, allowing him to learn about the more complex ways later in the game.

c) Sharing scaling

   The book from Schwab (2009) further discusses a method that encourages genetic variation by scaling the fitness score based on newly introduced genomes. Shared scaling can be used during gameplay to help a player that has encountered a stagnation in the genetic algorithm, as it may introduce new variations and preserve the progress that has already been made, which would otherwise force the player to restart the level.

After fitness numbers have been scaled and compared, the population of individuals must reproduce using either generational reproduction, where the previous generation is used to create and replaced by the next, or by steady-state reproduction, wherein a few new individuals replace several old ones (Schwab 2009). Following this example, a function could be made that allows the player to choose between modes of reproduction. Schwab (2009) defines taking the best out of a given population and copying them to the next generation as “elitism”, which he suggests not to be used too much as it can cause undesired results such as reaching a local maximum solution without any new parameters or ways to improve the AI. Such a pitfall could be implemented as a challenge that the player must overcome. Schwab (2009) describes other ways of reproduction, including: Roulette wheel selection, where every genome has a fitness-relative chance to be selected; Stochastic universal selection, which is similar to roulette wheel selection, except it keeps diversity high; Tournament selection, where a number of individuals are randomly drawn, and the highest scorer goes to the next generation.

As noted in Schwab (2009), after reproduction each pair of individuals are compared for crossover, randomly applied depending on a set ratio, swapping all the genes depending on the generated ratio. The crossover rate number may be used as another parameter to enable to player to further customise his playthrough and affect the outcome of reproduction, but fine-tuning such numbers can be a tedious task, so a similar but simplified ability with pre-set parameters should be implemented instead. Schwab (2009) describes that crossover methods include: Single-point crossover, where a random position on the genome signified where gene swapping will begin; Multipoint crossover, where two points are selected, between which genes are swapped; Uniform crossover, where all genes are swapped. Other similar methods exist, which call all be added as abilities that the player can unlock with progress and use to affect the outcome of his situation.

The last part is the mutation, where the genome is mutated using mutation operators like “Exchange mutation”, where two genes are swapped in the genome, and “Displacement mutation”, which signifies that two random genes are spliced, and their second parts are swapped (Schwab 2009). Many other mutation operators exist, which yet again could be used to further enhance the gameplay and develop the feeling of control that the player has.

Neural Networks

Computer scientists attempt to replicate the structure and functions of a real brain, resulting in an AI solution called a Neural Network, which can be used to understand and detect patterns in data. In modern times, big enterprises can use neural networks to determine the most profitable investment based on massive amounts of data about their clients. Mammal brains are often described as a large interconnected cluster of cells called neurons, which neurons connect to other neurons using dendrites for input and axons for output. The more or less a neuron is triggered, the easier or harder it will be to activate it again, this allows for the neural network to learn which action is preferable over the other. Inhibition occurs when a particular neuron deadens the electrical charge of another neuron (Schwab 2009), the opposite effect is called exhibition.

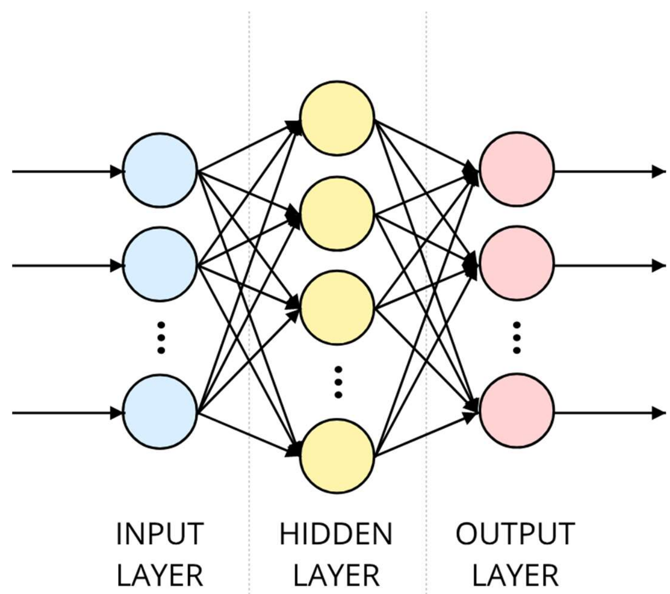


FIGURE 2.1 – NEURAL NETWORK LAYERS

As shown in Figure 2.1 – Neural Network Layers, the grey nodes (circles) represent neurons, while the connections between them symbolise dendrites and axons, all separated by layers that interact with each other. The input layer serves to provide data to the neural network, the hidden layer stores information that the neural network uses to detect patterns, and the output layer performs all needed calculations, which produce the end result.

Schwab (2009) recommends that the programmer ensures a minimal amount of input nodes, often even creating a calculated variable from multiple inputs that is passed to the neural network, as complexity rises quickly, and the system will struggle as it runs low on computational resources. It is ill-advised to allow the player to choose the number of input nodes, as it may be complex to program and also makes it possible for the player to overload his own machine. Often nodes in the hidden layer are made to be two times the amount of the input nodes, and only then that number is precisely adjusted up or down, depending on the way that the system reacts to it (Schwab 2009). The number of hidden layer nodes could be represented as a player-adjusted setting to enhance gameplay and learning.

There are different styles of learning, like supervised learning, where the weight of each input is adjusted depending on the output, reinforcement learning, where the neural network is rewarded when it performs well, and unsupervised learning, where a program is looking at the output and adjusts weights accordingly depending on the result from each execution (Schwab 2009). This project will focus on unsupervised learning, to allow the player to observe the algorithm in work and learn without having to understand when and where to reinforce the behaviour of the neural network, as this may deter users that are new to the material. The unsupervised learning method for this research project will be coupled with a genetic algorithm, which will be responsible for input weight optimisation.

2.5 User Interface

Computer interfacing is possible using hardware such as keyboard, mouse, display, speakers and other. The user interface provides a way for the computer to present information and for the user to interact with a targeted software in a manner that is efficient and easy to understand. The main topics of discussion that concern the user interface are the following:

a) Interaction
b) Presentation

Interaction

By using the keyboard, users can enter commands called "hotkeys" that are comprised of a key combination that interacts with the currently running software. The mouse provides a means for navigation without hotkeys, which can be used to select desired options in software menus. In video games, the mouse is often used to set the orientation of the player-controlled character.

Years of laboratory studies have concluded that keystrokes are much faster than the time to point to an object on the user interface using the mouse (Dillon 2003), which suggests that this project should implement hotkeys to allow the user operator to navigate through the software efficiently. It is important to note that similar keyboard shortcuts to functions are not always preferred, as at certain times the user would need a set amount of time to read and inform himself about an important notification. In such cases, hotkeys should be avoided, as it may happen so that the user skips an important notification by hitting the "Close" hotkey too fast, by mistake or by habit.

Presentation

It is important that the user interface of any software is presented in a way that allows for intuitive human interaction and accounts for people from different backgrounds. The user interface must inspire the user to explore it and use it to its fullest extent.

Dillon (2003) suggests that interface elements must be designed in a way that allows them to work in monotone, with colour added sparingly to guide the attention of the user. In part, this advice applies to software that is meant for professional work rather than entertainment, as colours can be a tool that also enhances user performance on detail-oriented tasks (Mehta and Zhu 2009). The advice from Dillon (2003) would apply to this project in a way that would enforce attention-grabbing colours on items such as informative boxes, that for example guide the player through a certain obstacle and thus are crucial for game progression.

Screen real-estate is limited by design, user interface presentation of options and information must be carefully created, ordered and displayed. Semiotic design approaches are often used to create user interface icons, coupled with pop-up text labels and descriptions that allow users to further understand a given function (Dillon 2003). It can be concluded that user-interface imagery must be designed in a way that would allow any person of any background to understand the meaning behind it. In cases where that is difficult to achieve, a supplementary pop-up descriptive text can be user to further clarify the meaning behind a given icon. It is mandatory to localise such descriptions in a language that the focus group can understand.

Users tend to ignore documentation and avoid training guides as they prefer to learn by analysing their own errors, which shifts the emphasis from error-free performance to informative feedback and the ability to undo user actions (Dillon 2003). This is particularly important, as the user interface should not restrict the user and strive for a perfect performance, rather guide him and allow him to learn from his own mistakes.

Dillon (2003) was published at a time when screens supported much lower resolutions and computers were not as powerful. Nevertheless, the advice presents generally applicable data to any generation of computing, as it derives its conclusions based on human psychology and physiology.

Following the same direction, elements such as voice and sound communication could be added to certain software for better user interfacing, allowing for voice commands and sound notifications. Voice commands are beyond the scope of this research paper, but sound notifications can be included that provide feedback to the player in cases where it is difficult to do so using visuals or as a way to garner, direct and reinforce user attention to a specific gameplay element.

3. METHOD

In this chapter, the research design, used answer the research question, will be described in detail, such that other researchers would be able to replicate it in order to achieve the same results, which would allow them to verify the conclusions in this paper.

3.1 Design

Developing a video game can be a very difficult task, and as such, it is not rare that even experienced developers will overestimate their own capabilities, forcing themselves to go beyond their limitations, soon to realise they can never meet their own expectations. As such, the game idea for this research project is quite simple, one that would fit comfortably within the time limit, and any time left after that can be used to improve upon the base game. The fact that a game is simple, does not necessarily mean it is bad or boring. Simple games never cease to amaze, starting from 1978 with titles like Space Invaders, all the way to modern ones, like Flappy Bird from the year 2013.

The game idea for this research project describes a simple triangle that must solve a basic maze using an AI. The AI settings are adjusted by the player, who must strive to achieve the best result possible using a certain set of values for each setting. Textual explanations will help guide the player into a better understanding and more precise optimisations of the AI algorithm, until he has mastered it and is able to adjust the AI of the triangle entity in such a way, that it is able to traverse the given maze with ease.

There are many types of AI that can be used to solve a maze, but for the purposes of this research project, a neural network will be used, as it can be more easily adapted later on to different types of projects that offer different types of tasks to be solved. For example, a simple rule-based system can be implemented, but compared to the neural network, it does not have that much settings, adjusting it can be a tedious task and it is only strictly suitable for a single purpose.

To allow the neural network to improve upon itself, a genetic algorithm can be implemented and used as a manager for each triangle entity. The genetic algorithm can use different functions, for example random generation, to produce new, more successful triangle entities, based on the performance of the previous ones. Values like generation count can be used as a metric for player performance measurement, while neural networks can be compared using a fitness value that is estimated based on how far the neural network guided the triangle entity into the maze, assuming the end of the maze is worth the maximum amount of fitness points.

Maze creation methods must be one of the first things to be implemented into the video game, as otherwise there would be no reliable way to test how well different neural networks perform and if their implementations provide a suitable solution for maze navigation.

Music and sound effects can be implemented as an improvement after the base video game is developed and working. Stimulating music can be used to help the players focus on the task at hand, reinforce their attention span in dull moments and reward them for their victories in a way that would make any listener feel like they have earned an achievement, which would deter them from surrendering in moments where they find a given game level too difficult.

To enhance learning and improve the experience for seekers of more detailed knowledge about the AI, a main menu can be implemented that can be used to either start the game or as an access point for an in-game manual that the player can use to better his understanding of neural networks and genetic algorithms. Such a manual can be supported with various imagery, which would be of great use to learners that prefer to gain knowledge through visual stimulation.

3.2 Requirements

An artificial intelligence must be created that uses machine learning algorithms such as a combination of genetic algorithms and neural networks. The AI must support a wide range of settings that will allow the user to experiment and understand how his actions affect the efficiency of the AI solution. A certain amount of the settings must be automated and hidden in the beginning parts of the game, as otherwise a player that is new to the topic will be confused and repelled by the complexity of the solution.

The video game product must be deployed on a popular platform, such as Windows, which will allow for easier spread and lessen the probability for compatibility issues. In cases where the study is delivered online to the participant, instructions have to be added to the game, so the player can understand what exactly he has to do in order to progress further and solve levels on his own. Ideally, a researcher will be always available to answer any queries that the participants may have.

A relaxing music can serve a purpose to enhance player enjoyment and provide an auditory experience, which can benefit users that tend to be impatient and would otherwise skip text-based instructions, only to be confused about elements of the game afterwards.

It is common for video games to present the player with a challenge to solve, which challenge could be a certain type of terrain that the AI must learn to traverse using the settings supplied by the user. A maze-generation system must be created in a way that would allow it to interact with the AI as well as provide an increasing difficulty with each level, which would encourage the player to explore different types of settings for the AI that would allow him to complete the level in a timely manner.

A user interface must be created that is easy to operate, intuitive and with enough tooltips and instructions so the player can access it at any time and read about how to solve the current level he is on.

At the end, a questionnaire must be used to gather information on the experience of each player, and then analysed to understand how interactive video games can be beneficial for artificial intelligence education.

3.3 Implementation

Implementing the AI was mostly done using the book from Schwab (2009) as a guide, as it describes how both genetic algorithms and neural networks can be programmed and used in a video-game. The knowledge and examples had to be adapted to Unity using programming language C#.

At first, a genetic algorithm was created by following the example set by the human genome. A genome would contain a list of genes, each of which would host a number of alleles. Each allele represents a type of data is used and manipulated by the genetic algorithm.

Software Version Control

Video game creation was done using Unity, version 2018.1.7. Version 2018.1.7 was chosen, because it was the latest one when product development began, after which updates were halted so no compatibility issues would arise, that would otherwise cause the project to slow down and cost time and resources to fix.

Software solutions were designed and programmed using Microsoft Visual Studio Community 2017, version 15.7.4. Updates were paused during the development period, that way the project could remain stable and the developer would not have to deal with new issues after each update. Furthermore, it is important to note that Unity supports only .NET version 3.5 with C# up to version 4.0.

Maze

Maze creation was coded by creating a class called "Corridor" that would take parameters of type Enum, which would symbolise a certain direction, for example "Up", "Down", "Left" or "Right". This way, the programmer can call upon the class to create a corridor that would follow the directions as instructed as the parameter that was passed, enabling dynamic maze generation. Such a class can make the transition towards randomly generated levels and mazes more efficient, as the class is entirely decoupled from other software elements.

The algorithm of the Corridor class is designed for 2D game environments, where the programmer, using the Unity editor, can create an array of directional instructions, which are then processed by the script, in order to create multiple entities of type "Wall" on both sides of the corridor, which would form in the necessary direction to create the requested shape and follow all instructions. At the end, an "End" wall is created, which can be used to detect collision with other entities, such as objects that are able to successfully solve the maze by crossing the end wall. Corridor creation logic can be observed in Figure 3.1 – Corridor Creation Basic Flowchart.

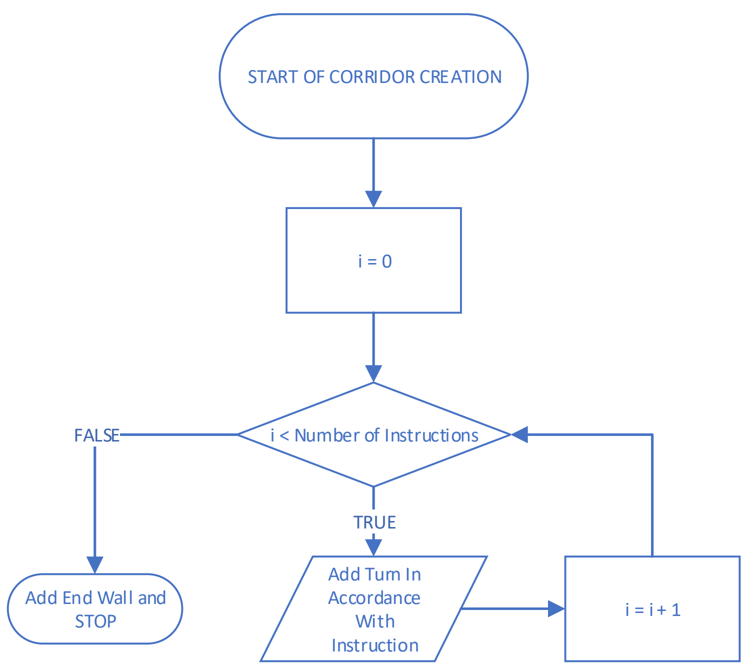


FIGURE 3.1 – CORRIDOR CREATION BASIC FLOWCHART

When examined in greater details, the algorithm work by using two “switch” functions. One to decide which direction the current instruction being processed is symbolising, and one to take action depending upon the previous direction that was already put in place. For example, an instruction “Up” with previous instruction “Up” would take the coordinates of the vectors of the two Wall entities forming the corridor and increment the “y” component of their last vectors, resulting in a new vector that is added to the end of each wall. A Wall entity is simply a collection of vectors that is rendered upon game launch. In practice, the last vector of “Left Wall” could have coordinates [x, y] = [0, 0]. Adding a direction of “Up” would result in another vector added to the collection that is equal to [0, 1]. That way, as the “y” component is increased and, in this case, representative of the in-game direction “Up”, the wall will render another line upwards of the previous line. This can be observed in the following figures, where the white lines are the Wall entities, the grey wall is the starting wall and the blue wall is the end wall:

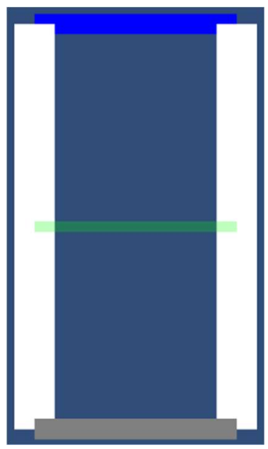


FIGURE 3.2 – CORRIDOR WITH DIRECTIONS: UP, UP

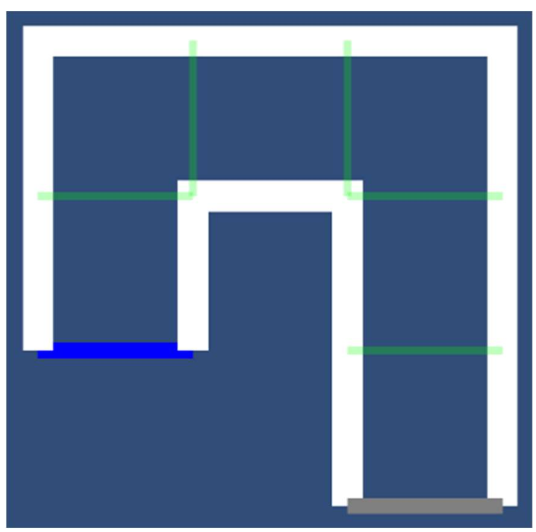


FIGURE 3.3 – CORRIDOR WITH DIRECTIONS: UP, UP, LEFT, LEFT, DOWN, DOWN

Similarly, other walls are constructed in other conditions, sometimes modifying the previous elements to create a turn in the corridor or to change direction.

As shown in Figure 3.4 – Corridor, Complex, the mazes built can reach a level of complexity that can offer a significant challenge. Currently, diagonal directions are not possible and are not included in level design.

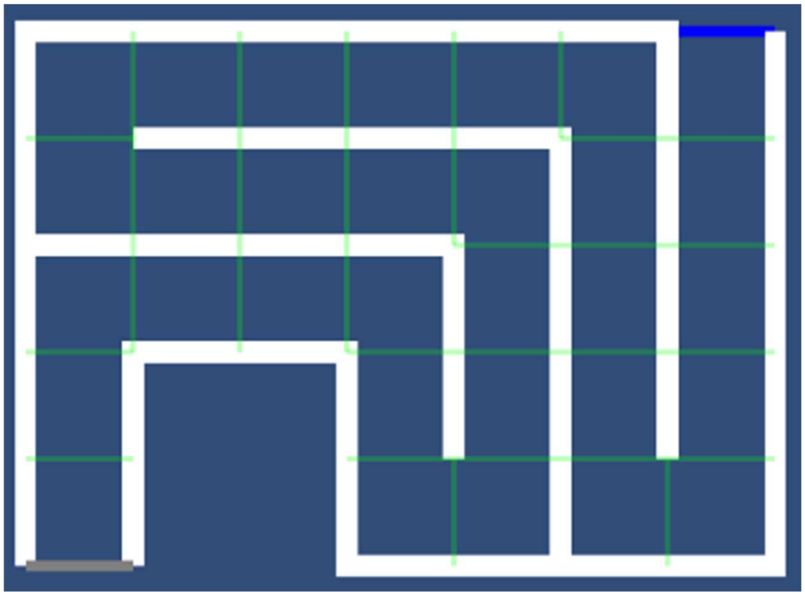


FIGURE 3.4 – CORRIDOR, COMPLEX

The green lines seen in Figure 3.4 – Corridor, Complex, Figure 3.3 – Corridor With Directions: Up, Up, Left, Left, Down, Down and Figure 3.2 – Corridor with Directions: Up, Up represent triggers that can be used by programmers to implement logic upon collision. They do not physically affect entities that cross them. Furthermore, the aforementioned figures represent levels in the game developed for this research project, with an increasing difficulty that would challenge the player with each game level successfully passed.

Neural Network

Completely decoupled from Unity Engine, the Neural Network C# class represents an algorithm that imitates the way that the human brain works. Each Neural Network includes a list of Neuron Layer classes that represent the input layer, the output layer, and the hidden layers, as seen and discussed in detail in Figure 2.1 – Neural Network Layers. In theory, the whole neural network can be represented using a single three-dimensional array, but in practice this tends to be confusing and difficult to understand.

The Neuron Layer class contains Neurons, each of which contain a set of weights. The number of weights is determined by the number of Neurons that are present in the previous layer, as such, each Neuron from the previous layer can output a weighted value into each neuron of the current layer, as illustrated in Figure 2.1 – Neural Network Layers. Each Neuron Layer implements a method called “Feed Forward” that inputs all its neurons into the next layer. This is the advantage of keeping neuron layers in a list, that way referring to the next or previous one can be done with ease.

Neurons are the most basic element of the Neural Network. Each Neuron has a definition for mutation and crossover, which are useful when later passed on to the class that represents the genetic algorithm. In this case, mutation simply randomises the weights inside the Neuron, while crossover swaps their places with a different

Neuron. This allows for full decoupling and high reusability of code, as functions and actions are passed on to different elements to use.

Neuron Layers use an activation function that further affects each input into the next layer. In the case of this project, it is a hyperbolic tangent. It is especially useful, as the input received is the distance to corridor walls, and value variation in the upper range should not have much meaning, as a reaction is required from the AI only when the entity is getting so close to a wall, that it is in danger of colliding with it. The hyperbolic tangent function can be observed in the following figure:

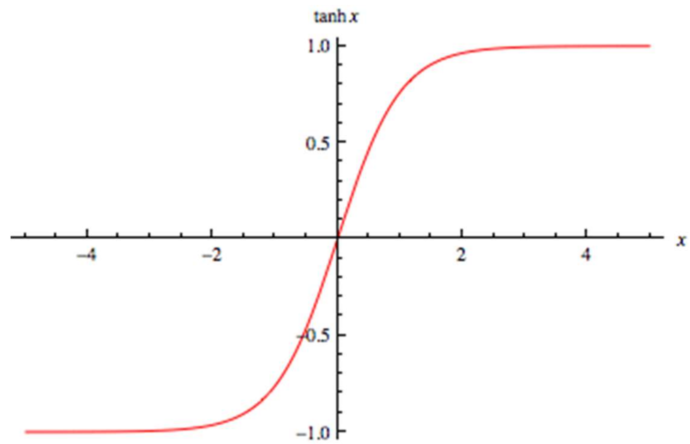


FIGURE 3.5 – HYPERBOLIC TANGENT (WEISSTEIN 2018)

Due to time constraints, the neural network does not implement a backpropagation algorithm. Rather, it relies on the genetic algorithm to improve at the task at hand.

There are no neural network settings that are accessible by the player, as the genetic algorithm presents a big enough challenge to understand and master.

Genetic Algorithm

The genetic algorithm serves a purpose to encapsulate neuron layers from the neural network and use them to create new generations, apply crossover and mutations. All of these are settings that are presented to the player as part of the gameplay.

The genetic algorithm is programmed inside a Genome class, which is made to mimic the human genome as close as possible. It includes a list of Gene classes and different methods to manipulate them. Each Gene holds a list of Alleles, which in this case represent the hidden neuron layers created using the Neuron Layer class. They are all passed by reference, so changes issues by the Genome class instantly reflect upon the neural network. The Gene class is also used to store the fitness for its set of neuron layers.

After the current generation has failed at the task, a new one is created by issuing a reproduce command to the Genome, which makes the Genome begin the reproduction process, using the Genes in the current population. First, all of the current Genes are sorted by their scaled fitness values, as discussed in the Artificial Intelligence section of the Literature Review chapter. Scaling methods are chosen by the player, which allows for great neural network customisation and greater possibility for optimisation. Parents for the new population are selected using a selection algorithm, again specified by the player. Afterwards, depending on a user-adjusted setting, a number of elites are chosen by fitness comparison. These elites are kept into the Genome untouched, while the rest of the Genes are replaced with their children. The player also chooses the type of Gene crossover. After each child Gene is produced, it stands a chance to mutate, which in the case of this research project is 5%, determined by experimentation based on the mazes in each level. Nevertheless, the user is granted control over the mutation type, which allows him to specify the effect that mutations have on the Genes.

Fitness is gained whenever an entity crosses over the green lines illustrated on Figure 3.3 – Corridor With Directions: Up, Up, Left, Left, Down, Down. An event is associated with each green line, where, upon collision, it tells the colliding entity to access its Gene and increments its fitness value.

The Genome is controlled and managed by a controller class that tracks every entity with an AI. That way, whenever all entities are no longer active, this can be detected, and the Genome can be instructed to create a new generation, which is assigned to a number of new AI entities that are created by the controller class.

Intelligent Entity

Intelligent Entity is a class that is made to be inherited by entities that aim to navigate using a neural network. It contains a reference to the gene, colour settings, positioning vectors, update ratios, neural network and a rigidbody class. The rigidbody class is used by unity to process objects that interact with its physics system, essentially enabling customisable options like gravity, angular drag, mass and other. For this specific project, the rigidbody has to be configured to reduce all sorts of sway in the object, as that would make system times difficult to control and the neural network will likely struggle to adjust. That being said, it is important for future researchers to know that the exact values used for these parameters are:

Mass	0.1
Linear Drag	1000
Angular Drag	1000
Gravity Scale	0

TABLE 3.1 – RIGIDBODY PARAMETERS

Furthermore, the Intelligent Entity calls upon a child-defined method each time it updates itself. This is important as it will be discussed in the Triangle class description.

Triangle

Inheriting from the Intelligent Entity class, Triangle defines methods that assist shape, input and output generation. The triangle shape in this case is created using a triangulator, by passing on three vectors that form a triangle with a relative vector magnitude to a given parameter by the programmer. Input is received using raycasting from several points on the triangle. Raycasting is a functionality that enables the programmer to track the distance between two points by casting a virtual laser or "ray", specifically as shown in the following diagram, which is also available in-game with a simplistic description for players to read up on:

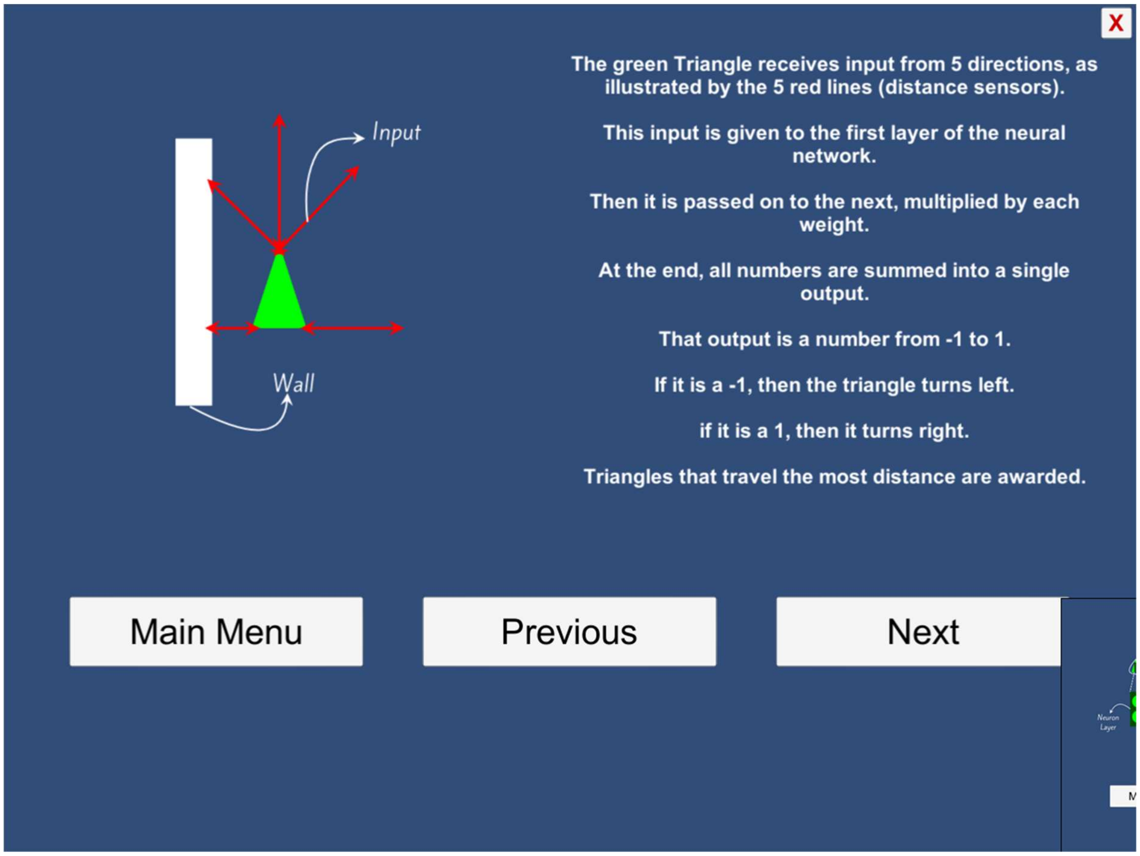


FIGURE 3.6 – TRIANGLE INPUT FUNCTIONALITY

As described, the triangle receives all distances and passes them to the neural network for processing using feed forwarding. The output received from the last neuron layer is then used to thrust the triangle to the left or to the right. This way, the neural network, using random generation and fitness-guided algorithms is able to learn how to navigate any in-game maze.

Main Menu

As seen in Figure 3.7 – Main Menu, the main menu is very simplistic and easy to use, with three buttons that let the player start the game, read more information on AI and how the game works or access research information about this project and the lead researcher. The “How it Works” page includes Figure 3.6 – Triangle Input Functionality as one of its educational pages, ranging from simple explanations to more complex diagrams and in-depth knowledge.

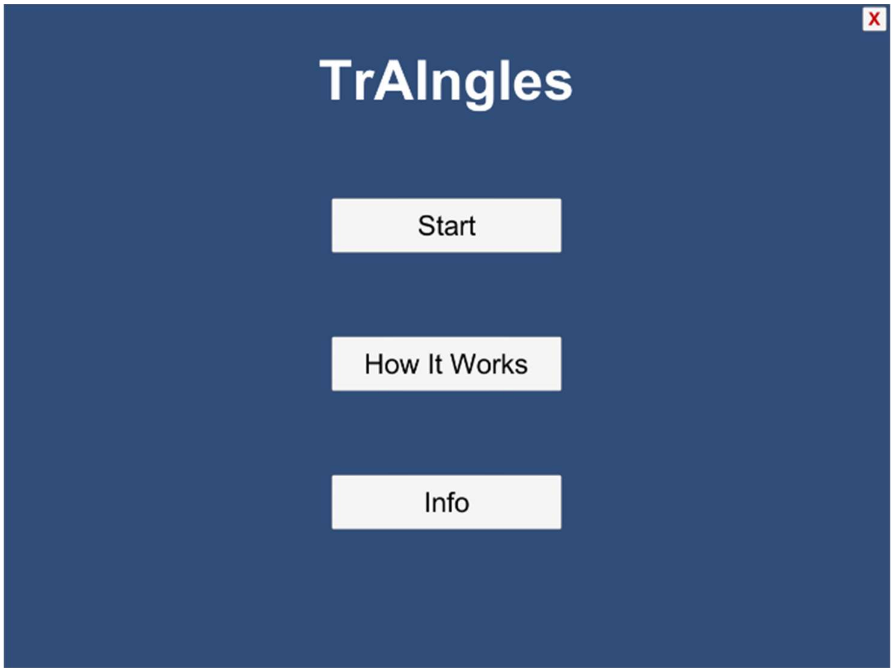


FIGURE 3.7 – MAIN MENU

Settings Menu

First level starts with nothing but a single option and a green hint that explains to the player what he should do and how he should do it, effectively becoming a very simple tutorial that is designed to let the players experience how different UI elements of the game work.

FIGURE 3.8 – SETTINGS BASIC

The more the player progresses, the more settings that will be unlocked for his to adjust and use to optimise the neural networks. On the last level, all settings are unlocked and the only hints available is the description on the right of each setting.

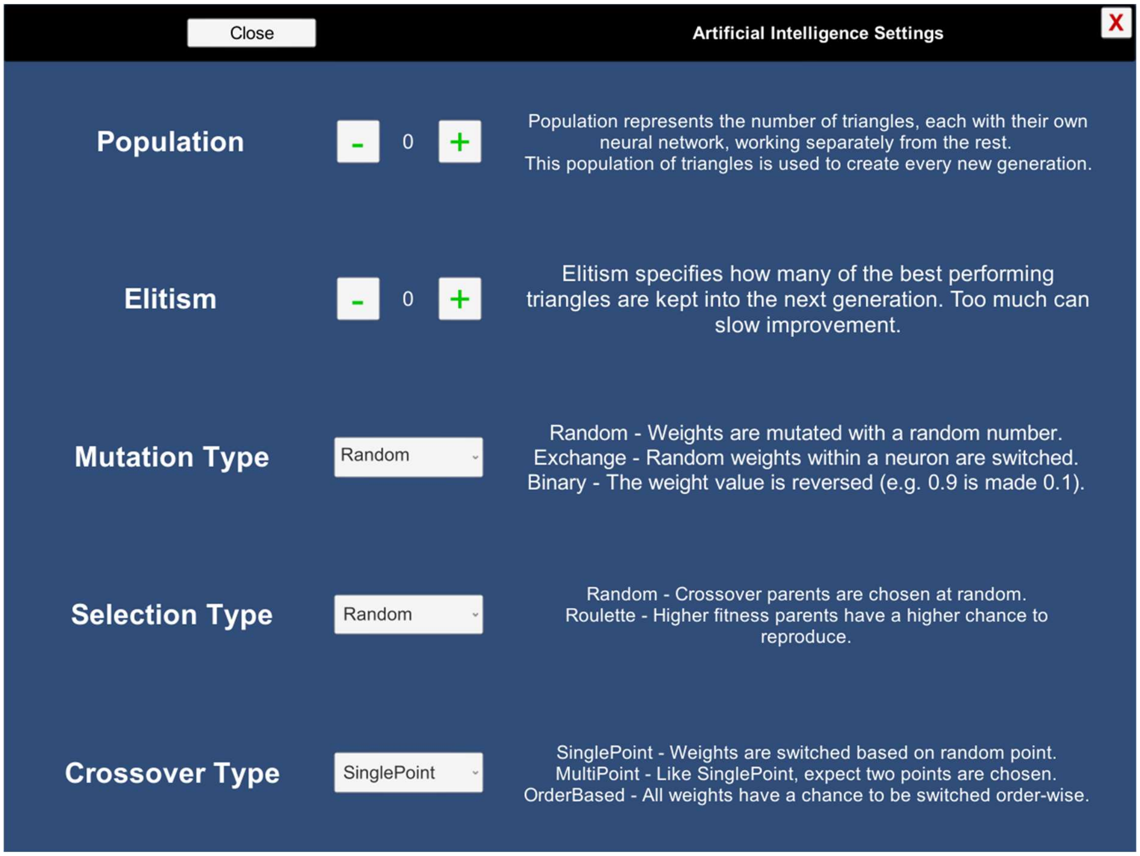


FIGURE 3.9 – SETTINGS ADVANCED

Music

Testing, as described in 3.4 below, showed that many players tend to skip over instructions before even reading them, which would confuse them, and they would be stuck on the first level. This is when it was decided that some type of calming music must be implemented, that will serve a purpose to keep the attention of the player on the instructions for longer and make him less likely to just skip them.

Parncutt (2014) talks about how major chords are associated with happiness and positivity, while minor ones are often used to trigger negative emotions. As such, background music was created for the video game, which was composed only of major chords, using a very small value of 10 beats per minute. Furthermore, a rewarding sound was created to come into effect every time a Triangle completes the maze. Musical composition was done using a freeware software called “Bosca Ceoil”, which is easy to use and provides and array of musical instruments that are fitting for the video game developed for this research project.

The result was an ambient looping soundtrack that plays throughout the whole game and a quick rewarding burst of several notes to provide the player with auditory feedback on his achievements.

3.4 Testing

To guarantee that the video game would be free of bugs and performing well, it was extensively tested by the main researcher for any problems including performance issues. Testing often revealed critical issues and interesting way of improvement. On one occasion it was noticed that the video game performance is not optimal when multiple entities that use machine learning are present. This performance drop would have had an effect on weaker systems which would put limits on how the study spreads and would restrict some users from having a stable and enjoyable gameplay. Problems with performance often result in a drop of the frames per second that the software can process, as such, the game may seem “choppy”, which would add noise to the results from the questionnaire as it would undoubtedly affect user response. Fixing this issue was done by limiting neural network update rate and input rate to five times per second, which resulted in huge performance gains, as otherwise updates and input would be done for each frame, sometimes reaching up to 60 times per second and more. This change was accepted as it had a negligible effect on the performance of the AI algorithm.

Other testing methods were based on player experience, where beta-testers would test the game and report their findings, such as bugs, improper difficulty, mistakes in the text and logic, user-experience improvements and system compatibility. One case found that certain types of resolutions would not work on smaller monitors, which helped adapt the software to different displays and limit user choices for resolution to only those that would fit their monitors well enough with cropping parts of the game.

3.5 Survey

Due to time constraints, this research project was unable to reach its goal of a focus group that consists of 30 people. The new focus group includes 24 students or tutors of Coventry University that have not received higher education on the topic of AI, of any gender, nationality and background, aged from 18 to 50 years old, all of which show an interest in the topic and know how to use a personal computer.

Data gathering was performed individually (face-to-face) in the library of Coventry University between 9:00 a.m. and 6:00 p.m., with each participant taking an average of 15 minutes to play the game and answer the questionnaire. Some participants were recruited through the internet, which allowed for greater time flexibility. Following an introduction to the survey procedure, participants were seated on a comfortable chair in front of a table and provided with a laptop to play the developed game, with the ability to ask questions and receive help from the main researcher when they feel like they are unable to progress in the game. After the full completion of all levels of the video game, participants were provided with an online questionnaire created using an online survey provider called “Jisc online surveys”, formerly called “Bristol Online Survey” or “BOS” for short, designed to understand how they feel about the game and gather their consent using a form that follows guidelines set by Coventry University.

The online questionnaire was structured in the following way:

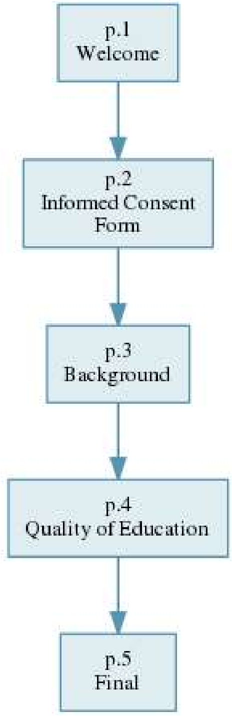


FIGURE 3.10 – QUESTIONNAIRE STRUCTURE (JISC ONLINE SURVEYS 2018))

Background information was gathered on age group and preferred way of learning using the following questionnaire style:

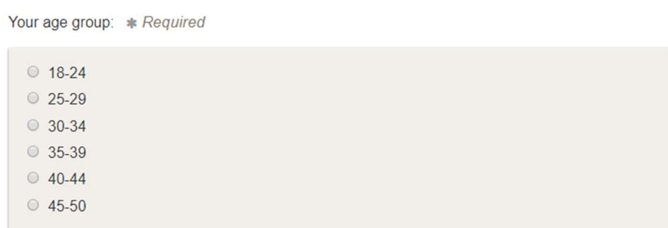
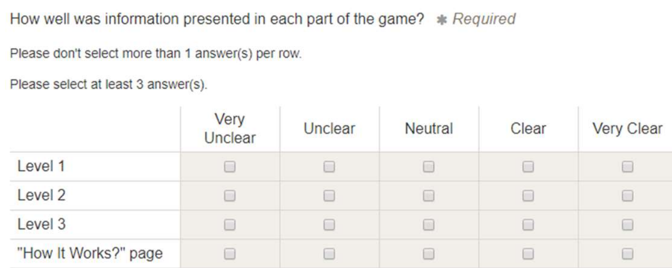


FIGURE 3.11 –QUESTIONNAIRE EXAMPLE BACKGROUND

Players were given enough time to complete each part of the developed product, and then they were presented with a questionnaire, with the main researcher always being available to answer any questions they have. Information was gathered about the quality of education that the video game provided them with, covering topics such as:

a) How well the information was presented in each part of the game
b) How interested the participant was in the game
c) How challenging the participant found each level to be
d) Which part of the game the participant found to be most educational
e) If the music made them more likely to read instructions
f) If the sound effects made them more interested in performing better
g) If the information was overwhelming and how that affected them

The way the questions were presented can be observed in the following screenshots:

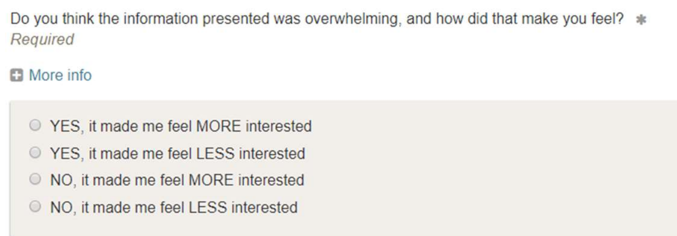

How well was information presented in each part of the game? * Required

Please don't select more than 1 answer(s) per row.

Please select at least 3 answer(s).

	Very Unclear	Unclear	Neutral	Clear	Very Clear
Level 1	☐	☐	☐	☐	☐
Level 2	☐	☐	☐	☐	☐
Level 3	☐	☐	☐	☐	☐
"How It Works?" page	☐	☐	☐	☐	☐

FIGURE 3.12 –QUESTIONNAIRE EXAMPLE TABLE QUESTION


Do you think the information presented was overwhelming, and how did that make you feel? * Required

More info

- YES, it made me feel MORE interested
- YES, it made me feel LESS interested
- NO, it made me feel MORE interested
- NO, it made me feel LESS interested

FIGURE 3.13 – QUESTIONNAIRE EXAMPLE BASIC QUESTION

The questions in this survey aim to help researchers understand what affect the produced video game had on players that were interested in the topic of AI. It can help companies develop their products better and for the right audience, observing the results and enhancing their product based on participant experience. Further research can benefit from and compare their findings with the help of the answers gathered by this survey.

Some important observations that were made during the survey, was that participants tend to skip right through most in-game instructions, which would force them to ask the assisting researcher on how to progress.

As agreed by Kelley et al. (2003), the advantages of this survey are the fact that it offers empirical data, produced by real-world observations, further backed up by the fact that the survey had a wide and easy spread using the internet, it offered a sizeable coverage and it was able to do so in a short amount of time. There are certain disadvantages to this type of survey, one main concern for this type of project is the lack of details and depth (Kelley et al. 2003), which in this case can be caused by the time and resource constraints. Nevertheless, successfully following the allocated time frame without any overestimation can lead to promising results that can serve as a base and as a collection of important conclusions for future researchers.

Boynton and Greenhalgh (2003) suggest using an existing instrument to gather questionnaire data, which can help understand and compare the results better. While possible, and a good candidate for that is “The Game Experience Questionnaire” by IJsselsteijn, de Kort and Poels (2013), due to resource limitations the game produced does not include enough gameplay elements to make “The Game Experience Questionnaire” relevant, as most of the questions will be targeting experience, which in this case is lacking or non-existent. What was done instead, was that several of the questions were based on “The Game Experience Questionnaire”, effectively enabling future researchers to compare the results of this study to the results of studies based on “The Game Experience Questionnaire”, as well as to their own collected data.

3.6 Project Management

Project management is important towards achieving efficient development process that will save both time and resources. There are many techniques used by project leaders, which, when adapted to the correct situation can yield amazing results. One of these techniques is called "Agile", and as described by Rasmusson (2018), "Agile is a time boxed, iterative approach to software delivery that builds software incrementally from the start of the project, instead of trying to deliver it all at once near the end.". This means that Agile attempts to create better software by making smaller steps progressively instead of all of them at once, as far as delivery is concerned.

To adapt the Agile method during the making of this project, frequent meetings with the main project supervisor were arranged bi-weekly, where there would be a product showcase and a progress discussion, which would lead to project evaluation and valuable information and suggestions that would help improve the product and make it better. This is exactly following the Agile plan as noted in Rasmusson (2018), where it is advised that little bits of project functionality are delivered continuously in short two-week cycles, which the source refers to as "iterations".

There are other methods similar to Agile, one of the more popular ones being "Scrum" but based on Coventry University guidelines for project progress and mandatory supervisor meetings, the Agile method was the most fitting one and the easiest one to use. In a way, the supervisor can be seen as the client while the researcher is the development team.

As observed in 9.2, the very first supervisor meeting was comprised of general queries about project structure, development planning and formatting. This allowed for the organised and clean arrangement of this paper early on, which helped build a base that serves a purpose to ease the implementation of other dissertation elements. The second meeting focused on more detailed issues like game engine choice, referencing, method discussion. It was very important to choose a game engine early on, as most of the research and development was done by referencing it and taking it into consideration. Diving right into AI and gameplay, the third meeting helped better understand how the game design should be done, which journals should be used and if there will be a need for a genetic algorithm alongside the neural network. The fourth meeting further reinforced the decision on AI with a showcase, diagrams and a quick but efficient demonstration. Fifth meeting showcased the full game to the main supervisor, allowing him to also understand how the questionnaire on it is created and how well the player is able to interact with different game elements. The sixth and last meeting was used for result overview and a discussion on future works, questionnaire analysis findings, a final presentation of the whole project and an overview of what was achieved.

Feedback received during each supervisor meeting as well as every suggestion helped shape the project into a better product with some features being implemented as fast as possible, while other, more demanding ones, were left at the end in case there was not enough time to implement them. In the end, the project was perfectly planned, and no corners were cut short, resulting in a stable product and a clear analysis of the results.

Rarely a problem would occur that would require immediate supervisor attention, as otherwise it may cause the project development to stutter. In such cases, electronic communication proved vital and a fast response was always appreciated, helping this research project complete within the given time frame.

3.7 Social, Legal and Ethical Issues

Social, legal and ethical issues need to be considered and resolved early on in any research project. Luckily, the survey used does not need to gather any identifying information, which anonymises the process and lowers the probability of any social, ethical or legal issues occurring during the data gathering and analysis process. Of all the people that took part of the survey, some were very cautious with their privacy, but all of them were happy to take part after seeing the questions and understanding how anonymised the questionnaire is. Furthermore, the developed video game does not gather any data on the user, nor does it implement any type of save or load function, which means that all the information is stored in variables that are immediately unallocated upon termination of the software.

The focus group consists only of adult participants. The whole developed video game, as well as the survey questions are in no way offensive or discriminatory. It is family friendly and does not touch on any sensitive topics.

Ethics approval certificate can be seen at Figure 9.1 – Ethics Approval Certificate.

4. RESULTS

Questionnaire results are displayed as learning cross-tabulated in 9.4 below and as raw table data in 9.3 below.

Each participant was found to be in the age range of 18 to 34 years, predominantly between 18 and 29 years, with none to basic education on the topic of AI. One participant proved to have received advanced education on artificial intelligence, and his result was filtered and thus not taken into account, as it is not suitable for this research.

Among the 23 participants, the most preferred way of learning was shown to be either by watching or by performing. It is important to note that the video game had less opportunities to learn by watching and more so by performing. What could have been done to cater to those that learn by watching is to provide video clips in the form of a tutorial to help them better understand how to use the UI and how to adjust the AI in order to achieve success. That being said, it is to be expected that the video game education level will be better understood and rated by those that chose performing as their most preferred way of learning. Less than a fifth of the participants chose reading as their most preferred way of learning, which would suggest that those people were keener on reading instructions and should have found the "How It Works?" page incredibly useful. Only a single person chose writing as his most preferred way of learning, which is not enough to draw conclusions on.

For the questions in the questionnaire that used a grading system with options similar to "Very Unclear, Unclear, Neutral, Clear, Very Clear", the following formula will be used, where "Very Unclear" is equal to 0% clarity and "Very Clear" is equal to 100% clarity:

$$\frac{0\% * a + 25\% * b + 50\% * c + 75\% * d + 100\% * e}{(a + b + c + d + e) * 100\%}$$

Where "a" stands for number of people that answered with "Very Unclear", b for number of people that answered with "Unclear" and so on, with "e" being the number of people that answered with "Very Clear". To summarise, the formula can be simplified as follows:

$$\frac{25\% * b + 50\% * c + 75\% * d + 100\% * e}{(a + b + c + d + e) * 100\%}$$

That way the average answer can be extracted to aid the process of drawing conclusions.

Clarity Rating	Reading	Watching	Performing
Level 1	**93.75%**	72.22%	83.33%
Level 2	**93.75%**	80.56%	91.67%
Level 3	**87.50%**	72.22%	83.33%
How It Works? page	**100%**	62.50%	88.89%

TABLE 4.1 – INFORMATION PRESENTATION LEARNING TYPE AVERAGE (BASED ON TABLE 9.3 AND TABLE 9.4)TABLE 9.8

The results are as expected, where the group that prefers to learn by reading finds all parts of the game clearer, which is most likely because of the fact that instructions are mainly text-based. These results highlight the importance of having different methods of communication that help the player understand basic concepts.

Summarising the data about the interest each player had in different game elements, the following table can be created and observed:

Interest Rating	Reading	Watching	Performing
Level 1	**87.50%**	69.44%	83.33%
Level 2	93.75%	77.78%	**94.44%**
Level 3	93.75%	80.56%	**100%**
How It Works? page	93.75%	66.67%	**97.22%**

TABLE 4.2 – INTERESET QUESTION SUMMARISED (BASED ON TABLE 9.3 AND TABLE 9.5)

The analysis of interest towards each element in Table 4.2 shows that during the first level, people that prefer to learn by reading express more interest, which is reinforced further by the fact that on the setup page of the first level there are multiple sentences describing how to use the population adjustment. As no visual examples are shown, the interest shown by people that prefer to learn by watching is still very low compared to the rest. As the levels progress, less and less textual instructions become available. At the same time, more adjustments are revealed to the player, especially in the third level, where four new settings are shown with only their description on their right. As such, it can be seen that people that learn by performing had a rise of interest, which reaches its maximal potential during the last level. What is interesting to note and unexpected to see is that performers rated the "How It Works?" page higher in interest than the readers, which page includes the most amount of text when compared to other game elements. People that prefer to learn by watching have rated the "How It Works?" page very poorly, which is also not anticipated as it included diagrams and instructional images. Such a radical result from the last row could be due to chance, because of the small amount of people in the focus group, or it could be because of something else like the fact that the "How It Works?" page shows itself to be less intrusive than other instructions. Further research is needed to reinforce and understand the results.

Data gathered on challenge ratings is analysed and shown in the following table:

Challenge Rating	Reading	Watching	Performing
Level 1	37.50%	**13.89%**	36.11%
Level 2	50%	**36.11%**	41.67%
Level 3	62.50%	55.56%	**52.78%**

TABLE 4.3 – CHALLENGE QUESTION SUMMARISED (BASED ON TABLE 9.3 AND TABLE 9.6)

Conclusions can be drawn from Table 4.3, that on average, all groups experienced an increase in difficulty as levels progressed. The people that prefer to learn by reading show that they found the game to be more challenging than those that prefer watching or performing. This could mean that readers were put off by the nature of the game and of the implemented AI, as to find the ideal setting often requires multiple test and experimentations with different adjustments to the neural network. Watchers may have found the game to be the least challenging as for the most part, the player simply has to sit back and watch how the AI learns. Those that learn by performing show a balanced level of challenge when compared to the other two groups.

On average, players seem to have found the trial and error part of the game expressed by the setup page as the most educational element, with slightly more votes than the descriptory text on the right of each setting. This is likely due to the fact that a big part of the participants preferred to learn by performing.

As no participant chose listening as their most preferred way of learning, to draw conclusions about music and sound effects about that group would be impossible, but this would be a great opportunity for future research to gather data on and analyse.

With background music in question, both players that learn by performing and those that learn by reading have decided that it makes them more likely to read written instructions, while those that learn by watching have voted the opposite. As a conclusion, the added background music does increase retention in most players but may also have the ability to distract others.

Unlike music, the sound effect at the end received great feedback, with almost all but 2 participants voting "Yes" or "No, but a different sound would" when asked if it made them more interested in performing better. This is proof that most players prefer sound effects, similar to the one when finishing a level successfully, as it adds another dimension to their achievement.

From Table 9.10, it can be concluded that some people did not feel overwhelmed by the information, but most did. Nevertheless, all but 2 participants decided that it made them feel more interested in the subject.

From the analysed data, conclusions can be drawn that, when attempting to educate people on the topic of AI, instructions tend to people that learn by reading, while trial and error is more interesting for people that learn by performing. A flaw in the video game produced by this research is that it did not include enough ways to communicate information, due to time and resource limitations. As such, people that prefer to learn by watching mostly felt less informed and less interested. Sound effects that reinforce player achievements are highly recommended, as most users responded well to them, while background music can have either a positive or a negative effect, usually dependant on the person. Last but not least, overwhelming amounts of information are not always a bad thing, as in most cases it stimulates the interest of the player.

The conclusions drawn by this paper can help researchers, developers and companies understand how video games can be used for education on the topic of artificial intelligence, specifically machine learning and neural networks. Take note that the same results may not apply to video games that focus on different topics, as all participants were interested in the topic of AI and wanted to learn more on the subject, as well as the fact that educational techniques used in this research project may not be applicable to other spheres of education.

5. DISCUSSION

This paper has observed how players react to different interactive educational techniques on the topic of AI.

The performed literature reviewed covered immense amounts of information on different complex topics in order to choose the ideal settings for this project. Alas, the research lacked experts on different game engines, as well as AI methods, as such it relied only on books and articles to choose the correct path. With more researchers, highly skilled in different spheres, this research could have chosen a more efficient way, perhaps even building a game engine that is specifically tailored to the requirements of the research.

AI implementation was successful, and incredibly so given the short time period. Ideally, a better AI could be developed that is easier to understand and more intuitive to teach.

Game design mostly included textual instructions to the lack of a game artist, which could have made elements such as explanatory video clips possible, benefitting people that prefer to learn by watching.

While this project did its best to communicate in as many ways as possible, auditory learners would have certainly appreciated spoken instructions on each AI setting.

As the deadline approached, research was cut short with only 23 participants taking part of the survey. This proved to have an ill effect on results, as whole groups of learners were not represented at all. The results from the survey would have had an even more broad application if more people were to take part.

Nevertheless, this research project managed to summarise several different subjects into a product that would otherwise be expected to take at least half a year to make, gathering enough research data from the questionnaire to draw valuable conclusions.

6. Critical Review

To choose the appropriate methods for this research project, books and articles were used as a source of suggestions, information and guidance.

This project chose to base its findings on the user preferred way of learning, which proved to be inefficient as the focus group was not large enough and it was spread too thin especially concerning people that prefer to learn by reading, where conclusions were drawn based on 4 answers.

While neural network and genetic algorithms can be very intriguing, machine learning technologies such as rule-based AI could have been easier for those new to the topic, which would have made for a better experience. It is important to note that simpler AI could prove to be not interesting enough for some players.

Using Unity game engine was efficient and appropriate as it has capabilities that could have been used to deliver the game to multiple platforms, increasing the reach of the survey, sadly time restrictions did not allow for this, as certain issues occurred with UI scaling on different resolutions.

Product quality assurance was done with the help of assistant research colleagues to ensure that the final product ran without any problems on all targeted machines. Many bugs were caught and fixed.

Project conduct quality assurance was kept in check by the main supervisor, who would always be ready to recommend what the next step should be and how to improve work that was already done, along with suggestions on elements that should be implemented into the project.

One of the major risk factors was gathering people for the research group, as on some days it would be hard to find anyone that is willing to take part of the research, as such, it was always unsure if the deadline would be met. On the first day 14 people agreed to take part of the survey. That number plummeted to 4 on the second day. Risk analysis and work breakdown is shown in the Gannt charts below, specifically Figure 6.1, Figure 6.2, Figure 6.3 and Figure 6.4.

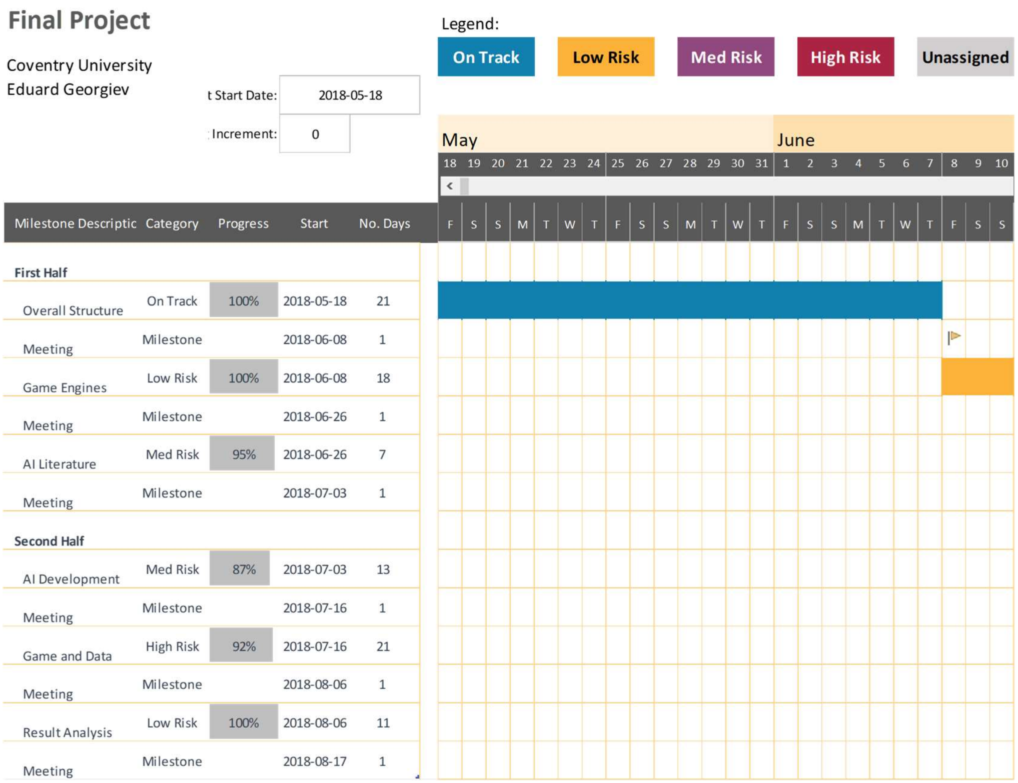


FIGURE 6.1 – GANNT CHART PROJECT MANAGEMENT PART 1

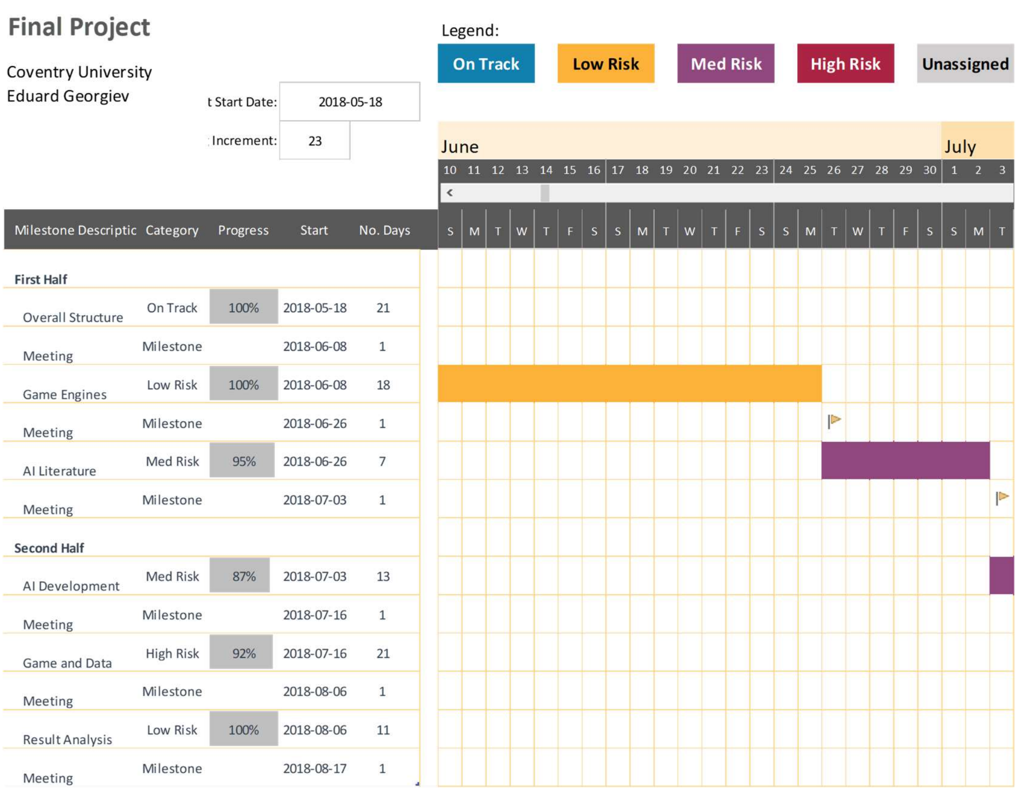


FIGURE 6.2 – GANNT CHART PROJECT MANAGEMENT PART 2

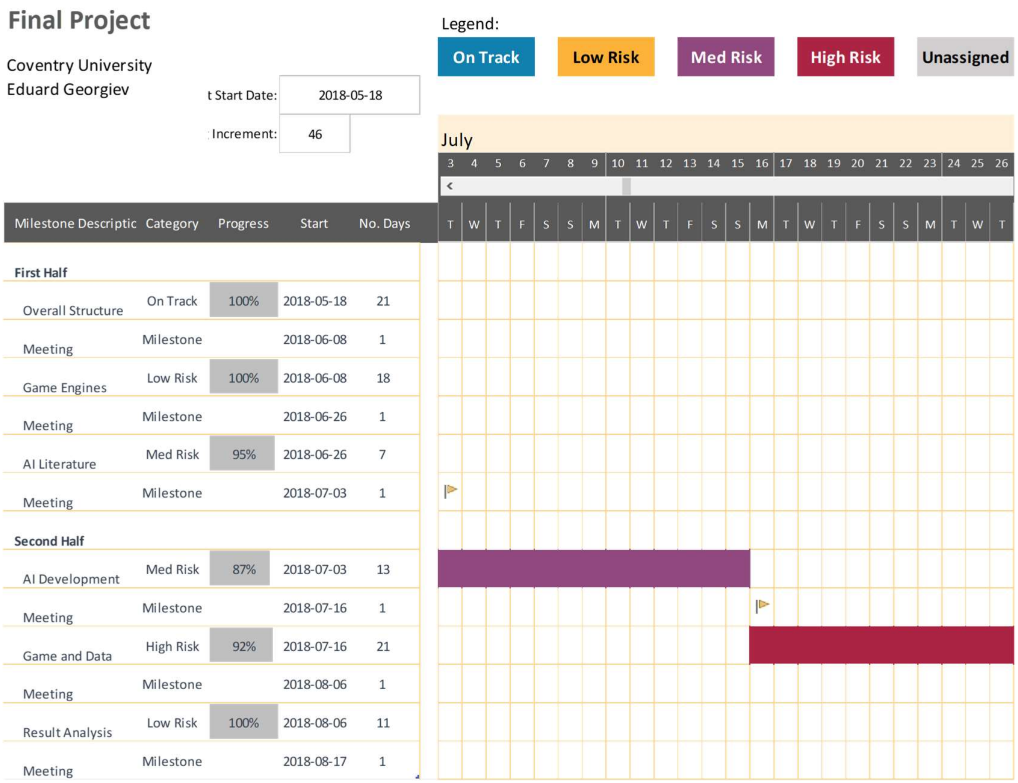


FIGURE 6.3 – GANNT CHART PROJECT MANAGEMENT PART 3

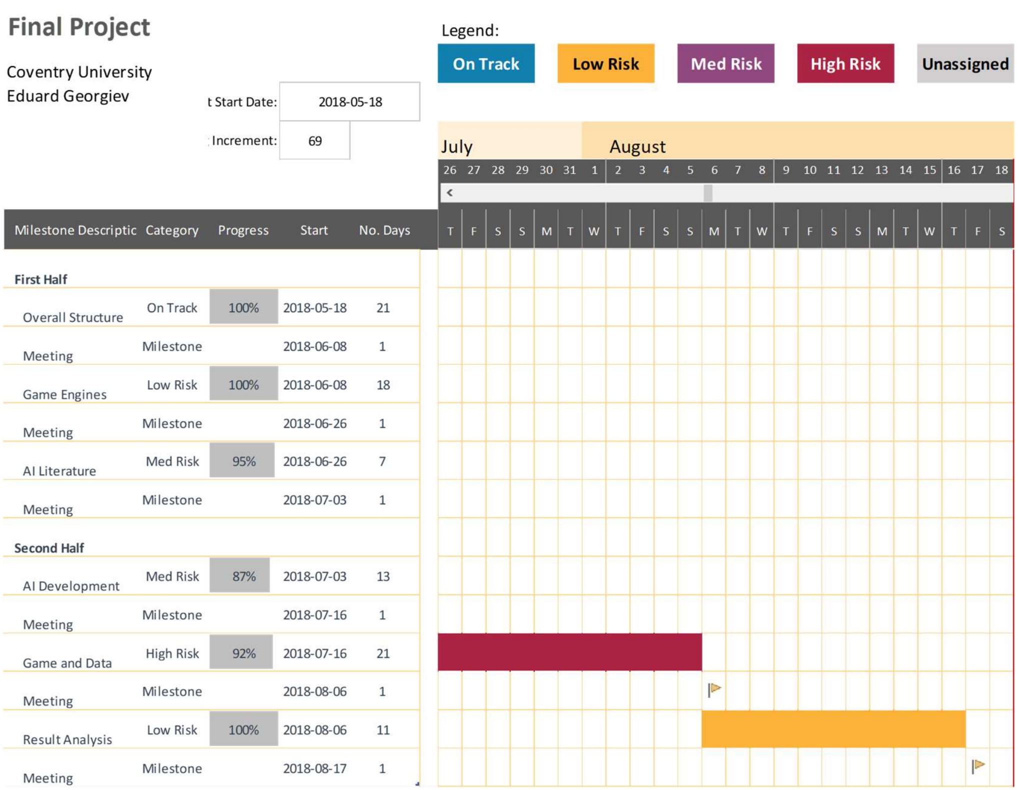


FIGURE 6.4 – GANNT CHART PROJECT MANAGEMENT PART 4

7. CONCLUSIONS

The results from this research show how the interactive nature of games can be used to educate people that have different learning styles, specifically when used with chosen techniques such as textual instructions, diagrams and trial and error environment.

While the focus groups were not tested on knowledge retention, the questionnaire involved questions on the way they felt about educational presentation and how well they reacted to different game elements and different ways of interaction. This is the first step towards making progress in education on the topic of AI using video games, as there would be no knowledge retention without understanding how to effectively communicate with the player in the first place. In summary, it was found that players that learn by reading find textual instructions easier to understand than the rest of the groups, while those that prefer to learn by performing were more interested in the trial-and-error part of the game.

Other research articles exist on similar topics, but this one takes learning styles into account and compares results based on them and based on the different game elements, which are specific to this research project. This is what makes the project original and intriguing towards future researchers. Furthermore it is rare that a whole AI solution is implemented to solve such simple tasks like maze navigation, which is the path that his project decided to embark upon, and while the AI development carried a lot of risk with it, it proved to be worth it in the end when all came together and many participants were amazed by the capabilities of the video game.

7.1 Future Work

Future work should involve a better questionnaire that covers more topics with improved cross-tabulation and more precise questions that are self-explanatory, featuring a bigger focus group for more accurate results.

Existing systems for determining learning style can be implemented, some of which come with their own questionnaire. This will be of great help towards understanding how exactly the player prefers to learn, instead of asking him to identify that on his own.

In the long-term a more developed AI with backpropagation can be used to implement many more levels, the possibility for multiplayer and a competitive leader board, as modern gaming has proved, competition is an important part of most video games.

Artists can be used to enhance gameplay graphics, as this was one of the recommendations given to the main researcher. This would allow for visual representation of different settings such as instructive and voiced video clips. More appropriate music and better sound effects are always welcome to improve gameplay and the feeling of achievement.

The UI can be redesigned to be more intuitive with tooltips and in the long-run animations that will help guide the player, especially those that skip through instructions and thus are often unable to progress.

8. References

Amazon (2018) *Amazon Lumberyard – Build Your Most Ambitious Games* [online] available from: <https://aws.amazon.com/lumberyard/> [24 June 2018]

Bosca Ceoil (2018) *Bosca Ceoil* [online] available from: <https://boscaceoil.net/> [17 August 2018]

Boynton P. and Greenhalgh T. (2003) *Selecting, designing, and developing your questionnaire* [online] available from: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC420179/> [5 August 2018]

Craighead, J., Burke, J. and Murphy, R. (2008) *Using the unity game engine to develop sarge: a case study* [online] available from: <https://www.researchgate.net/profile/Jeffrey_Craighead/publication/265284198_Using_the_Unity_Game_Engine_to_Develop_SARGE_A_Case_Study/links/55d33fdf08aec1b0429f32f4.pdf> [8 June 2018]

Dillon, A. (2003) *User Interface Design*. *MacMillan Encyclopedia of Cognitive Science*, Vol. 4, London: Macmillan, 453-458. [online] available from: <https://repository.arizona.edu/bitstream/handle/10150/105299/UiDAd03.pdf?sequence=1> [26 June 2018]

Ermi, L. and Mäyrä, F. (2005) *Fundamental components of the gameplay experience: Analysing immersion* Worlds in play: International perspectives on digital games research, 37(2), pp.37-53. [online] available from: <http://summit.sfu.ca/system/files/iritems1/260/26f2f5aea2e3389e2a6d5c30e824.doc> [27 June 2018]

Frey, C.B. and Osborne, M.A. (2013) *The future of employment: how susceptible are jobs to computerisation?* [online] available from: <https://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf> [2 June 2018]

Galway, L., Charles, D. and Black, M. (2008) *Machine learning in digital games: a survey*. Artificial Intelligence Review,29(2), pp.123-161. [online] available from: <https://www.researchgate.net/profile/Leo_Galway/publication/220638059_Machine_learning_in_digital_games_A_survey/links/0046351d6deada1bc4000000/Machine-learning-in-digital-games-A-survey.pdf> [2 June 2018]

Geron, A. (2017) *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media, Inc.

Godot (2018) *Godot Docs* [online] available from: <http://docs.godotengine.org/en/3.0/> [9 June 2018]

Gregory, J. (2014) *Game Engine Architecture, Second Edition.* Taylor and Francis Group, LLC

Harrigan, K.A., Collins, K., Dixon, M.J. and Fugelsang, J. (2010) *Addictive gameplay: what casual game designers can learn from slot machine research*. In Proceedings of the international academic conference on the future of game design and technology (pp. 127-133). ACM. [online] available from: <https://s3.amazonaws.com/academia.edu.documents/29100279/addict.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1530049239&Signature=GfdRls3biT0WbtgQxq3MhyOjxvo%3D&response-content-disposition=inline%3B%20filename%3DAddictive_gameplay_what_casual_game_desi.pdf> [26 June 2018]

IJsselsteijn, A., de Kort, W. and Poels, K. (2013) *Game experience questionnaire.* Technische Universiteit Eindhoven, European Community - New and Emerging Science and Technology (NEST) programme [online] available from: <https://research.tue.nl/en/publications/the-game-experience-questionnaire> [8 August 2018]

Jisc Online Surveys (2018) *Dashboard* [online] available from: <https://admin.onlinesurveys.ac.uk> [18 August 2018]

Jordan, M.I. and Mitchell, T.M. (2015) *Machine learning: Trends, perspectives, and prospects.* Science, 349(6245), pp.255-260 [online] available from: <http://www.cs.cmu.edu/~tom/pubs/Science-ML-2015.pdf> [2 June 2018]

Ke, F. (2008) *A case study of computer gaming for math: Engaged learning from gameplay?* Computers & education, 51(4), pp.1609-1620. [online] available from: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.407.859&rep=rep1&type=pdf> [27 June 2018]

Kelley K., Clark B., Brown V. and Sitzia J. (2003) *Good practice in the conduct and reporting of survey research.* International Journal for Quality in Health Care, Volume 15, Issue 3, 1 May 2003, Pages 261–266, [online] available from: <https://doi.org/10.1093/intqhc/mzg031> [5 August 2018]

Manyika J. (2017) *A Future That Works: AI, Automation, Employment, and Productivity* [online] available from: <https://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/risk/downloads/170622-slides-manyika.pdf> [2 June 2018]

Mehta R. and Zhu R. (2009),"*Blue or Red? Exploring the Effect of Color on Cognitive Performance*", in NA - Advances in Consumer Research Volume 36, eds. Ann L. McGill and Sharon Shavitt, Duluth, MN: Association for Consumer Research, Pages: 1045-1046 [online] available from: <http://www.acrwebsite.org/volumes/14185/volumes/v36/NA-36> [26 June 2018]

Parncutt, R. (2014) *The emotional connotations of major versus minor tonality: One or more origins?* [online] available from: <http://journals.sagepub.com/doi/abs/10.1177/1029864914542842?journalCode=msxa> [17 August 2018]

Pashler, H., McDaniel, M., Rohrer, D. and Bjork, R. (2008) *Learning styles: Concepts and evidence* [online] available from: <https://pdfs.semanticscholar.org/6275/2ca4c446ca7328f8c284f5385f1af1c4212e.pdf> [6 June 2018]

Petridis, P., Dunwell, I., De Freitas, S. and Panzoli, D. (2010) *An engine selection methodology for high fidelity serious games* [online] available from: <http://researchrepository.murdoch.edu.au/id/eprint/26726/1/engine_selection_methodology.pdf> [8 June 2018]

Rasmusson J. (2018) *What is Agile?* [online] available from: <http://www.agilenutshell.com/> [16 August 2018]

Russel, S. and Norvig P. (2016) *Artificial Intelligence: A Modern Approach*. Third Edition. Pearson Education, Inc.

Schell, J. (2008) *The Art of Game Design*. Elsevier Inc.

Schwab, B. (2009) *AI game engine programming* [online] available from: <ftp://nozdr.ru/biblio/kolxo3/Cs/CsAi/Schwab%20B.%20AI%20game%20engine%20programming%20(2ed.,%20Cengage,%202009)(ISBN%201584505729)(O)(741s)_CsAi_.pdf> [6 June 2018]

Scirra (2018) *Official Construct 2 Manual* [online] available from: <https://www.scirra.com/manual/1/construct-2> [9 June 2018]

Unity Technologies (2009) *Unity – Unity Machine Learning tools and resources* [online] available from: <https://unity3d.com/machine-learning> [6 July 2018]

Weisstein, E. (2018) *Hyperbolic Tangent.* Mathworld – A Wolfram Web Resource [online] available from: <http://mathworld.wolfram.com/HyperbolicTangent.html> [14 August 2018]

Yudkowsky, E. (2008) *Artificial intelligence as a positive and negative factor in global risk.* [online] available from: <https://www.researchgate.net/profile/James_Peters/post/Can_artificial_Intelligent_systems_replace_Human_brain/attachment/59d62a00c49f478072e9cbc4/AS:272471561834509@1441973690551/download/AIPosNegFactor.pdf> [2 June 2018]

9. Appendices

9.1 Ethics Approval Certificate

Coventry University

Certificate of Ethical Approval

Applicant:

Eduard Georgiev

Project Title:

Artificial intelligence education using video games

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

Date of approval:

21 May 2018

Project Reference Number:

P70383

FIGURE 9.1 – ETHICS APPROVAL CERTIFICATE

9.2 *Signed Supervisor Meeting Records*

M102CEM
RECORD OF SUPERVISOR MEETING

Meeting Number: 1

Date: 08.06.2018

Topic: Overall Structure

Project Topics
Project Structure
Topic Clarification
Work Summary
Tips on Referencing
Formatting

Student: Eduard Rumen Georgiev	**Supervisor:** Dr Jianbing Ma
ID: 8240390	**Signature:** J. Ma

FIGURE 9.2 – SUPERVISOR MEETING NUMBER 1

M102CEM
RECORD OF SUPERVISOR MEETING

Meeting Number: 2

Date: 26.06.2018

Topic: Game Engines and Referencing

Addressed Issues
Game Engines Reviewed
New additions to the dissertation
Tips on topic order and naming
Tips on References
Method discussion
Other

Student: Eduard Rumen Georgiev	**Supervisor:** Dr Jianbing Ma
ID: 8240390	**Signature:** J. Ma.

FIGURE 9.3 – SUPERVISOR MEETING NUMBER 2

M102CEM
RECORD OF SUPERVISOR MEETING

Meeting Number: 3

Date: 3 of July, 2018

Topic: References, Books, Journals, other

References Gameplay

Books

Journals

Artificial Intelligence

Genetic Algorithms

Game Design

Student: Eduard Rumen Georgiev	**Supervisor:** Dr Jianbing Ma
ID: 8240390	**Signature:** J. Ma.

FIGURE 9.4 – SUPERVISOR MEETING NUMBER 3

M102CEM
RECORD OF SUPERVISOR MEETING

Meeting Number: 4

Date: 16.07.2018

Topic: Artificial Intelligence

Artificial Intelligence
Neural Networks
Genetic Algorithms
Diagrams
Demonstration

Student: Eduard Rumen Georgiev	**Supervisor:** Dr Jianbing Ma
ID: 8240390	**Signature:** J. Ma

FIGURE 9.5 – SUPERVISOR MEETING NUMBER 4

M102CEM
RECORD OF SUPERVISOR MEETING

Meeting Number: 5

Date: 06.08.2018

Topic: Study, Game

Questionnaire
Study information
Gameplay Demonstration
Data Gathering
Compatibility
Decoupling and Reuse

Student: Eduard Rumen Georgiev	**Supervisor:** Dr Jianbing Ma
ID: 8240390	**Signature:** J. Ma

FIGURE 9.6 – SUPERVISOR MEETING NUMBER 5

M102CEM
RECORD OF SUPERVISOR MEETING

Meeting Number: 6

Date: 17.08.2018

Topic: Results, Analysis, Presentation

Result Overview

Future works

Questionnaire Analysis

Presentation of Work and Results

Final Overview

Student: Eduard Rumen Georgiev	**Supervisor:** Dr Jianbing Ma
ID: 8240390	**Signature:** J. Ma

FIGURE 9.7 – SUPERVISOR MEETING NUMBER 6

9.3 Questionnaire Results (Jisc Online Surveys, 2018)

3 Your age group:

Rank value	Option	Count
1	18-24	9
2	25-29	9
3	30-34	5
4	35-39	0
5	40-44	0
6	45-50	0

Mean rank	1.83
Variance	0.58
Standard Deviation	0.76
Lower Quartile	1.0
Upper Quartile	2.0

TABLE 9.1 – QUESTIONNAIRE RESULTS AGE GROUP

4 Have you received any education on Artificial Intelligence?

Rank value	Option	Count
1	No	10
2	Yes (Basic)	13
3	Yes (Advanced / Higher Education)	0

TABLE 9.2 – QUESTIONNAIRE RESULTS EDUCATION

5 What is your MOST preferred way of learning?

Rank value	Option	Count
1	Reading	4
2	Writing	1
3	Listening	0
4	Watching	9
5	Performing	9
6	None of the above	0

TABLE 9.3 – QUESTIONNAIRE RESULTS LEARNING

How well was information presented in each part of the game?

Level 1 6.1

Rank value	Option	Count
1	Very Unclear	1
2	Unclear	2
3	Neutral	0
4	Clear	7
5	Very Clear	13

Mean rank	4.26
Variance	1.24
Standard Deviation	1.11
Lower Quartile	4.0
Upper Quartile	5.0

Level 2 6.2

Rank value	Option	Count
1	Very Unclear	1
2	Unclear	0
3	Neutral	0
4	Clear	7
5	Very Clear	15

Mean rank	4.52
Variance	0.77
Standard Deviation	0.88
Lower Quartile	4.0
Upper Quartile	5.0

Level 3 6.3

Rank value	Option	Count
1	Very Unclear	1
2	Unclear	1
3	Neutral	2
4	Clear	7
5	Very Clear	12

Mean rank	4.22
Variance	1.13
Standard Deviation	1.06
Lower Quartile	4.0
Upper Quartile	5.0

"How It Works?" page 6.4

Rank value	Option	Count
1	Very Unclear	1
2	Unclear	1
3	Neutral	3
4	Clear	3
5	Very Clear	14

Mean rank	4.27
Variance	1.29
Standard Deviation	1.14
Lower Quartile	4.0
Upper Quartile	5.0

TABLE 9.4 – QUESTIONNAIRE RESULTS PRESENTATION

How interested were you in each part of the game?

Level 1 7.1

Rank value	Option	Count
1	Very Uninterested	0
2	Uninterested	2
3	Neutral	3
4	Interested	7
5	Very Interested	11

Mean rank	4.17
Variance	0.93
Standard Deviation	0.96
Lower Quartile	4.0
Upper Quartile	5.0

Level 2 7.2

Rank value	Option	Count
1	Very Uninterested	1
2	Uninterested	0
3	Neutral	0
4	Interested	7
5	Very Interested	15

Mean rank	4.52
Variance	0.77
Standard Deviation	0.88
Lower Quartile	4.0
Upper Quartile	5.0

Level 3 7.3

Rank value	Option	Count
1	Very Uninterested	1
2	Uninterested	0
3	Neutral	0
4	Interested	4
5	Very Interested	18

Mean rank	4.65
Variance	0.75
Standard Deviation	0.87
Lower Quartile	5.0
Upper Quartile	5.0

"How It Works?" page 7.4

Rank value	Option	Count
1	Very Uninterested	1
2	Uninterested	0
3	Neutral	2
4	Interested	6
5	Very Interested	14

Mean rank	4.39
Variance	0.93
Standard Deviation	0.97
Lower Quartile	4.0
Upper Quartile	5.0

TABLE 9.5 – QUESTIONNAIRE RESULTS INTEREST

8 How challenging was each level?

8.1 Level 1

Rank value	Option	Count
1	Very Easy	10
2	Easy	3
3	Normal	7
4	Difficult	1
5	Very Difficult	2

Mean rank	2.22
Variance	1.65
Standard Deviation	1.28
Lower Quartile	1.0
Upper Quartile	3.0

8.2 Level 2

Rank value	Option	Count
1	Very Easy	3
2	Easy	7
3	Normal	8
4	Difficult	5
5	Very Difficult	0

Mean rank	2.65
Variance	0.92
Standard Deviation	0.96
Lower Quartile	2.0
Upper Quartile	3.0

8.3 Level 3

Rank value	Option	Count
1	Very Easy	3
2	Easy	3
3	Normal	6
4	Difficult	7
5	Very Difficult	4

Mean rank	3.26
Variance	1.58
Standard Deviation	1.26
Lower Quartile	2.5
Upper Quartile	4.0

TABLE 9.6 – QUESTIONNAIRE RESULTS CHALLENGE

9 Which part of the game did you find MOST educational?

Rank value	Option	Count
1	Level Objective (Presented at the start of each level)	2
2	Setup Page Hint (Shown in green text on the Setup page)	2
3	Setup Page Setting Explanation (Text on the right of each setting)	6
4	Setup Experimentation (Trial and Error)	10
5	"How It Works" page	3

TABLE 9.7 – QUESTIONNAIRE RESULTS MOST EDUCATIONAL

10 Would you say that the background music made you MORE likely to read written instructions?

Rank value	Option	Count
1	Yes	14
2	No	7
3	No, but a different music would	2

Mean rank	1.48
Variance	0.42
Standard Deviation	0.65
Lower Quartile	1.0
Upper Quartile	2.0

TABLE 9.8 – QUESTIONNAIRE RESULTS MUSIC

11 Would you say that the sound after every successful attempt made you MORE interested in performing better?

Rank value	Option	Count
1	Yes	20
2	No	2
3	No, but a different sound would	1

Mean rank	1.17
Variance	0.23
Standard Deviation	0.48
Lower Quartile	1.0
Upper Quartile	1.0

TABLE 9.9 – QUESTIONNAIRE RESULTS SOUND EFFECT

12 Do you think the information presented was overwhelming, and how did that make you feel?

Rank value	Option	Count
1	YES, it made me feel MORE interested	13
2	YES, it made me feel LESS interested	2
3	NO, it made me feel MORE interested	8
4	NO, it made me feel LESS interested	0

Mean rank	1.78
Variance	0.87
Standard Deviation	0.93
Lower Quartile	1.0
Upper Quartile	3.0

TABLE 9.10 – QUESTIONNAIRE RESULTS OVERWHELMING INFORMATION

13 How would you improve the game, in a way that will help you become more educated, interested and invested in the topic of Artificial Intelligence?

Showing all 14 responses Show less
Maybe change the triangle to another shape just to make more interesting.
More pictures to explain the game properly
I feel that the information guide should be more interactive and easy to understand
Keep the good work
Extend the "how it works" section :)
more effects when they don't make it / make it
More effects to make the game a bit more dynamic and engaging to play and a level editor to test out the AI
In the how to page, maybe explain the neurons with analogies.
better animation:)
I'd add more levels so that 3 new concepts (mutation, selection, crossover), which were abruptly added at level 3, could be introduced gradually. I'd also keep the instructional text to a minimum and show "How it works" after first level, instead of having it as a separate page. That way, people would be more likely to read the explanation, as their attention would already be grabbed by first level.
Think this game is amazing and very interesting indeed and could get used to it everyday. Design is incredible and the whole background was well thought out.
keep up your good work
Make the information slightly easier for non-AI people to understand. Also, give more information as to what each AI change does to the triangles.
My opinion this game is amazing, the background was thoughtful and professional as well. Definitely would recommend a family member to play it since it provides so much fun.

TABLE 9.11 – QUESTIONNAIRE RESULTS TEXT RESPONSES

9.4 Questionnaire Results, Cross-Tabulated with Learning Preference (Jisc Online Surveys, 2018)

6 How well was information presented in each part of the game?

6.1 Level 1

Level 1	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Unclear	0	0	0	1	0	0	0	1
Unclear	0	0	0	1	1	0	0	2
Neutral	0	0	0	0	0	0	0	0
Clear	1	0	0	3	3	0	0	7
Very Clear	3	1	0	4	5	0	0	13
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

6.2 Level 2

Level 2	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Unclear	0	0	0	1	0	0	0	1
Unclear	0	0	0	0	0	0	0	0
Neutral	0	0	0	0	0	0	0	0
Clear	1	0	0	3	3	0	0	7
Very Clear	3	1	0	5	6	0	0	15
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

6.3 Level 3

Level 3	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Unclear	0	0	0	1	0	0	0	1
Unclear	0	0	0	0	1	0	0	1
Neutral	1	0	0	1	0	0	0	2
Clear	0	0	0	4	3	0	0	7
Very Clear	3	1	0	3	5	0	0	12
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

6.4 "How It Works?" page

"How It Works?" page	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Unclear	0	0	0	1	0	0	0	1
Unclear	0	0	0	0	1	0	0	1
Neutral	0	0	0	3	0	0	0	3
Clear	0	0	0	2	1	0	0	3
Very Clear	4	1	0	2	7	0	0	14
No answer	0	0	0	1	0	0	0	1
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.12 – CROSS-TABULATED PRESENTATION ANSWERS

7 How interested were you in each part of the game?

7.1 Level 1

Level 1	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Uninterested	0	0	0	0	0	0	0	0
Uninterested	0	0	0	2	0	0	0	2
Neutral	0	0	0	1	2	0	0	3
Interested	2	0	0	3	2	0	0	7
Very Interested	2	1	0	3	5	0	0	11
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

7.2 Level 2

Level 2	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Uninterested	0	0	0	1	0	0	0	1
Uninterested	0	0	0	0	0	0	0	0
Neutral	0	0	0	0	0	0	0	0
Interested	1	0	0	4	2	0	0	7
Very Interested	3	1	0	4	7	0	0	15
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

7.3 Level 3

Level 3	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Uninterested	0	0	0	1	0	0	0	1
Uninterested	0	0	0	0	0	0	0	0
Neutral	0	0	0	0	0	0	0	0
Interested	1	0	0	3	0	0	0	4
Very Interested	3	1	0	5	9	0	0	18
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

7.4 "How It Works?" page

"How It Works?" page	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Uninterested	0	0	0	1	0	0	0	1
Uninterested	0	0	0	0	0	0	0	0
Neutral	0	0	0	2	0	0	0	2
Interested	1	0	0	4	1	0	0	6
Very Interested	3	1	0	2	8	0	0	14
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.13 – CROSS-TABULATED INTEREST ANSWERS

8 How challenging was each level?

8.1 Level 1

Level 1	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Easy	0	0	0	6	4	0	0	10
Easy	2	0	0	1	0	0	0	3
Normal	2	0	0	2	3	0	0	7
Difficult	0	0	0	0	1	0	0	1
Very Difficult	0	1	0	0	1	0	0	2
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

8.2 Level 2

Level 2	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Easy	0	0	0	1	2	0	0	3
Easy	1	0	0	4	2	0	0	7
Normal	2	1	0	3	2	0	0	8
Difficult	1	0	0	1	3	0	0	5
Very Difficult	0	0	0	0	0	0	0	0
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

8.3 Level 3

Level 3	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Very Easy	0	0	0	2	1	0	0	3
Easy	0	0	0	0	3	0	0	3
Normal	3	0	0	2	1	0	0	6
Difficult	0	1	0	4	2	0	0	7
Very Difficult	1	0	0	1	2	0	0	4
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.14 – CROSS-TABULATED CHALLENGE ANSWERS

9 Which part of the game did you find MOST educational?

Which part of the game did you find MOST educational?	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Level Objective (Presented at the start of each level)	0	0	0	2	0	0	0	2
Setup Page Hint (Shown in green text on the Setup page)	1	0	0	1	0	0	0	2
Setup Page Setting Explanation (Text on the right of each setting)	2	0	0	2	2	0	0	6
Setup Experimentation (Trial and Error)	1	1	0	3	5	0	0	10
"How It Works" page	0	0	0	1	2	0	0	3
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.15 – CROSS-TABULATED MOST EDUCATIONAL PART ANSWERS

10 Would you say that the background music made you MORE likely to read written instructions?

Would you say that the background music made you MORE likely to read written instructions?	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Yes	3	0	0	2	9	0	0	14
No	0	0	0	7	0	0	0	7
No, but a different music would	1	1	0	0	0	0	0	2
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.16 – CROSS-TABULATED BACKGROUND MUSIC ANSWERS

11 Would you say that the sound after every successful attempt made you MORE interested in performing better?

Would you say that the sound after every successful attempt made you MORE interested in performing better?	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
Yes	3	1	0	7	9	0	0	20
No	1	0	0	1	0	0	0	2
No, but a different sound would	0	0	0	1	0	0	0	1
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.17 – CROSS-TABULATED SOUND EFFECTS ANSWERS

12 Do you think the information presented was overwhelming, and how did that make you feel?

Do you think the information presented was overwhelming, and how did that make you feel?	What is your MOST preferred way of learning?						No answer	Totals
	Reading	Writing	Listening	Watching	Performing	None of the above		
YES, it made me feel MORE interested	3	1	0	3	6	0	0	13
YES, it made me feel LESS interested	0	0	0	2	0	0	0	2
NO, it made me feel MORE interested	1	0	0	4	3	0	0	8
NO, it made me feel LESS interested	0	0	0	0	0	0	0	0
No answer	0	0	0	0	0	0	0	0
Totals	**4**	**1**	**0**	**9**	**9**	**0**	**0**	**23**

TABLE 9.18 – CROSS-TABULATED OVERWHELEMING INFORMATION ANSWERS