Dynamic Gaming Difficulty Calculation: A Study On The Impacts Of Procedural Difficulty Calculation On Player Performance And Immersion In Video Games.

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Authorship Statement

This dissertation is based on the results of research carried out by myself, is my own composition, and has not been previously presented for any other certified or uncertified qualification.

The research was carried out under the supervision of Mr Mark Spiteri.

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June 5, 2022

Copyright Statement

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Acknowledgements

I would like to express my gratitude to my family and friends for all their support throughout these years, where I have arrived today has been aided tremendously by the people who are closest to me, and for that I am eternally grateful.

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Abstract

Dynamic Difficulty Adjustment (DDA) is a concept that can be utilised by game developers to adaptively balance a game's difficulty according to a player's unique skill level. This can be done by analysing the performance of the player and modifying the values of variables that are tied to the game's scene, these variables can be in relation to environment such as obstacles, opponents, and the player himself.

However, despite this research field having many implementations from past research, it is evident that dynamic difficulty adjustment has a very low adoption rate in modern releases of popular digital interactive media. This signifies that more research is required to further understand how DDA can be properly implemented in a gaming environment.

This research aims to investigate and understand the role and effect DDA has on players in terms of immersion level and performance in gaming. Specifically, how do these readings compare when there isn't a DDA system utilised. To achieve this, a dynamic difficulty system will be developed and utilised in a 3D shooter game, and from there on an experiment will be conducted with participants which will be split into two phases, the first not making use of the DDA system whilst the second one does. Once

the experiment is completed, the results which measure the performance, immersion, and how the difficulty was perceived will be evaluated by doing comparisons between both phases. This so it can be identified how the overall experience of the participants differentiates when comparing both phases.

The results show that DDA can positively affect the overall performance of end-users, however its affect varies with certain skill levels. Beginner level participants were found to benefit the most since their performance improved the highest when compared to the other skill groups. For immersion, it was seen that beginners also had the highest readings, whilst for higher skilled participants it fluctuated depending on their performance since for some, the adjustments were more frequent which made them more noticeable.

The findings from this research provide further insight into DDA, demonstrating that while DDA systems can provide superior game experiences for certain skill groups, specific drawbacks can reduce its effectiveness. These recommendations can be of interest to game developers, who are interested in implementing a DDA system for their games, since a better understanding is provided of how it can be developed and utilised.

Chapter 1

Introduction

Dynamic difficulty adjustment involves the modification of a game's scenario, by altering the behaviours, features, and values of entities, depending on the skill level of the player. The idea behind this concept is to create a proper gaming environment where each player regardless of skill, is presented with a challenge during the level which is suitable for their unique skill (Zohaib, 2018).

However, even though this technology exists and has been researched many times in the past, it is evident in the modern gaming industry that dynamic difficulty adjustment systems aren't utilised in popular releases. Which makes the concept almost completely unheard of for the majority of the end-users. This is an indication that even though DDA has been improved throughout the years due to the continued research on the subject, more studies and evaluations need to be done, because the very low adoption rate of DDA systems signify that more work still needs to be done.

The aims and goals for research is to gain knowledge and understand the role and influence of difficulty adjustment has in gaming, specifically how an algorithm based of adjusting game states and heuristics can affect the user experience and immersion in 3D shooter games. How will that correlate with player performance and efficiency and what appropriate procedures should be taken to reduce error during player analysis. To accomplish this, a DDA system will be developed and implement it in a gaming environment, and from there a test is conducted which is split into two separate phases, the first not utilising the DDA system whilst the second one does. After the test, an evaluation would identify how the overall experience of the participants differentiates when comparing both phases.

This chapter will provide an introduction of the study by first discussing the scope of this research, the background and context of the research field, which is then followed by the personal motivation, from there on the research aims, objectives and questions, the significance of this study, and finally the structural outline.

The specialist terms for this subject include Dynamic Difficulty Adjustment (DDA), Immersion, Performance and Player.

1.1 The Scope

The scope when researching articles and dissertations that follow the same or a similar research field is to learn about how a multimedia approach was taken when it came to dynamic difficulty in gaming, the methodologies that the authors adopted when conducting practical tests, how the algorithms were specifically used during these tests, how the results of the experiments turned out and what limitations occurred and what needed more research so to increase efficiency and lessen difficulty when conducting practical public testing.

1.2 Background of the Study

Dynamic difficulty Adjustment in modern gaming is considered to be when the data values of various objects in a gaming environment are modified in real-time depending on the player's performance (Zohaib, 2018). Examples of these data values can be the health, damage, and speed of the player or the enemy. Using DDA can be a good opportunity for the game's difficulty to correspond accordingly to the unique skill of a player, so a challenging experience can be provided (Zohaib, 2018). A commonly accepted theory is that players enjoy unpredictability during gameplay experiences, however, they might feel "cheated" if games are adjusted during sessions. For adjustments to be effective, they must be performed without disrupting the core player experience (Hunicke, 2005).

One of the methods of approach that can be taken when developing a DDA system is by affecting the artificial intelligence(AI) of a game. This works by having the system determine how the difficulty of the AI should be adjusted, so a suitable challenge is presented by the player. The process works by examining the performance of the player and comparing it to the performance of the enemy, and from there on evaluating if the difficulty should be lowered or increased (Silva, Nascimento Silva and Chaimowicz, 2017).

Another method to note is known as system orientation structure, where difficulty is only increased after the player has passed certain checkpoints. A different method can be also applied, which is player oriented, this can work by either having the difficulty be manually controlled by the end-user via pressing assigned buttons, or by adjusting the difficulty only based on the player's performance instead of comparing it with AI (Ang and Mitchell, 2017).

Dynamic difficulty in multiplayer can also be utilised, for example in an environment where people are pitted against each other. The DDA system would work by comparing performances, and the lowest performing player is given a boost to assist them (Baldwin, Johnson and Wyeth, 2014).

1.3 Hypothesis and Research Questions

The main objective of this study is to examine how a dynamic difficulty adjustment system can have a positive impact on the end-user when applied correctly in a gaming environment. To properly evaluate this statement, these questions were written to define the individual goals:

1. How does a real-time dynamic challenge adjustment algorithm affect the performance of the player?
2. Do Players notice the adjustment? And if so, does it affect their enjoyment, frustration or perception of game difficulty?
3. How is the level of engagement affected through dynamically difficult games?

1.4 Personal Motivation

The reasons for choosing this research theme are personal interest to see what kind of results are obtained if a player goes through two or more levels in a FPS or RPG, with the difficulty level starting at a default point and progressing dynamically throughout the game, and later seeing how it changed according to the individual.

It also would be interesting to see, if creating a set of rules and regulations that dictates how the level of challenge should be changed, would yield better results in terms of player enjoyment, immersion, and performance. When compared to games that only have static difficulty settings.

Currently, at the time of writing this study, there isn't a definitive answer to this specific topic, so developers aren't always too sure what would be the best choice.

1.5 Significance of Study

The immediate anticipated contributions this study is going to provide is that game developers will have a better understanding in how to properly use and implement a DDA system when developing their own games, which will improve the quality of all the levels in games that will use these techniques.

The long term benefits and effects of the findings in this study will be that better algorithms will be created that can decide and alter the game's properties during gameplay so to how a human would. So an unbalanced set of challenge levels would be greatly reduced and minimized to where an end-user could enjoy the gameplay more and have an increasingly pleasant, engaging and immersive experience.

1.6 Structural Outline of Study

In the literature review chapter, existing literature from previous work is reviewed to identify the different key development approaches done within the context of dynamic difficulty adjustment. Their results obtained and the limitations will also be examined to see what made their system capable, and what could have been improved.

The methodology chapter will present the main approach of the development DDA system of this study, with justifications supporting the decisions taken. It will also discuss the adoption of a mixed methods approach of obtaining the data from participants during the experiment.

In the results chapter, all of the gathered data from the participants will be displayed in an organised format. The results for both phases will be split into 3 sections, the first will general questions about the participant to identify their skill level, the second questions will focus on the overall experience, and the third section will display the in-game statistics and biometric readings.

The discussion chapter focuses on comparing the results of both the first and second phase of the experiment, with plausible explanations of how these results came to be, so a justified answer for the research questions can be stated. This chapter also focuses on the encountered limitations of the study and what could have been improved.

The conclusion will be the final chapter of the study, it will present a summary of the key research findings that are in relation to the research aims and questions, as well as the values and contribution.

Chapter 2

Literature Review

Dynamic difficulty Adjustment in modern digital interactive media is known to be when a game's features, behaviours, scenarios, and data values are modified in real time depending on the player's performance. The advantage of using Dynamic Difficulty Adjustment (DDA) is that the game's difficulty can correspond accordingly to the unique skill of a player, so a challenging experience can be provided (Zohaib, 2018). It is a commonly accepted theory that players enjoy unpredictability and uncertainty during gameplay experiences, however, they might feel "cheated" if games are adjusted during sessions. In order for an adjustment to be effective, it must be performed without disrupting or degrading the core player experience (Hunicke, 2005).

This literature review contains research about multiple procedures and techniques on applying a DDA system in a game environment, both for multiplayer and single player games. One of these approaches is by using artificial intelligence adjustment, which works by analysing the performance level of the player, to determine how the difficulty of the AI should be adjusted accordingly to adapt to the players' skill level. In many cases, a set of parameters are normally identified within the environment. These parameters are used to measure players' performance and go through an analysis process, for example kill count, deaths, and level. Once these are obtained, an assessment is conducted to determine who the top performer is to see if a difficulty adjustment is warranted, the top performer can either be the human player or AI.

Another similar example can be found in a multiplayer context in an environment where people are pitted against each other, this is known as a PvP (Player versus player) setting. A DDA system is integrated by doing comparisons of performances, similar to the previous example, but this time only comparing human players, rather than AI vs. Humans. Where the lowest performing player is given combat boosts such as increased health, and/or damage.

Other methods where DDA can be used in gaming is a system orientation structure, this is where the difficulty is increased after certain checkpoints reached by the player, since that is an indication of the player's progression throughout the level. Normally the difficulty has a limitation set, not to scale infinitely and make the difficulty impossible.

Another approach is by using player oriented DDA, which includes changing the values of the variables of the digital environment depending on the performance of the player instead of altering the behaviour of the AI. This system normally evaluates how the player is doing in the level, and once an assessment is conducted instances such as obstacle speed, enemy damage, and anything that can affect the difficulty are changed to accommodate the player's skill. Player oriented DDA can also be called directly by the player to change the difficulty, one way this can be done is by pressing a set of buttons, with each one having the ability to increase or decrease the condition.

2.1 Artificial Intelligence in DDA

A study was conducted in 2015 by Paula Silva, Nascimento Silva, and Chaimowicz that saw participant players go against AI controlled opponents in a test environment of the game 'Defense of the Ancients'. The purpose of the experiment was to analyze how an adaptive AI character would respond and react to a player's inputs and actions, and determine if a balanced, fair and enjoyable environment was achieved by managing to adjust the difficulty level according to the opponent's skill. The dynamic difficulty was spanned into 3 different sections, where the adaptive AI would alternate and switch between 3 difficulty modes, according to performance of the participant. These modes were 'Easy' mode, whilst the rest followed with 'Regular' and 'Hard' Mode. The difference between them being that with each difficulty entry, the AI would be able to commit much more actions that would provide a challenge for the opposing player. The reason for there being 3 different types of difficulty modes, was to simulate players that had different skill levels, that being beginner, intermediate, and expert. The below figure summarizes the differences between the modes:

		Artificial Intelligence		
		Easy Mode	Regular Mode	Hard Mode
Defense Strategy	Defend Allied Towers	X	X	X
	Retreat	X	X	X
	Item Manipulation		X	X
Attack Strategy	Main Attack	X	X	X
	Target Selection	X	X	X
	Track Enemy Hero			X
	Cast Spell			X

Figure 2.1: A figure that shows the strategies for each of the artificial intelligence agents. From the paper: "Dynamic Difficulty Adjustment on MOBA Games" (Silva, Nascimento Silva and Chaimowicz, 2017).

In order for the adaptive AI to dynamically adjust its difficulty in real time during gameplay, the researchers designed a system that after a certain amount of time, the game would evaluate the performance of both players and determine who was the top performer. The game would calculate performance by using the following equation:

$$P(x_t) = H_l - H_d + T_d$$

Where $P(x_t)$ is the performance of player x on time t. H_l is the character (hero)'s in-game level, H_d is the death count of the player, and T_d is the amount of towers that are destroyed. After $P(x_t)$ was calculated, the game then measures the performance of the other player y using the same equation, and after that, it would work out the difference between them using the following equation:

$$\alpha = P(x) - P(y)$$

With $P(x)$ representing player x which is the adaptive AI whilst player y is the actual human player, α the difference among performances. The system then evaluated the α variable to see if it is under or over a specific threshold, if so then the difficulty was adjusted accordingly (reference to figure 2.1).

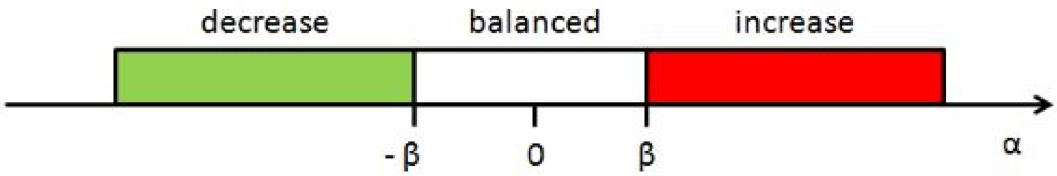

Figure 2.2: The diagram that displays the verification performed by the adjustment system. From the paper: "Dynamic Difficulty Adjustment on MOBA Games"(Silva, Nascimento Silva and Chaimowicz, 2017).

Figure 2 above represents the thresholds mentioned, with the β variable meaning how far a player can perform better or worse than the other, without considering the game unbalanced. If the value of β was a large number, then the adjustment occurred less frequently, since α may have taken some time to overcome β. Likewise, if β was a small number, then the adjustment occurred more frequently, since it may have overcome β more easily. If α stayed within the limits values of $-\beta$ and β, it meant that both players were having similar performance and therefore, the match was currently balanced. It is important to note that the adaptive AI always started with the difficulty being set to 'Regular' by default.

Data was obtained and analysed in a quantitative format, by participants answering a post-test questionnaire, which tackled various aspects related to how the game experience was perceived. For each question, participants noted their agreement or disagreement using ratings from 1 (lowest) to 5 (highest) with 3 being classified as "indifferent".

In order to obtain more accurate and objective results, only participants that have played the game Dota at least once were enrolled. This was done to avoid problems in understanding interface elements and/or the game's mechanics. A pre-test evaluation of the players took place which regarded their skill level, among the 11 participants, five rated themselves as beginners, four as intermediary players and two as experts. The players were split into 2 groups, 6 of them played against the AI controlled opponent, whilst the rest went against the static difficulty enemy.

When it came to the players feeling if they were more involved in the game world rather than the real world (immersion), 73% of players felt indifferent whilst 18% agreed and the remainder disagreed. However, it can be observed that an enjoyable experience was still provided because 91% stated that they did not want to quit the game at any moment and 73% would replay the game again in the future. For difficulty, the results show that 64% felt that the game wasn't challenging whilst the other 36% did find a challenge. When asked if a balanced environment was established, 27% agreed whilst 73% disagreed.

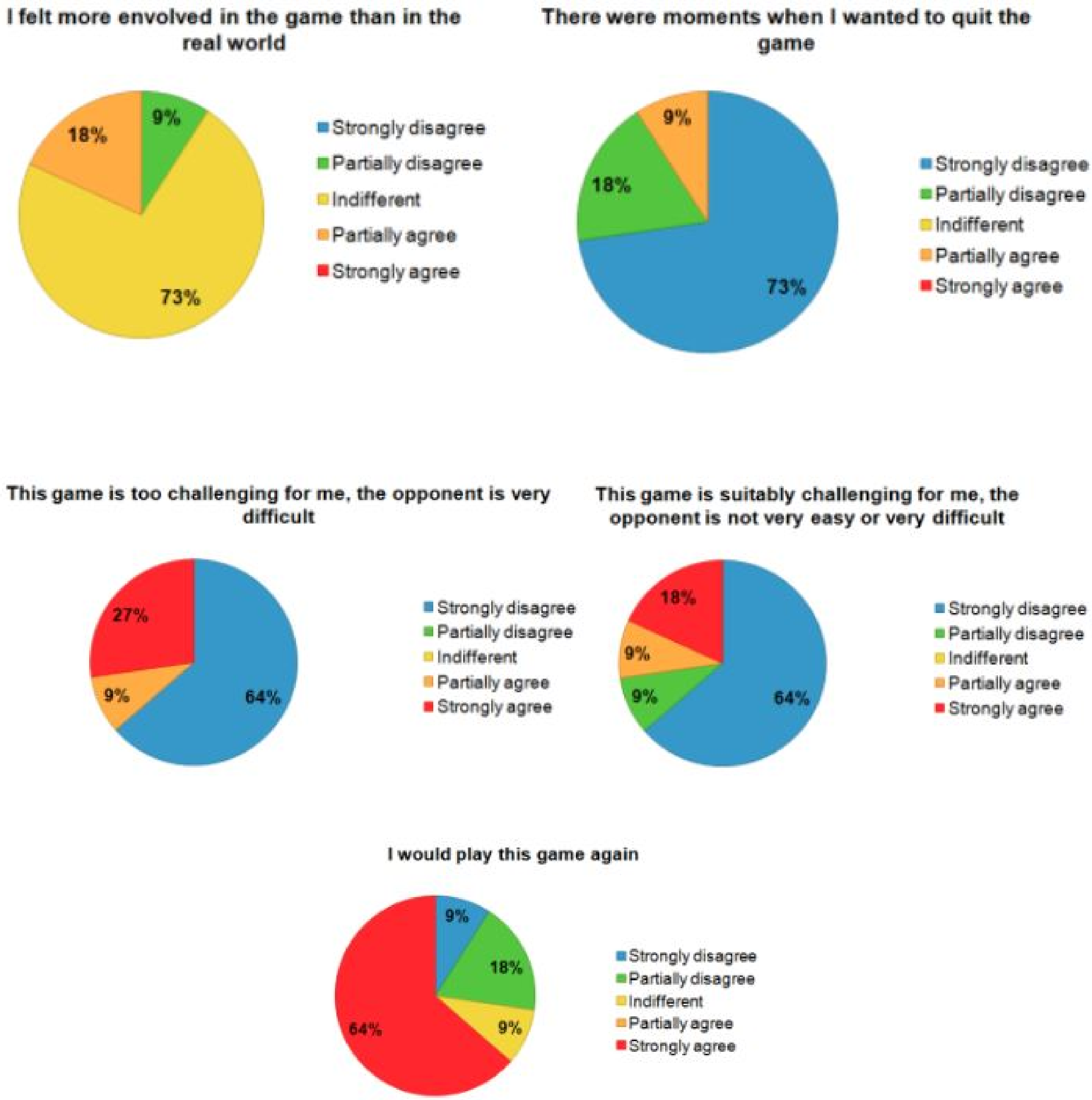

Figure 2.3: The charts that represent the answers given by the participants from the questionnaire. From the paper: "Dynamic Difficulty Adjustment on MOBA Games" (Silva, Nascimento Silva and Chaimowicz, 2017).

After the results were analysed, both of the expert volunteers were asked to play on both maps, to get an assessment of both AI characters. After comparing the experience they had on each map, the experts said that the opponent from map A (dynamic agent) presented a more fluid behaviour and they preferred to play against it. They also stated that both maps were not very challenging for them, and maybe it could be more suitable for players with little experience that are attempting to learn the game. The researchers believe that this occurred due to complex strategies hence, defeating higher-skilled players was not developed within the AI mechanism they used. It was also stated that for future work, the dynamic difficulty adjustment mechanism will be improved to include a wider range of diverse strategies, and to possibly implement a machine learning system where the AI would track the player's behaviour and use it to their advantage (Silva, Nascimento Silva and Chaimowicz, 2017).

2.2 Multiplayer

A different study conducted in 2014 by Baldwin, Johnson and Wyeth also aimed to investigate how the presence of DDA influences the player experience and performance, but from a multiplayer perspective rather than single player. The study also investigated how player awareness of the use of DDA affects the player experience and behaviour.

64 participants were split into a group of 2-4 players, who went against each other in a controlled offline local area network (LAN) environment, the reason for this is to mitigate any issues that can be created by latency that exists in an online network. The PC game selected for the experiment was Unreal Tournament III (UT3), due to its broad representation of the first-person shooter genre. Additionally, UT3 uses simplistic core gameplay mechanics common to all FPS games, minimizing the learning curve for participants to feel comfortable understanding and controlling the game.

The participants were required to score kills against each other in order to obtain the highest final score at the end of a 10 minute match. The DDA system worked by when a player's score fell more than 3 points below the leader's score, the algorithm assists the low performing player by providing an additional 50 shield points in addition to the standard 100 health points. This allowed the assisted player to take more damage before being defeated. To avoid any interference with this effect, health and shield pick-up items were removed from the game environment.

A total of three matches were done per group, the first without the algorithm, the second with the algorithm activated but without telling the players, and the third informing the players. However, the order of Match 1 and 2 was randomized between each group of participants to minimize the effect of practice on the player experience.

The results were obtained in a mixed methods approach, by quantitively measuring the mean scores and the electrodermal activity (EDA) of the participant's skin during matches, so the level of arousal could be recorded. The researchers state that high EDA values would be an indication of when the participant is being challenged, while lower EDA readings indicate a reduced challenge. The qualitative form of measurement was done by participants completing a subjective survey after each match.

The results for player performance after the experiment showed that the highest average score (9.8) was achieved in the match where there was no DDA, the lowest average score (6.3) on the other hand was in the match where the participants weren't aware of the DDA. Meanwhile, the final match which had the DDA and also informed the players of the system had an average score of 7.8.

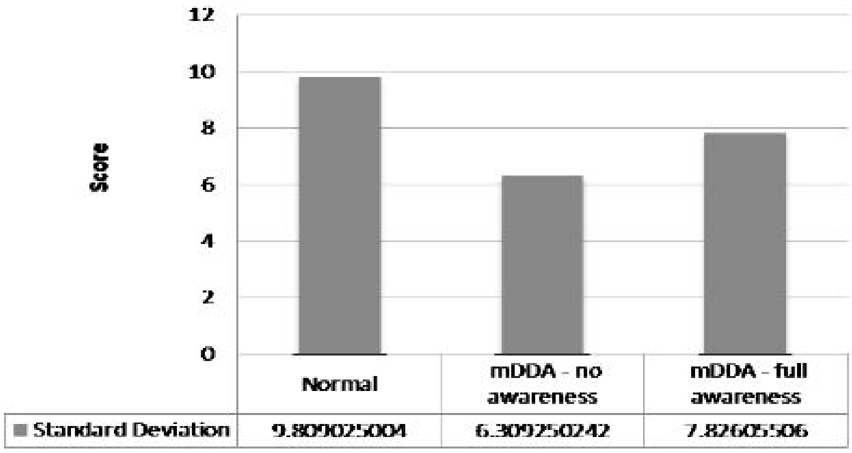

Figure 2.4: The in-game player score across 3 matches. From the paper: "The Effect of Multiplayer Dynamic Difficulty Adjustment on the Player Experience of Video Games" (Baldwin, Johnson and Wyeth, 2014).

In the biometric readings, it was seen that assisted players in the second match had the lowest readings in EDA, the researchers suggested it could be because of the reduced challenge due to assisted performance. Contrarily, high EDA values were recorded for unassisted players in match 2, with the reason being that a higher challenge was dynamically created by having opponents with an in-game statistical advantage. This was supported by the reduced difference in performance indicated by the match results.

For the final match, both assisted and unassisted participants had the highest recorded EDA values of all 3 matches. These much higher readings indicated that players were much more aroused than previous matches, with the researchers stating that it might be related to having an increased challenge to adapt to the presence of DDA as a new game mechanic during gameplay. However, the awareness of DDA had a much greater impact on assisted players than unassisted players. The researchers also stated that this might have been related to DDA providing an indication of low performance due to the knowledge of receiving assistance.

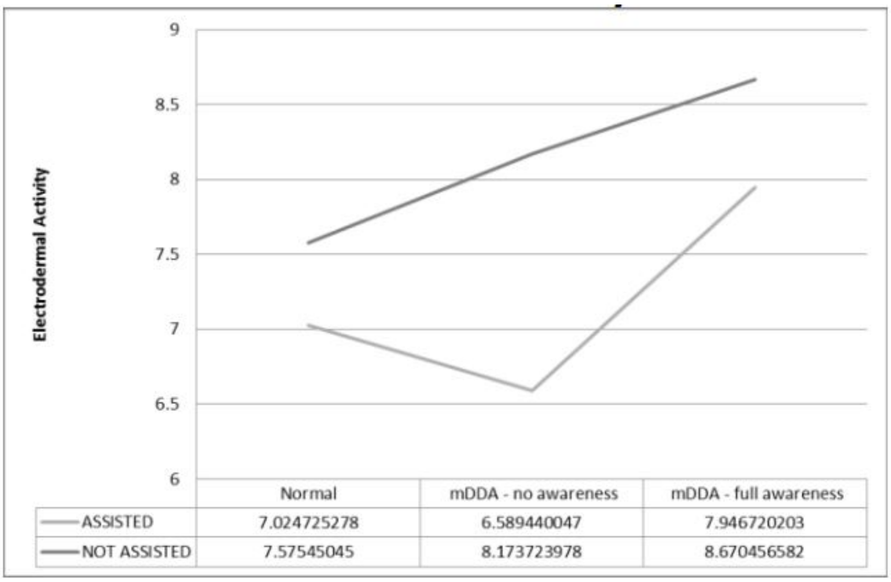

Figure 2.5: The Electrodermal activity values across the 3 matches, divided by low-performing (assisted) and high-performing (unassisted) participants. From the paper ”The Effect of Multiplayer Dynamic Difficulty Adjustment on the Player Experience of Video Games” (Baldwin, Johnson and Wyeth, 2014).

In the discussion and conclusion, it was stated that the presence of DDA did successfully improve the performance of assisted players, by reducing the difference in performance between all players in the match which provided a more even playing field. This was supported by the EDA readings which indicated reduced challenge for assisted players and increased challenge for unassisted players.

However, when the participants were made aware of the DDA in the 3rd match, the effects of the algorithms were reduced, the researchers suspected that this was because unassisted players might have exploited the DDA system, to adapt their tactics and behaviour to compensate for their disadvantage, for example avoiding head-to-head battles due to the knowledge that opposing players may have been assisted with shield points. The survey results also showed some of the assisted players wrote that receiving assistance is an indicator of low performance, in comparison to opponents may increase frustration and anxiety. The researchers also had a similar conclusion to the previous study, where it was stated that whilst DDA can be beneficial in an online environment, further study in determining the optimal implementation of DDA to competitive multiplayer video games is required (Baldwin, Johnson and Wyeth, 2014).

2.3 Player Oriented DDA

A study conducted in 2017 by Ang and Mitchell examined how the presence of DDA affects the player experience compared to the non-presence of DDA. An experiment was done which saw 30 participants play through 3 variations of Tetris, the first with no DDA, the second with system-oriented DDA (rDDA), and the last with player-oriented DDA (pDDA). The focus was to see how a traditional DDA system compared to player-oriented DDA in terms of player experience, and to how it would also compare without the presence of DDA. In contrast to the previous research mentioned, this one allowed the players themselves to alternate the difficulty level in real-time during gameplay.

In the no DDA section, the drop rate of the Tetris tiles remained constant throughout the game session. In the rDDA condition, the drop rate increased by one difficulty level for every 10 lines cleared. In the pDDA section, the drop rate was decreased or increased by one difficulty level each time the player tapped on the Z or X button respectively on the keyboard. Each difficulty aspect controlled the falling rate of the Tetris Blocks, with each section starting with a base drop rate but every time the difficulty increased the drop interval time was reduced by 30%.

The player experience was measured only quantitively by having participants answer a questionnaire after each section, with each question utilizing the Likert scale (1=Strongly Disagree to 5=Strongly Agree). The questions consisted of participants being asked to rate their experience in terms of challenge-skill balance, concentration, immersion, the passage of time, and so on and so forth. After the experiment, the results showed that both implementations of the DDA improved the players' game experience when compared to the implementation without DDA. The questionnaire data supports this by doing direct comparisons of the segments with and without DDA, which showed that the conditions with DDA made players encounter higher levels of enjoyment, self control, concentration on task at hand, clearer goals, action-awareness merging and loss of self-consciousness and time. This confirmed the first hypothesis, which stated the aforementioned.

However, the study did find an important drawback in the system-oriented DDA implementation, players stated that their sense of control felt diminished when compared to both other segments of the test. This might have possibly resulted in negatively impacting the user experience, which could have been amplified to the point where it degraded the overall experience. Another drawback that the questionnaire showed, was that players encountered high levels of self-consciousness and awareness of time during the player-oriented DDA test. The researchers stated that this was because the participants were consciously self-evaluating their performance during the test, stating that this is a source of concern since the immersion, and concentration factors of the questionnaire were directly affected negatively because of this.

One of the limitations of this study when comparing it to the other sections of this literature review is that the system-oriented DDA used is a ramping form of dynamic difficulty, rather than the more commonly used adaptive form. The main difference being that ramping DDA allows for the game difficulty to automatically rise depending on player performance, while adaptive DDA allows for the difficulty to automatically either rise or fall depending on player performance. If an additional segment was added to the test in where an adaptive form of the system-oriented DDA was used, it might have been possible that the results would have been more varied, which might have seen the adaptive DDA to be favoured by the players instead (Ang and Mitchell, 2017).

2.4 Increasing Replay Ability using DDA

Research conducted in 2020 in China saw researchers investigate how a DDA integrated system can extend the life of hyper casual endless smartphone games. The writers of the research claimed that a matter in question existed where endless game, characteristically have very short play sessions and minimalistic design. Which in turn, causes players who play these games to stop completely once their skills have reached a certain level, or when they cannot improve their skills enough to reach the required goal.

To combat this issue, a hypothesis was first written, this consisted of trying to prove how a dynamic difficulty adjustment system allows the player to continue to play longer, which ultimately extends the life of a game. And how a DDA System lessens the player's experience with frustration after failing.

To achieve this, an experiment was organized which saw seven participants go through two different versions of a prototype, one which used a dynamic difficulty adjustment system, the other used a more traditional approach which was a quick progressive difficulty system (QPD). A similar approach can be noted in the dissertation mentioned in previous section, with QPD being similar to the sDDA system used for the research of Ang and Mitchell in 2017 (Ang and Mitchell, 2017). Both of these systems sharing the concept of difficulty getting progressively higher as time passes, until a limit is reached and the difficulty scaling stops.

The prototype was a 2D game where the player controls a moving character and, within a level, has to traverse through moving obstacles to achieve the objective, which was to arrive at a set destination. In the game, the player had five lives, and the game ended when the player lost all of their lives.

The QPD was designed in a similar way to how difficulty works in an endless video game such as Temple Run, by continuing to increase the value of elements until the maximum value is reached. In the game, the difficulty level for each element was controlled by the player's score. If the player scored 5 points without losing health in that time, then that player moved to the next level. In total there were five different levels of difficulty, the level of difficulty could only be increased with the only way to return to an easier level, was if the player lost all his lives which led to the "Game Over" screen. When the level of difficulty was increased, the game modified elements such as obstacle size and movement speed by increasing them to provide a greater challenge.

The DDA system on the other hand, when compared to the QPD, also increased the difficulty but it could also lower it, which the QPD wasn't able to carry out. If the player faced trouble with a given level, then the difficulty was reduced. This was done by checking if the player lost health during a level, if so then the system would determine that the previous difficulty was more appropriate, hence returning to it.

This research took a mixed methods analysis approach to tackle the hypothesis, the data collected consisted of the game's final score of the player, their numerically rated answers from the surveys, and given answers from a final interview. The participants were separated into two groups which can be seen in Figure 6. Both played two different versions of the game, which were the version with DDA and QPD. During the test, none of the participants knew that they were playing two different games.

Figure 2.6: The progression process of the experiment, from the paper ”Hyper-Casual Endless Game Based Dynamic Difficulty Adjustment System For Players Replay Ability” (Yang and Sun, 2020).

For the query regarding frustration in the hypothesis, the survey consisted of a question that asked the participants what their frustration level was during the level. This was answered using a Likert scale from 1 (least) to 5 (most).

The results which can be seen in Figure 2.7, were split between participants who identified themselves as either experienced/hardcore, or casual gamers. This was done so a more in-depth analysis could be performed that saw how participants with different skill levels performed, and to also see how their results differentiated.

After the experiment, the results showed that experienced participants that played the DDA version always scored more points than those who started with the QPD version. With the former learning faster and identifying strategies earlier. When it came to frustration and enjoyment evaluation for experienced participants, regardless of which version that was started with, both aforementioned values increased steadily. However, the experienced participants who began with the QPD version then moved to the DDA, even though their scores were better, some of their evaluation values were lower due to both frustration and enjoyment, even though they didn't know at the time that they played two different versions. Players who started with the DDA version on the other hand weren't affected, after moving to the QPD version, their evaluations still increased. After the participants were informed that there were two versions, most said that they preferred the QPD version over the DDA, stating that they believed it to include more challenges and to be more interesting than the DDA version.

The results for participants who identified themselves as being on a casual skill level, show that those that started with the QPD level enjoyed the DDA level less. This can be seen by observing that positive evaluations were made until they played the DDA version, which shows that the frustration values increased. However, for the casual participants who began with the DDA version, their enjoyment was not reduced after they played the QPD version, but their frustration values were higher than those for the DDA version. They stated that they believed they played only one version, and they thought that their scores decreased due to their abilities. After being informed that there were two versions, most casual participants reported that they preferred the DDA version because they could obtain more points. They felt that the ability to obtain more points made the DDA version more fun than the QPD version.

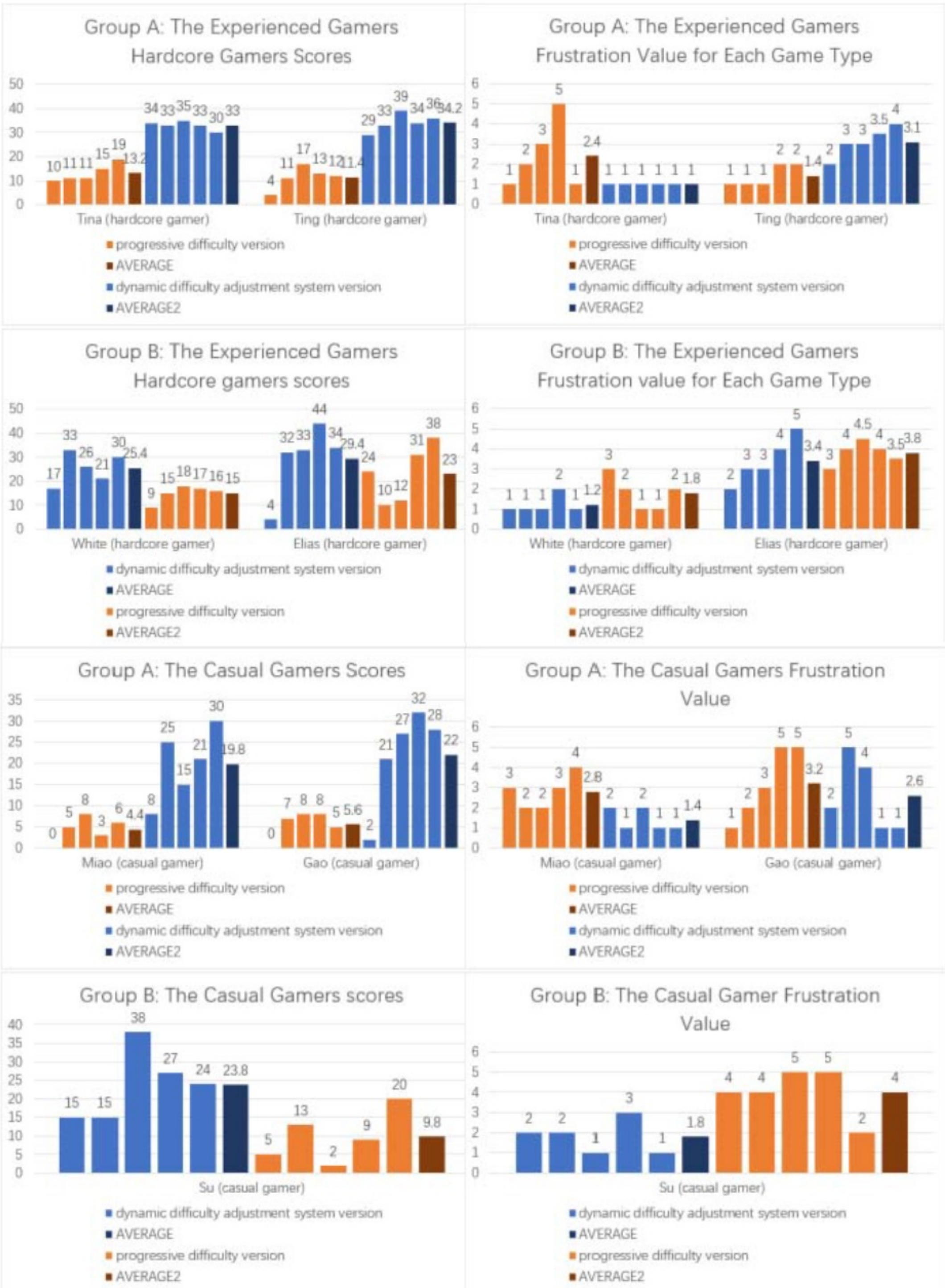

Figure 2.7: The experiment results obtained, from the paper "Hyper-Casual Endless Game Based Dynamic Difficulty Adjustment System For Players Replay Ability" (Yang and Sun, 2020).

The researchers stated in the conclusion of their dissertation that the DDA version would be more suitable as a tutorial mode, because it would allow the player to learn faster. The reason for this is that experienced players would prefer to face challenges directly rather than having to warm up since it can be considered as a waste of time. Furthermore, regarding the hypothesis, it was stated that a DDA system used in a gaming environment can extend the life of the game since it can allow a player to engage with it for longer periods of time. This is because the DDA system increased the survivability of the participants during the levels, which also reduced the frustration of the players after they failed as can be seen in the questionnaire results, hence answering the 2nd hypothesis.

However, the writers wrote at the end, that the DDA system wasn't perfect and can be improved. It was suggested that by including more adjustment methods, both the types of participants that had either an experienced or casual skill level, could have been better individually served (Yang and Sun, 2020).

Chapter 3

Research Methodology

The main objective of the methodology, was to create a process that observed and collected data from participants , which was then analysed, so a definite answer was made, which determined if Dynamic Difficulty Adjustment in games can have a positive impact for the end user when applied correctly. The main approach to accomplish all the goals, was to create a system that would determine in real time, the difficulty level in a gaming environment, where players can have unique, enjoyable and immersive experiences. Their player performance data statistics would then be collected, categorised depending on the type of level, and then analysed and compared to construct a conclusion to the research questions.

A similar approach by Ang and Mitchell in 2017, as well as Yang and Sun in 2020 was done in their research's methodology, however instead of having the participants play the regular and DDA levels sequentially, it was decided to split the experiment of this research into 2 separate phases (Ang and Mitchell, 2017) (Yang and Sun, 2020).

The first phase was in a regular gaming environment where participants would take part in without a DDA system being present. Their statistics would then be gathered which included their performance, answers from the questionnaire and average heartrate. After this, the development of the DDA system started and upon completion, the same process was ensued in a 2nd phase which utilised the aforementioned system.

The procedure, techniques, and practices that were used in this methodology were inspired by the methods used in the research referenced in the literature review. However, these methods were n unique to this dissertation to accommodate the circumstances presented in the hypothesis.

3.1 Difficulty Balance and Evaluation

In order to achieve an answer from the hypothesis, a Dynamic Difficulty Adjustment system was designed and developed to suite a gaming environment. The first step in doing so, was to first construct mathematical formulas, that would fit a scenario in where a player's performance would be calculated and rated, in which then it would be compared to the previous performance rating. Each calculation would occur after a specific amount of time. The difference would be worked out between the current performance rating and the previous. If a certain threshold was met, the difficulty would be lowered or increased accordingly.

This was a similar approach to how Paula Silva, Nascimento Silva, and Chaimowicz used in their methodology, but instead of doing formulaic comparisons between the player and enemy, the system would do the differentiations using only the player's statistics. The reason for this decision was because the Unity 3D game utilized for this evaluation used multiple enemies rather than 1, so it was found to be more appropriate for the system to focus solely on the player's performance (Silva, Nascimento Silva and Chaimowicz, 2017).

In order to obtain the desired results the DDA system requires for evaluation and adjustment, it was necessary to determine which variables needed to be analysed and how that information was to be used. It was required to choose the most important and logically justifiable data so the best possible outcomes could be achieved. This was done by noting what the referenced previous work did, by seeing the variables they used, and how a similar but effective approach could be done for this dissertation. The analysed data and the evaluation process are described below:

Enemy Removals: This feature was the number of enemies that were removed (or can be referred to as killed/eliminated) by the player, it gave a good notion of the player's performance and whether there was progress. Therefore, if the player was progressing quickly during the game, it represented that balancing needed to occur. This feature was split into 2 categories for the testbed, enemy grunt(normal) kills and elite enemy kills. The difference between these variables is that elite enemy kills were incremented when the player eliminated the stronger enemy type, which had more HP and Attack Damage. The reason why this was done was to expand the approach that the researchers Paula Silva, Nascimento Silva, and Chaimowicz did in their methodology, by instead of having 1 enemy type (in their study this was the 'Tower'), a 2nd but tougher opponent type was added to further analyse if the participant was finding the game too easy, and if so then it would be clearer that an adjustment would be needed (Silva, Nascimento Silva and Chaimowicz, 2017).

Player Deaths: This feature was responsible for displaying the amount of times the player had died during that specific time frame in the match. The amount of deaths was one of the most important features to be measured, since it represented how the player was finding the game's challenges, because a high death count meant that the player was struggling so the difficulty should be lowered.

Time: This variable was chosen because in order to perform dynamic difficulty adjustment, the game's evaluation needed to be done from a time to time verification standpoint, so it could be confirmed if the game was presenting challenges suitable to the player's performance. This worked by attaining the latest performance evaluation (P.E.), and from there on the last P.E. from previous time frame got acquired in which from there they were compared by calculating the difference between them.

DDA Functionality

The approach to the development of the dynamic difficulty system focuses on how a player's current performance compares to their previous. This was done by utilising the in-game variables mentioned previously, firstly by constructing mathematical formulas that would determine how the overall performance is calculated. This was applied by the following formulae:

$$P(\alpha) = P(x) - P(y)$$

With P representing performance, and x and y both time frame variables which are current and previous respectively, and α is the overall performance. Time frames were separated by 15 second intervals, with the latest interval being the current performance and the one before being the previous. After that, the formulae for how the performance P of the player is defined was written:

$$P = G + E + S + D$$

With all of the variables apart from P being representations of points earned by the player. G and E are both points earned by eliminating grunt and elite enemies respectively, S means Score Point, and D represents Death Point.

The method in how the two formulas were written is similar to how the Paula Silva, Nascimento Silva, and Chaimowicz wrote their formulas in their 2017 research, by comparing and finding the difference between the current and past performance (Silva, Nascimento Silva and Chaimowicz, 2017). The difference here being that the overall performance of the player is being calculated rather than the performance difference between the player and the AI. The reason why this was done was mentioned already, but to recapitulate the Unity 3D game utilized for this evaluation used multiple enemies rather than 1, so it was found to be more appropriate for the system to focus solely on the player's performance.

Also, the method in how the performance was calculated has been expanded, by including more variables that factor in to how the player is doing. One of these variables are enemy removals, which are split into 2 categories, grunt and elite kills, the other research only used 1 elimination type. The reason for this change was mentioned previously as well, which is because the inclusion of a 2nd and tougher enemy type would make it clearer if the participant was finding the game too easy. So overall, 4 variables are used to calculate performance rather than 3.

This paper also briefly mentioned utilising a point scoring system for each variable used in the performance formula, which in terms of functionality will be explained in the next section. This approach differentiates from what the researchers mentioned did, since they worked out the skill of the player by including the core variable values in their calculations. This was done to enhance the approach the other researchers used, by creating a more advanced and in-depth process that would hopefully determine the performance of the player more efficiently.

Points System

Points were obtained by doing a compare and contrast analysis between the data acquired from the current time frame and the one before it. For example, if more grunt eliminations occurred now than before, then +1 point to Current Performance, however if fewer points were acquired now then –1 point. If the Overall Performance was found to be 1 or greater after the analysis, then the evaluation determined that the difficulty should be increased, else if it was –1 or less, then the difficulty was lowered. The following flow charts demonstrate how the system works.

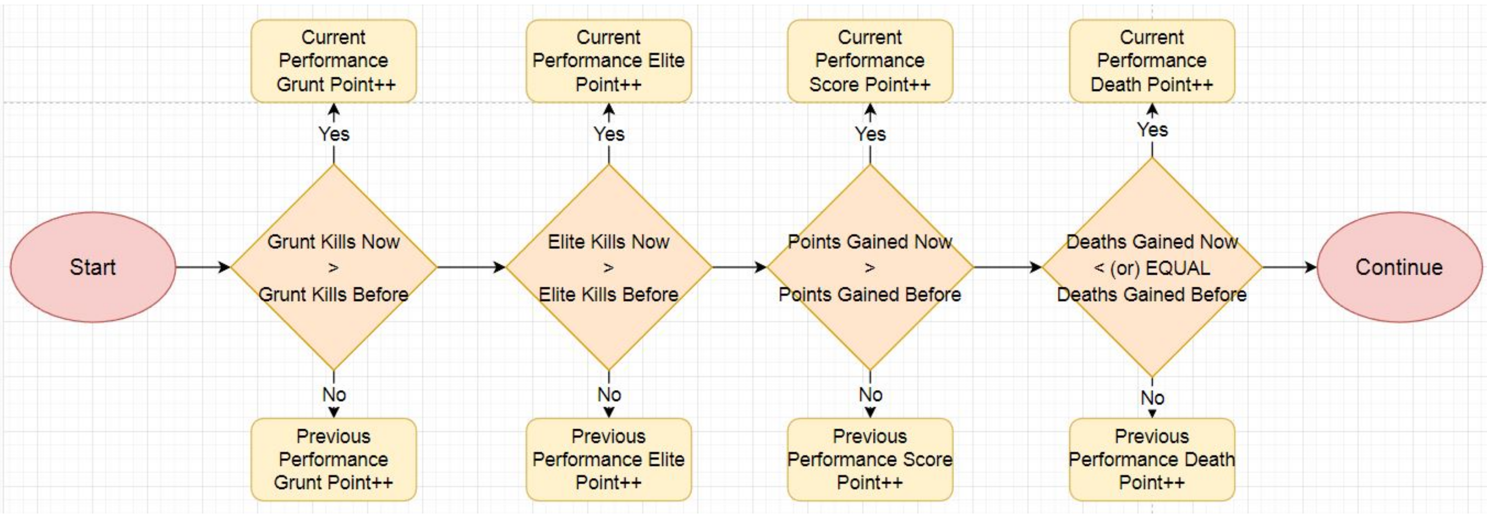

Figure 3.1: A figure that shows how points are handled in the DDA system, this illustration is the first part of the process.

This process was called every 15 seconds, the first part of the operation did the comparison of the acquired variable values of the current and previous time frame. It gave a point to either side depending on the criteria, it would then go to the next decision symbol after the yes or no. After the first part of the process was done, it continued with the next part which calculated the overall performance by finding the difference between the current and previous performance. After the calculation, the system increased or lowered the difficulty depending on the value of the overall performance.

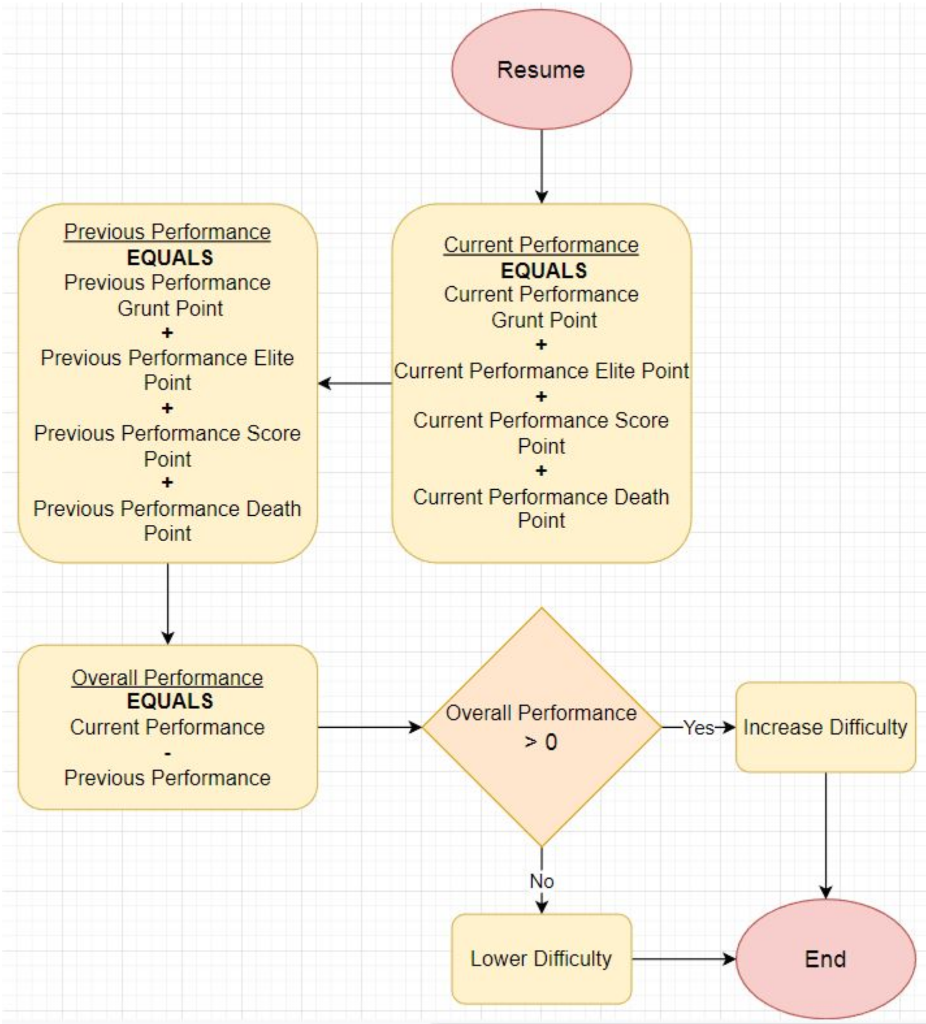

Figure 3.2: This figure demonstrates the second part of the process, which calculates the difference of the current and previous performance. From there, it will determine to either lower or increase the difficulty.

Note: The system could not increase or decrease the difficulty more than a specific point because a limitation was set. This will be discussed in detail later on.

After the performance and difficulty evaluation was done, the statistics of the current performance got transferred to the variables that represented the previous performance. This part of the process was referred to as the Reset, since the current performance statistics were all set to 0.

The Procedure

The DDA system functioned by conducting an evaluation every 15 seconds as mentioned above, this as always done except for the very first time frame, since there was no previous data to compare to. So instead, for the first time frame the DDA system only transferred the statistics of the current performance to the variables of the previous performance, and set the current statistics to 0. This was the same method that was mentioned in the previous section's paragraph.

The flowchart below shows how the game handles this policy, by checking if the first time frame has been passed, if not then the reset method is called. After this, the DDA commences with the performance comparisons.

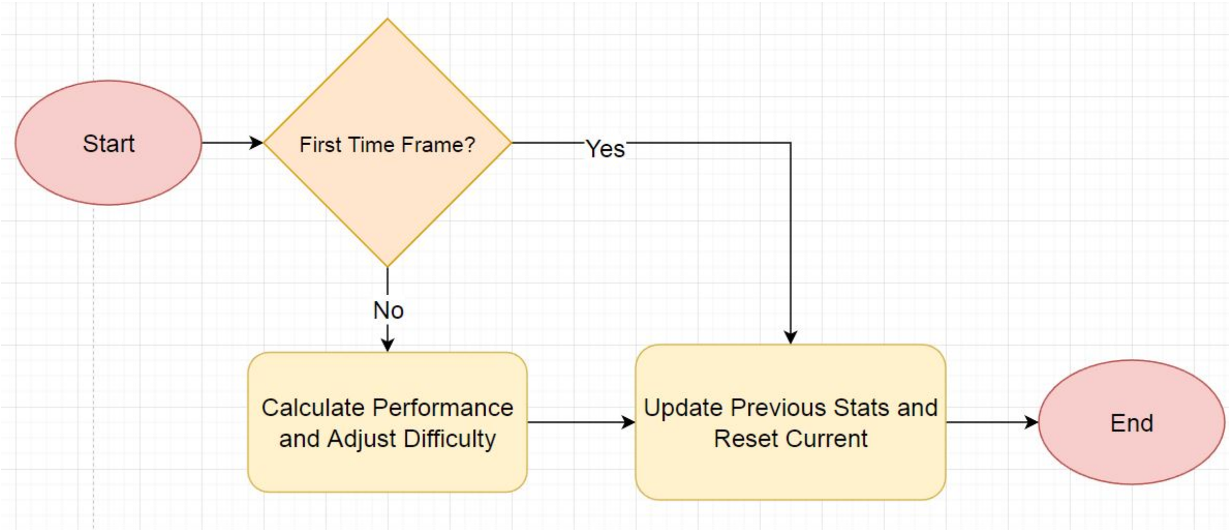

Figure 3.3: This diagram shows how the DDA system handles the first time frame during the level.

Difficulty Range

In the game, there was a set of 5 different levels of difficulty that the player could experience, which ranged from Very Easy to Very Hard. The game used a numerical format to identify the difficulty levels, this ranged from –2 which was the easiest, to 2 which was the most challenging, and it always started in the standard difficulty mode which was 0. It is important to note however, that the difficulty could not go higher or lower than the aforementioned range because a limitation was set, if for example a player was in difficulty level 2 and performed very well, the game could not increase the difficulty further on from there, and vice versa if the difficulty level was –2. Each difficulty level affected some of the variables in the game of either the Player, Grunt, or Elite Enemy, these included Health Points, Speed, Damage, and Spawn Rate.

Overall, this was similar to how Paula Silva, Nascimento Silva, and Chaimowicz did in their research by having a set of defined difficulty modes ranging from Easy to Hard, and each of them would change how the AI functioned by increasing or decreasing the number of actions it could do (Silva, Nascimento Silva and Chaimowicz, 2017). The difference here was that more difficulty modes were added from 3 to 5, and that instead of adjusting the AI the game would adjust the aforementioned variables. The following chart demonstrates the changes done by each difficulty level:

	Grunt Enemy	**Elite Enemy**	**Player**
2	+30% HP +10% Speed +50% Attack Dmg +10% Spawn Rate	+10% Speed +10% Spawn Rate	/
1	+10% HP +5% Speed +25% Attack Dmg	+5% Speed	/
0	Default Values	Default Values	Default Values
-1	-20% HP -10% Speed -30% Attack Dmg -15% Spawn Rate	-10% HP -10% Speed -15% Spawn Rate	/
-2	/	Unable To Spawn	+20% Speed

Table 3.1: This table shows the difficulty stages that can occur throughout the level. -2 is the easiest whilst +2 is the most challenging.

It is important to note that all of the variable changes were based on the original value of the variable, and not an addition to what the value currently was. For example, if an increase from difficulty level 1 to 2 occurred, the health addition for an enemy was 130HP, which was 30% based on the initial value of the enemy HP which was 100, and not 110HP which was what the value was previously in difficulty level 1.

Exceptions

Due to the increasing HP of the regular enemies in the higher difficulty levels, it was noticed during development that the player might naturally obtain fewer kills, especially during Difficulty Level 2. This would result in obtaining a lower performance than the previous time frame, even though no deaths might occur and the player might not even be struggling. To resolve this issue, it was decided that if the player manages to reach the second difficulty level, the only way to go back down would be for the player to lose a life, and if 15 seconds pass with no deaths occurring, then the performance evaluation would be skipped. The reason why this was implemented is that it is logical that a player might obtain fewer kills since the enemies have higher HP in the final difficulty level, so for the challenge to be continually appropriate for the user, it is ideal to only scale back the difficulty when a death occurs.

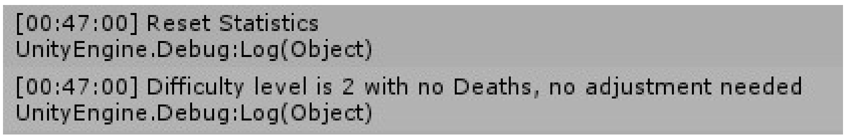

Figure 3.4: This shows how the DDA system handles one of the exceptions placed.

This was similar to how Yang and Sun in 2020 applied their DDA system for their research, in their case when a player lost all their HP, the DDA system would return the game to the previous difficulty. The difference in this research being that this design is only implemented on the hardest difficulty (Yang and Sun, 2020).

Another exception to note was that death point variable which was part of the Performance formula, functions slightly different when compared to the other point variables.

In this case, it was determined that if the player hasn't died during the time frame or has the same amount of deaths as the previous, then a point would be given, the reason for this being that if a player isn't losing lives constantly, then it was an indication that they were not struggling with the difficulty, similar to the approach of difficulty level 2.

Flowchart

Overall, everything that has been explained in this section can be visually illustrated by the following flowchart, which demonstrates how the entire process of the DDA system functions.

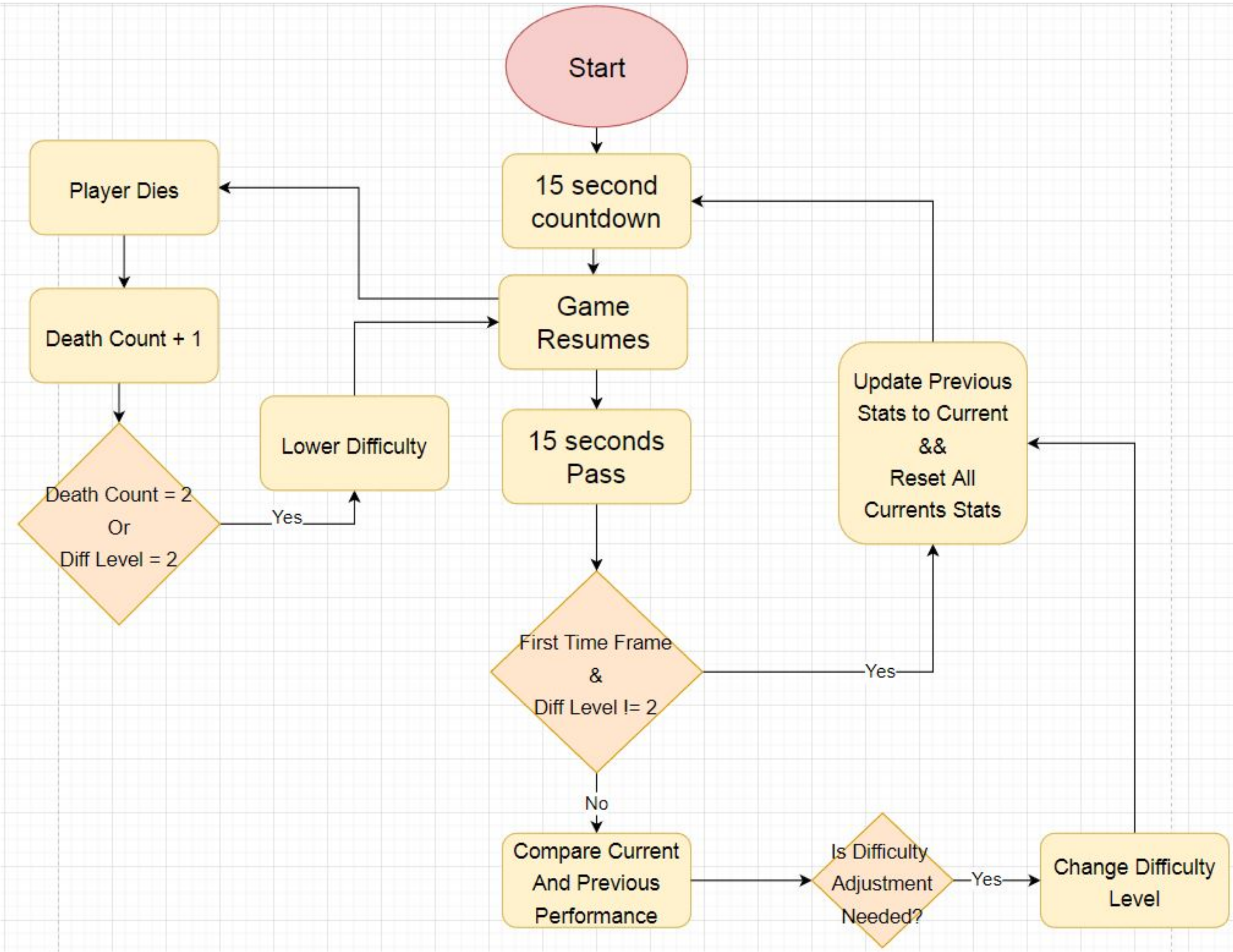

Figure 3.5: This flowchart illustrates how the entire DDA system operates.

Note: The "Is Difficulty Adjustment Needed?" Decision Symbol connects with the "15 second countdown" symbol if the answer is no. Another hidden connection is with the Decision Symbol "Death Count = 2 Or Diff Level = 2" and "Game Resumes" Symbol if the answer is no. These were not shown in the chart for the sake of neatness.

3.2 Forms of Measurement

A mixed methods approach was conducted in order to achieve the proper form of empirical data required, that would suffice the inquires presented by the hypotheses. This data consisted of both quantitative and qualitative statistics, with the former being obtained using player gameplay statistics, a questionnaire, and biometric data, and the latter was obtained using open questions presented by the questionnaire.

This method of collecting data was similar to how Baldwin, Johnson and Wyeth did in their research, by using a mixed approach utilizing surveys, and biometrically by calculating electrodermal activity of the participant's skin during matches (Baldwin, Johnson and Wyeth, 2014). However, this dissertation instead employs the use of a heart rate monitor to measure the level of engagement, awareness, and noticeability of difficulty changes for the player.

The way this was done was that during the experiment, the participant would wear the Xiaomi Mi Band which is what was used to measure the heart rate, and right before the level began the HR reading was activated for that period of time. After the level was completed, the average and maximum HR of the participant during that time frame was read and noted.

This research also captured the performance statistics of each individual player, these included: total number of kills which were divided between normal and super enemy kills, deaths, and total score. The method in which these were collected was by having all the variables being read and exported to a text file once the level was complete.

The questionnaire was created using Google Forms featured 2 sections, the first contained questions asking about the participant's own skill level in regards to 3D shooting games. This was done so that whilst comparing performance results, only individuals who are on the same or similar skill level could be compared, and not everybody at once, so an imbalance of unfair comparisons could be avoided.

The other section contained 5 questions asking about the participant's overall personal experience, these were:

1. Rate how immersed you felt
2. Rate the overall difficulty of the level, from too easy to too hard
3. Was this difficulty appropriate for your skill?
4. Rate the likelihood of playing this game again
5. Do you have any suggestions for improvements for the game?

The first 4 questions were answered using a Likert Scale rating system, were participants answered using a range from 1 to 5, with 1 representing the least value and 5 representing the most value. A neutral answering possibility was omitted in order to provoke a positive or negative tendency. The last question was the only one to require an answer that needed to be typed out manually.

2nd Phase Questions

The questionnaire for the 2nd phase was updated for the 2nd phase of the experiment, this was done to accommodate answering the second and third questions of the hypothesis. The update included 3 new questions in the segment the player answered after playing the game. These consisted of asking if any changes in the difficulty were noticed, if the game adapted suitably to their skill level, and if the adjustment affected their experience. The last question mentioned being the only one with a qualitative answer, and the second one requiring a Likert scale rating from 1 to 5.

3.3 The Experiment

Once it was defined which of the game's variables needed to be analysed, the creation of a mathematical equation was required to be constructed based on these variables. The purpose of this was to utilize this equation for the logic and procedure of a DDA system that is needed for the experiment, so the questions of the hypothesis could be answered.

3.3.1 Phase 1 (No DDA)

This was the phase that participants first took part in, this section did not utilise a DDA system with the selected game. The procedure of the experiment was that the players sat down and first answered questions regarding their overall skill level of 3D shooters. This was done to differentiate the performance data of Beginner, Experienced, and Expert players. After answering the first section of the questionnaire, the participants went through a tutorial level for at least 5 minutes, this was so they could get used to the feel, controls, and mechanics of the game. After this, the proper level ensued and the heart rate monitor was activated, once the level was completed the performance data was gathered along with the average and maximum heart rate. The final questions of the questionnaire were then answered and the experiment was completed, these questions asked the player to rate their experience, immersion, the overall difficulty and if it was appropriate for their skill level, and what could have been improved.

The game in this phase functioned by starting the player off with facing a small amount of enemies at first, with more spawning gradually as the game progressed throughout the 3-minute timer, however since no DDA was present, the player and the enemies did not have their variables affected whatsoever. This was to some degree similar to what Ang and Mitchell did in their paper, by having a system oriented DDA system that increased the difficulty over time, in which they increased the drop rate for every 10 lines cleared (Ang and Mitchell, 2017).

3.3.2 Phase 2 (DDA)

This phase was done at a later stage, after the first one was completed, the results were analysed, and the DDA system was developed and tested properly. The procedure for this section was nearly identical to the previous, with the participants going through the same pattern but instead the DDA system was utilised for the selected game, and the questionnaire contained some additional questions to how the dynamic difficulty affected their experience.

3.4 The Resources Utilised

3D Shooter

The selected game is a 3D Isometric Zombie Shooter made using Unity called 'Zombie Forest' and it was developed by Tuure Kettunen. The objective of the game is to survive against an endless amount of spawning enemies for 3 minutes. Zombie Shooter features 2 types of enemies:

1. **Regular (Grunt) -** Granted 100 points when killed, normal speed. Spawning rate was one per 1 second.
2. **Larger Variant (Elite) -** Granted 1000 points when killed, slowest enemy but has the most health, uses the same animations as the regular enemy but has a bigger model, does the most damage. Spawning rate was one per 10 seconds.

The mechanics of the game were straightforward, the player could move around freely whilst firing an unlimited amount of bullets from an automatic weapon, and being able to throw a limited supply of grenades that dealt a high area of effect damage. Grenade drops randomly spawned throughout the map and could have been picked up to be used later. When the player died, he respawned at the centre of the map and was invulnerable and ignored by the enemies for 2 seconds. The was to prevent a chain reaction of the player continuously dying exactly when respawning.

One thing to note is that the game originally featured an enemy variant that would charge at the player rapidly and dealt a considerable amount of damage, however this opponent was removed during the development stage of the methodology, it was found that this enemy was difficult to balance properly and if left in game would have most likely caused the player frustration.

Chapter 4

Results

A mixed method approach was done in this study to gather all the data from the participants. The results for each phase are split into 3 parts, the first and second part are from the questionnaire with Part 1 asking participants general questions about their own experience and skill level, Part 2 which was done after the level was completed asked about the participant's overall personal experience, and Part 3 contains the in-game statistics and heart rate.

The difference between the 1st and 2nd phase is that the 2nd phase contained additional questions about dynamic difficulty since the level implemented the DDA system.

4.1 Phase 1

The following are the statistics obtained from the first phase of the experiment, each of the 15 participants' data has been analysed and compared by both skill level, and overall results.

4.1.1 General Data (Part 1)

This section covers the questions from the segment of the questionnaire, such as Gender, Age group, and overall skill level.

Gender

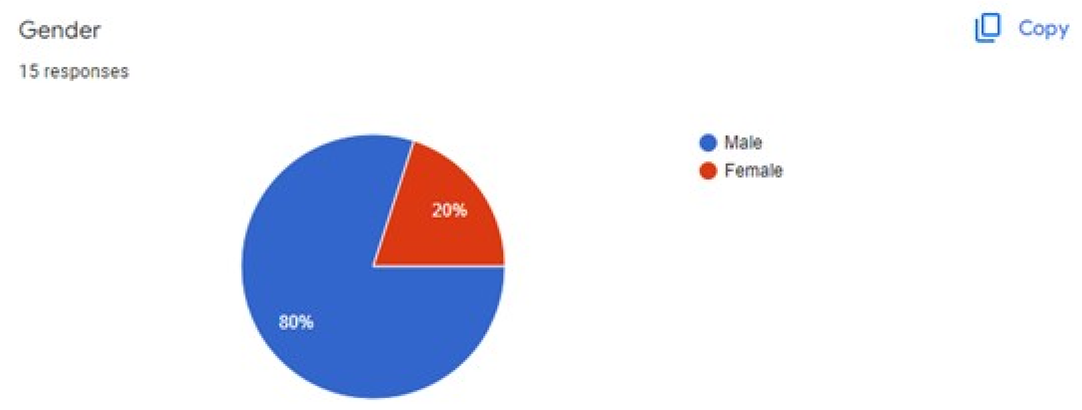

Figure 4.1: Phase 1: Gender

Age Group

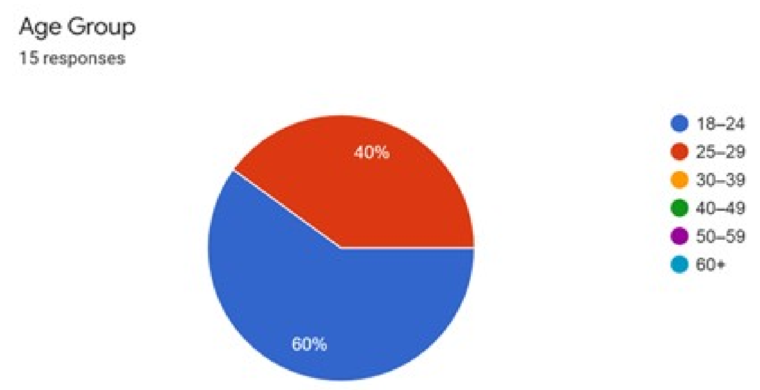

Figure 4.2: Phase 1: Age Group

Past Experience

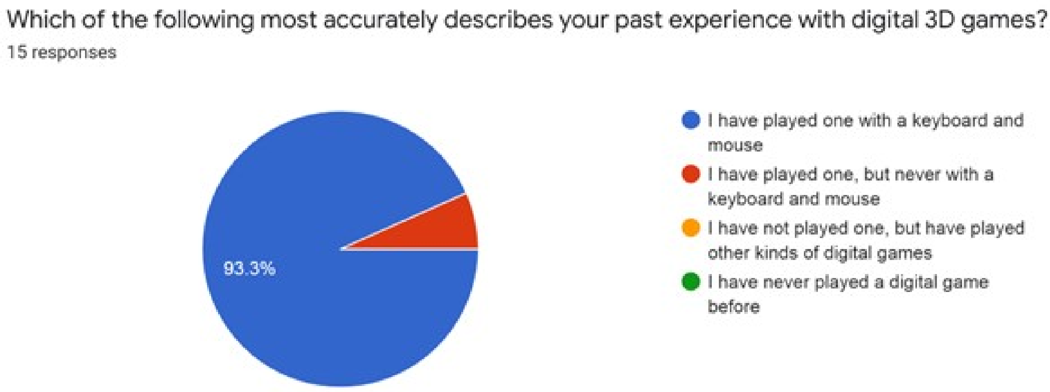

Figure 4.3: Phase 1: Past Experience

Skill Level

The most important part to note in this section would be skill level. Since it is one of the most useful data when evaluating difficulty analysis. From the 15 participants, 4 were beginners, 7 experienced and 4 experts.

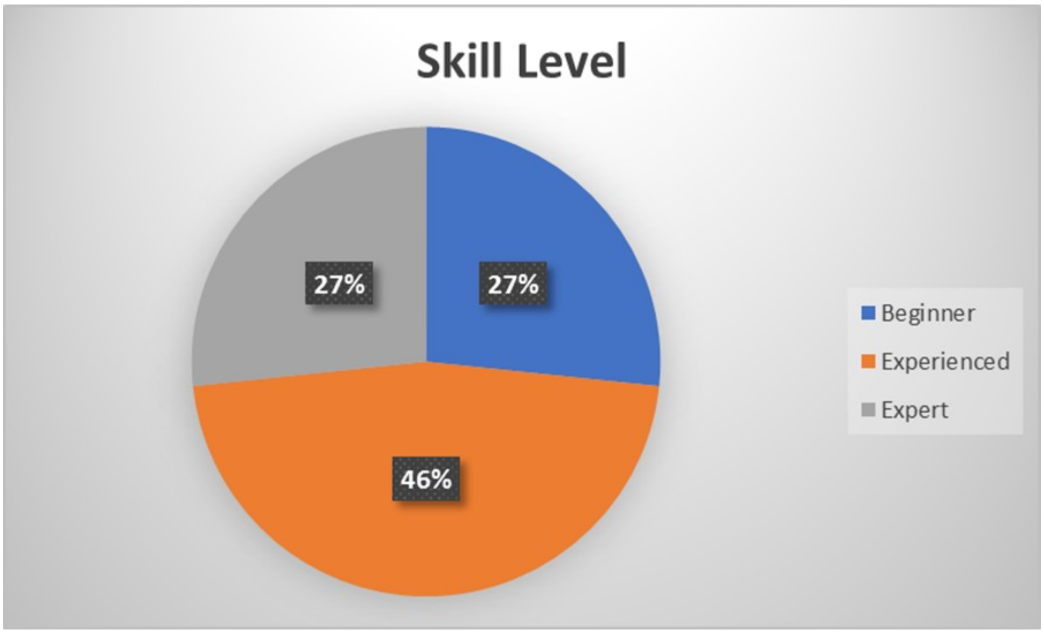

Figure 4.4: Phase 1: Skill Level

4.1.2 Level Experience (Part 2)

All questions from this subsection were obtained from the second segment of the questionnaire, which was done after the level was completed. All questions are in relation to the participants' overall experience.

Immersion

The following is the recorded immersion level of the participant after completing the first level.

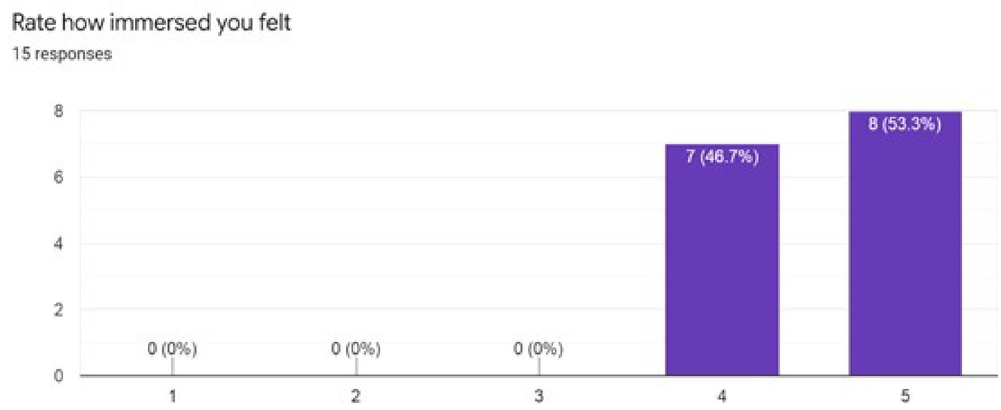

Figure 4.5: Phase 1: Immersion Readings

Beginner: 75% (4) —— 25% (5)

Experienced: 29% (4) —— 71% (5)

Expert: 50% (4) —— 50% (5)

Overall Difficulty

This question asked the participant how they felt about the difficulty. Requesting them to rate it from too easy to too hard.

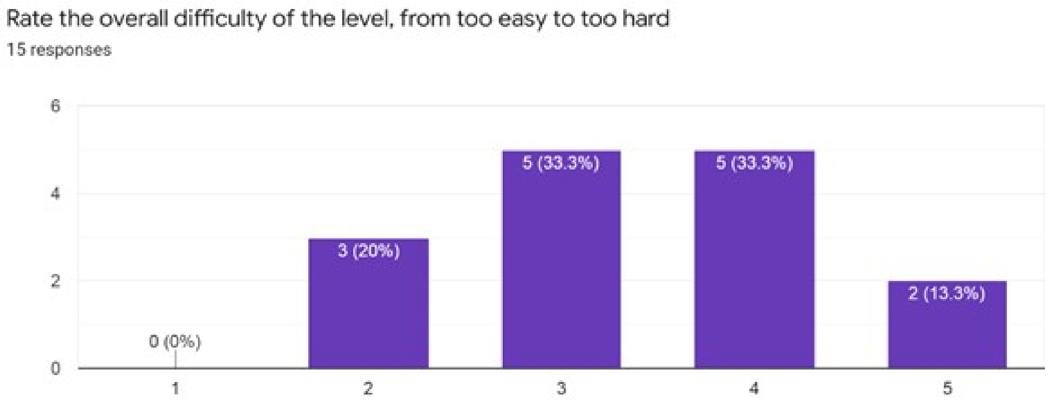

Figure 4.6: Phase 1: Overall Difficulty

Beginner: 25% (3) —— 25% (4) —— 50% (5)

Experienced: 28% (2) —— 43% (3) —— 29% (4)

Expert: 25% (2) —— 25% (3) —— 50% (4)

Difficulty Reflection

This question asked the participant if they thought the difficulty level was appropriate for their skill level.

Figure 4.7: Phase 1: Difficulty Reflection

Beginner: 75% (3) —— 25% (5)

Experienced: 15% (2) —— 14% (3) —— 57% (4) —— 14% (5)

Expert: 25% (2) —— 50% (4) —— 25% (5)

Likelihood Of Playing The Game Again

The following question asked the participant what is the probability of them to play this game again.

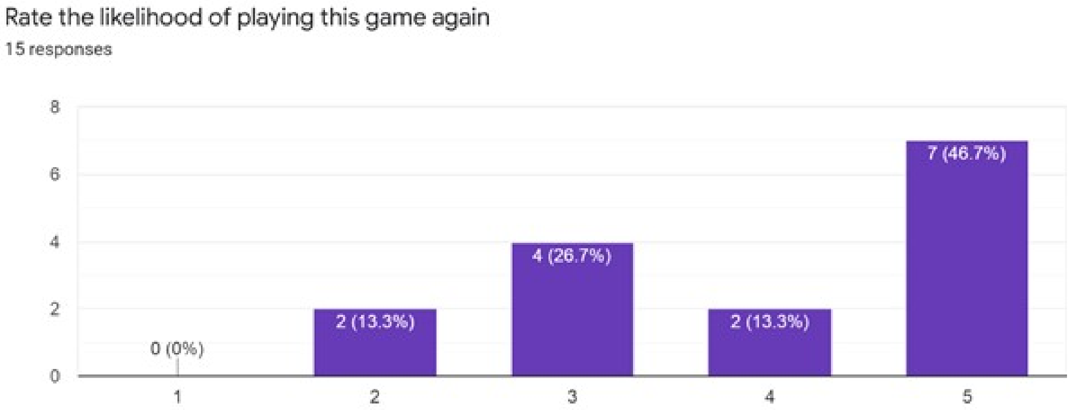

Figure 4.8: Phase 1: Likelihood Of Playing The Game Again

Beginner: 50% (2) —— 25% (4) —— 25% (5)

Experienced: 43% (3) —— 57% (5)

Expert: 25% (3) —— 25% (4) —— 50% (5)

Participant Suggestions

This section covers the written suggestions given by the participants, their input is regarding how the overall experience can be improved. This part was optional. From the 12 responses that were given, these are the highlights:

- "The number of zombies that appear increased a bit too fast compared to when you start, so as a beginner in shooting games it was a bit too difficult for me. so maybe slower pacing."
- "Starts off slow at the beginning and then goes to an appropriate difficulty, but then gets a bit overwhelming."
- "A difficulty slider can be useful for some players."
- "Maybe some other weapons"

- “More different zombie types”
- “More variety in powerups (e.g other things instead of grenades)”

4.1.3 Game Statistics (Part 3)

The following statistical measurements are from the completed level, which are the in-game statistics and heart rate of the participants. All have been arranged and analysed according to the skill level of the participant. With each category having its average calculated.

Score

Beginner: 13725

Experienced: 20357.14

Expert: 21400

Kills

Beginner:

- Average Kills: 81
- Grunt Kills: 74.75
- Elite Kills: 6.25

Experienced:

- Average Kills: 114.86
- Grunt Kills: 105

- Elite Kills: 9.86

Expert:

- Average Kills: 126.25
- Grunt Kills: 116.5
- Elite Kills: 9.75

Death Count

Beginner: 10.25

Experienced: 2.57

Expert: 1.75

Heart Rate

Beginner:

- Average: 79.5
- Average Max: 88.75

Experienced:

- Average: 78.57
- Average Max: 83.86

Expert:

- Average: 79.5
- Average Max: 85.25

4.2 Phase 2

Once the first phase was completed, the procedure of the test was repeated again at a later date with another 15 participants, but this time the implemented DDA system. The structural format of how the data was collected and analysed remains unaffected.

4.2.1 General Data (Part 1)

This section covers the questions from the segment of the questionnaire, such as Gender, Age group, and overall skill level.

Gender

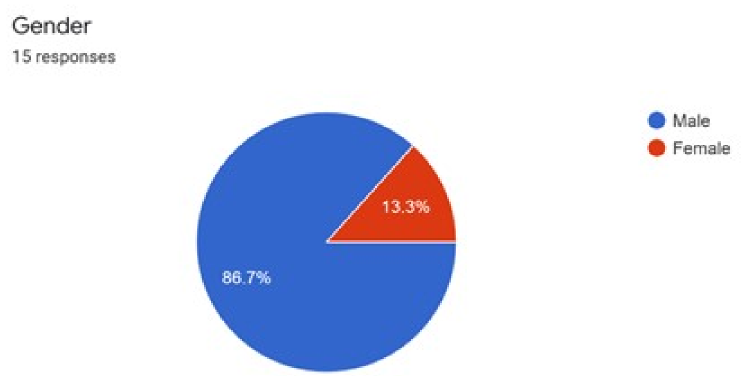

Figure 4.9: Phase 2: Gender

Age Group

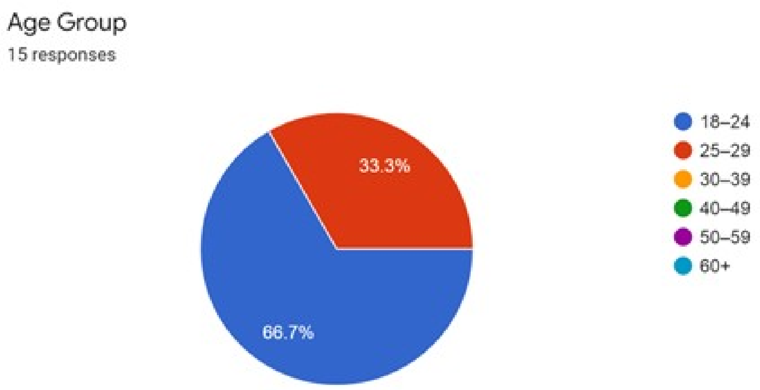

Figure 4.10: Phase 2: Age Group

Past Experience

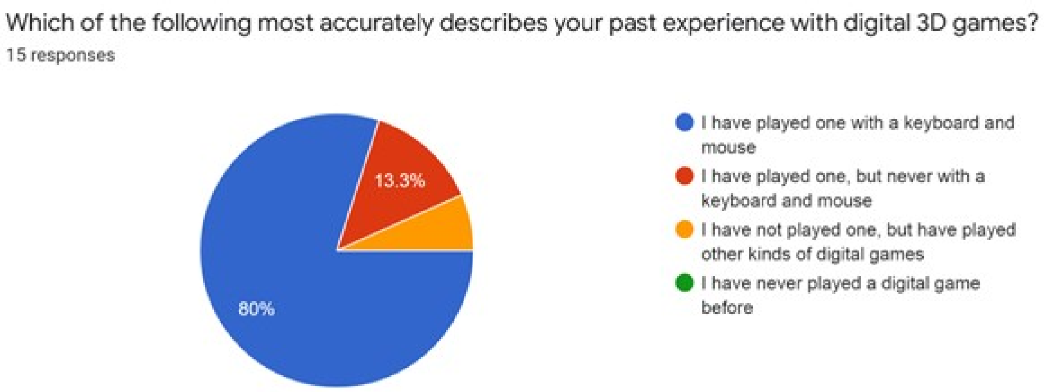

Figure 4.11: Phase 2: Past Experience

Skill Level

This time out of 15 participants, there were 3 beginners, 8 experienced, and 4 Experts.

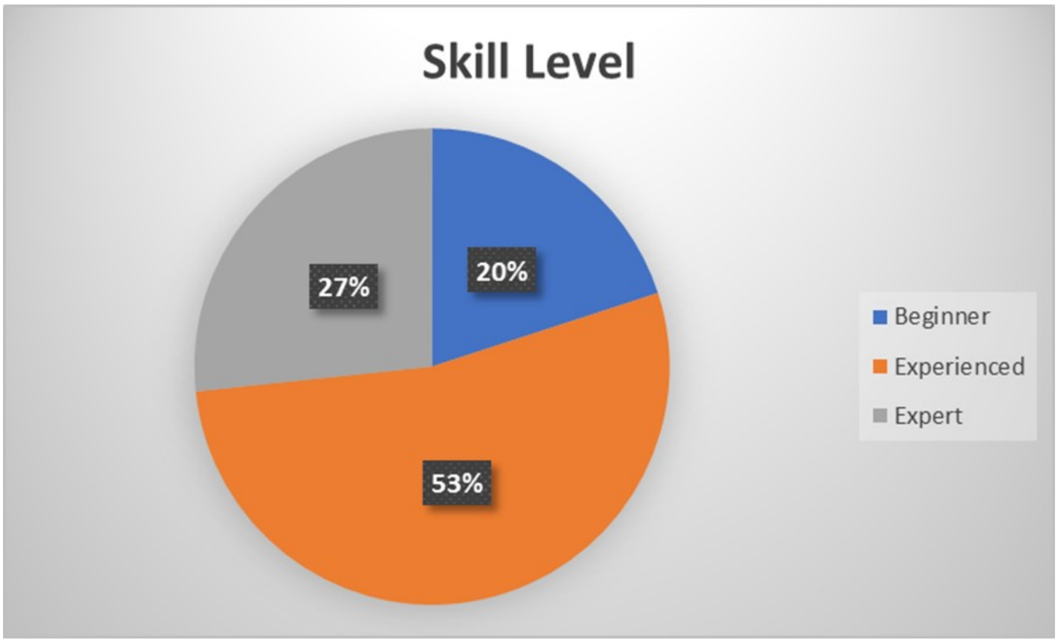

Figure 4.12: Phase 2: Skill Level

4.2.2 Level Experience (Part 2)

All questions from this subsection were obtained from the second segment of the questionnaire, which was done after the level was completed. All questions are in relation to the participants' overall experience. In this phase, you will also see the newly added questions as mentioned in the methodology.

Immersion

The following is the recorded immersion level of the participant after completing the first level.

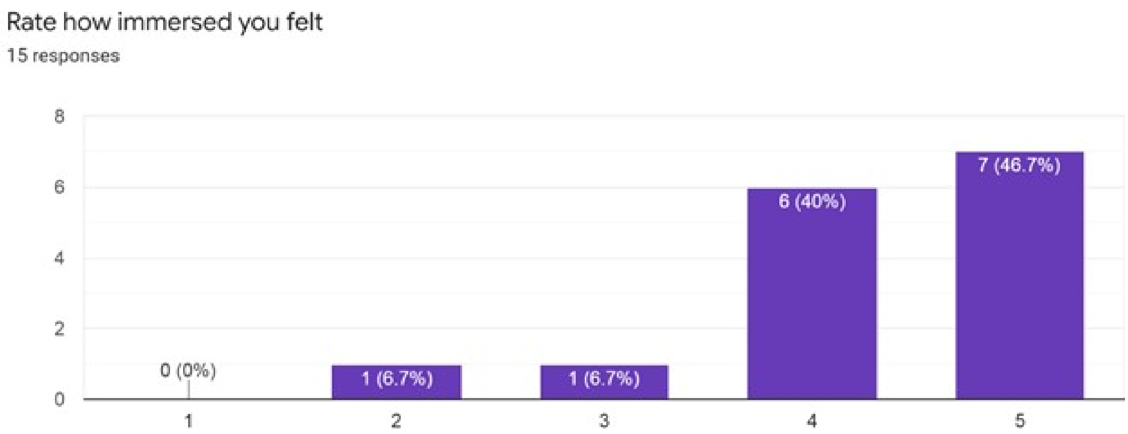

Figure 4.13: Phase 2: Immersion Readings

Beginner: 100% (5)

Experienced: 12% (2) —— 63% (4) —— 25% (5)

Expert: 25% (3) —— 25% (4) —— 50% (5)

Overall Difficulty

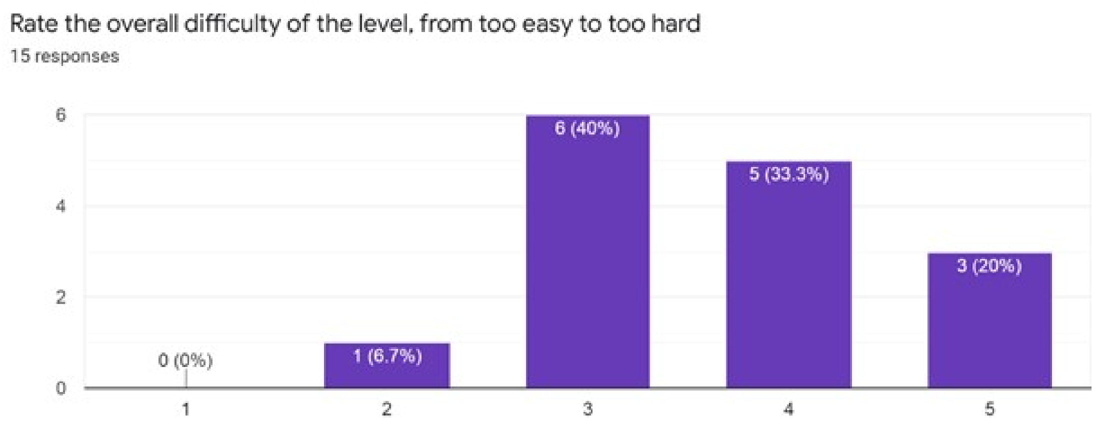

Figure 4.14: Phase 2: Overall Difficulty

Beginner: 33% (3) —— 33% (4) —— 33% (5)

Experienced: 12% (2) —— 63% (3) —— 25% (4)

Expert: 50% (4) —— 50% (5)

Difficulty Reflection

Figure 4.15: Phase 2: Difficulty Reflection

Beginner: 33% (3) —— 33% (4) —— 33% (5)

Experienced: 50% (4) —— 50% (5)

Expert: 25% (3) —— 25% — (4) —— 50% (5)

Likelihood Of Playing The Game Again

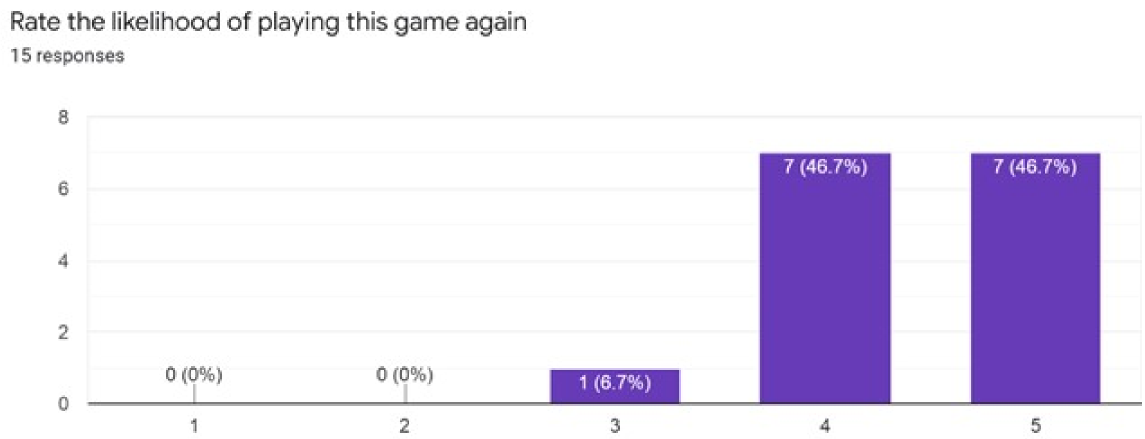

Figure 4.16: Phase 2: Likelihood Of Playing The Game Again

Beginner: 25% (4) —— 75% (5)

Experienced: 12% (3) —— 38% (4) —— 50% (5)

Expert: 75% (4) —— 25% (5)

Participant Suggestions

This section covers the written suggestions given by the participants for the 2nd phase, their input is regarding how the overall experience can be improved. This part was optional. From the 9 responses that were given, these are the highlights:

- "More Mechanics Features - Reloads, Sprint, Different Enemy, Waves, Footsteps, Better Ambient Sounds ect"
- "Remove the waiting time to throw the grenade after shooting (at the moment it is around 1.5 seconds?)"
- "Maybe a timer that shows when I can throw the grenade since there is a cooldown

after shooting."

- "Different guns and more pick ups and more different type of enemies"
- "More strategies and gameplay depth"
- "More guns"

DDA Questions

This part of the results are the last 3 questions added for the 2nd phase, these questions focused specifically on the DDA system and how it was perceived by the participant.

Awareness

The first question asked if the participant noticed any changes in the difficulty during gameplay. An overwhelming majority answered yes with only 1 attendant saying no.

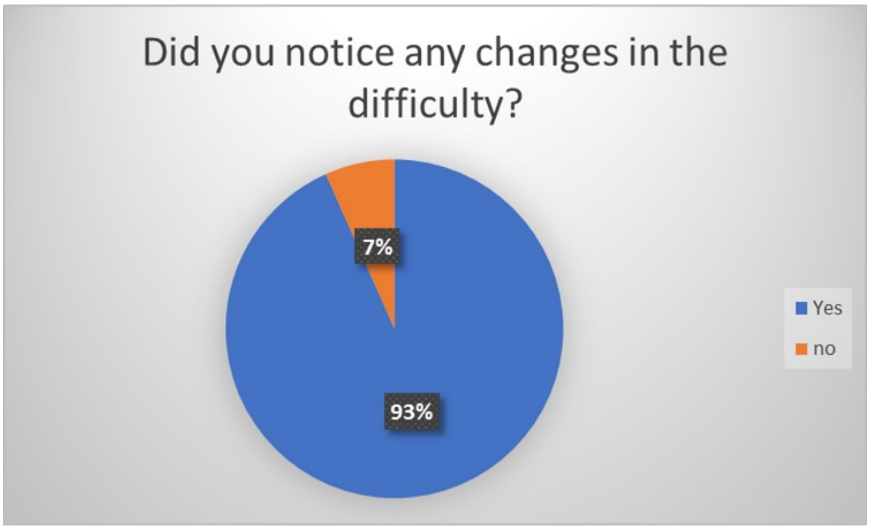

Figure 4.17: Phase 2 DDA: Awareness

Adaption

This question asked if the game adapted appropriately to their skill level.

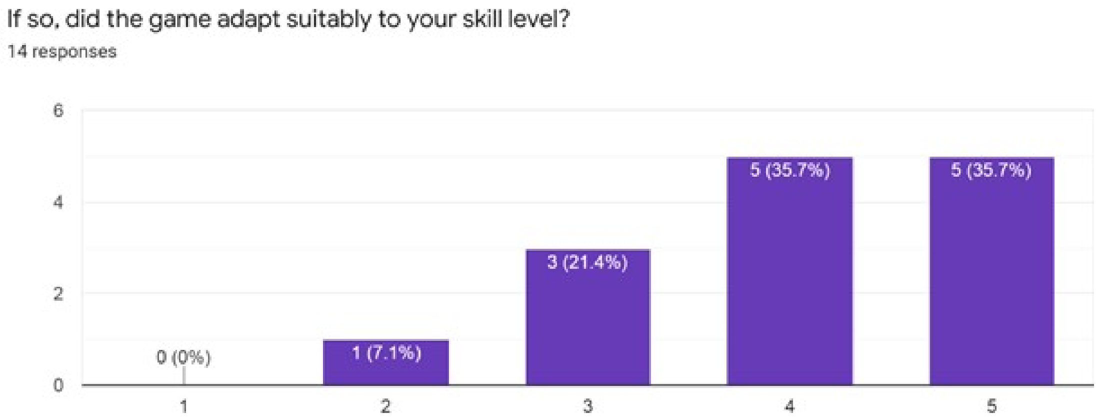

Figure 4.18: Phase 2 DDA: Adaption Figure 1

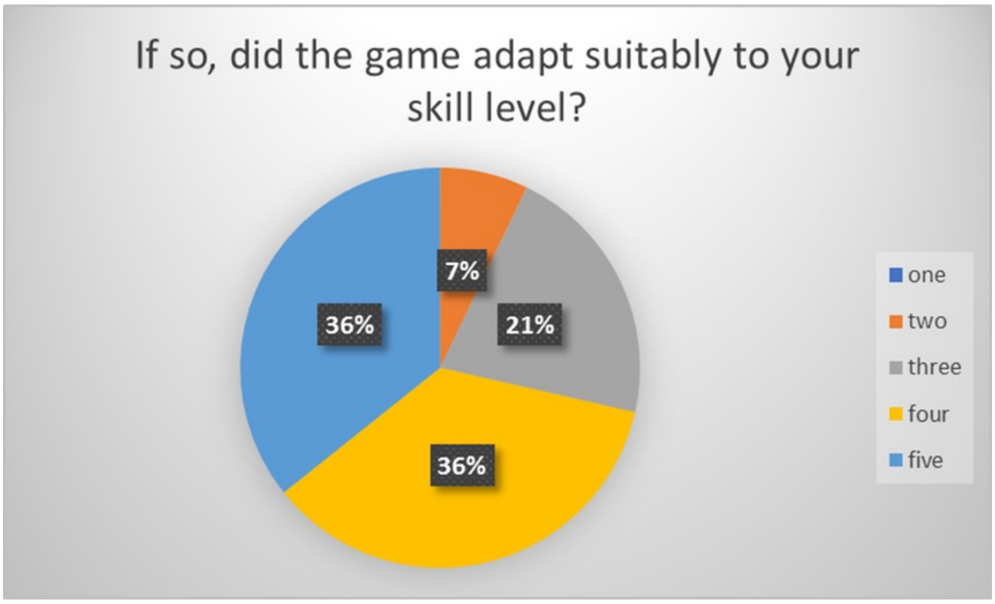

Figure 4.19: Phase 2 DDA: Adaption Figure 2

Beginner: 33% (2) —— 33% (3) —— 33% (5)

Experienced: 14% (3) —— 43% (4) —— 43% (5)

Expert: 25% (3) —— 50% (4) —— 25% (5)

Experience

The last question about the DDA system inquired how the difficulty adjustment affected their experience with the game. This was a written optional comment. These were the responses:

- "Made the game more immersive."
- "It made the game harder by spawning many more zombies than in the beginning, which in fact made me die at one point."
- "It was better"
- "Was more enjoyable for me to be able to play the game suited for my level of experience."
- "It made it more immersive, and required I focus more on what is happening."
- "Good and Necessary"
- "Started off slow but got but got more difficult later on, made me increase focus"
- "The difficulty kept jumping up and down, made it very noticeable"
- "Would be better if it was an option for the level to have it, or to only use it in the beginning as a suggestion to what your difficulty should be"
- "Felt more immersed"

4.2.3 Game Statistics (Part 3)

The following statistical measurements are from the completed level, which are the in-game statistics and heart rate of the participants. All have been arranged and analysed according to the skill level of the participant. With each category having its average calculated.

Score

Beginner: 17533.34

Experienced: 24500

Expert: 25225

Kills

Beginner:

- Average Kills: 124.34
- Grunt Kills: 118.67
- Elite Kills: 5.67

Experienced:

- Average Kills: 147.13
- Grunt Kills: 136.25
- Elite Kills: 10.88

Expert:

- Average Kills: 144.5
- Grunt Kills: 139.75

- Elite Kills: 11.25

Death Count

Beginner: 8.34

Experienced: 3.63

Expert: 4

Heart Rate

Beginner:

- Average: 84.67
- Average Max: 90.34

Experienced:

- Average: 88.13
- Average Max: 97.38

Expert:

- Average: 82.75
- Average Max: 92

Chapter 5

Discussion

The main objective of this study is to examine how a dynamic difficulty adjustment system can have a positive impact on the end-user when applied correctly in a gaming environment. To properly evaluate this statement, these questions were written to define the individual goals:

1. How does a real-time dynamic challenge adjustment algorithm affect the performance of the player?
2. Do Players notice the adjustment? And if so, does it affect their enjoyment, frustration or perception of game difficulty?
3. How is the level of engagement affected through dynamically difficult games?

The following sections will focus on comparing the results of both the first and second phase of the experiment, so properly written answers for the research questions can be justified, since they will each be supported with a plausible explanation from the collected data.

5.1 Player Performance

This section focuses on the first research question of the hypothesis, which is how a real-time dynamic challenge adjustment algorithm affects the performance of the player. The best approach to investigate real time dynamic difficulty, would be to identify how to in-game statistical results differentiate from the first and second phase.

First off, we can see that the overall average scores for every skill level in the 2nd phase are higher than in the 1st phase. Beginner players gained a 21.7% increase, the experienced with 16.9%, and expert players have an enhanced score of 15.2%. We can see here that the average score for all skill levels in the 2nd phase is higher, with every increase being over 10%.

We can also see that the average kills for all 3 of the categories which are total, grunt, and elite are higher in the 2nd phase. The only exception in this phase is that beginners have about 10% less in average elite kills. It can be noted that beginners have the greatest percentage increase in average kills, with it being 36.64%. This is because in the lower difficulty levels, the game got dynamically adjusted for enemies to have lower health, which made it less challenging for players to obtain more kills. It is important to note however, that lower difficulty levels decreased the spawn rate, but this change would only take a proper noticeable effect, if the game continued in the low difficulty regions, since normally when the game goes from 0 to –1 difficulty, there is already a considerable number of enemies already present. So, this change would only be felt if the game resumed continuously in this state.

Experienced and expert participants also gained more average kills overall in each category, with the increases being 28.1% for experienced and 14.46% for experts. But despite the DDA system making the game more challenging by increasing the health of the enemies, the players managed to get more kills this time because the spawn rate also increased. This made the opportunity to obtain kills more accessible, because more enemies were present on screen. Also, most of the experienced/expert players figured out that by using the grenade, they can throw into a large crowd and obtain a copious amount of kills at once. Furthermore, for the aforementioned reasons is why both experienced and expert players obtained higher average scores and kills in the 2nd phase.

For death count however, it can be observed that whilst beginner players died less frequently in the 2nd phase, with a deduction of 18.6%, both of the experienced and expert players have a higher average death count, with the former being a 41.25% increase and the latter 128.57%. The reason for this outcome is that beginner players, have a higher chance of playing the game in the lower difficulty range, which makes the regular grunt enemies do less damage, from being 2 hits to kill the player to 3 hits for both low difficulty levels. To top it off, in difficulty level -1 enemies also run slower, and have a reduced spawn rate. In difficulty level –2, elite enemies stop spawning and the player go 20% faster. This in turn, lessens the chances for players in lower difficulty levels to be killed, which helps them during gameplay if they are struggling.

For experienced and expert player on the other hand, they will naturally experience the game in the higher difficulty regions, from 1 to 2. This resulted in higher average death counts because the DDA system, increased the HP, speed, and damage done of the enemies, which raised the chances of players being killed since the game dynamically got more challenging. For expert player especially, it is less of a challenge for them to reach the highest difficulty level, which made them more susceptible to having a higher average death count than experiences skill level players.

The results obtained here show a similar resemblance to the results that were achieved by Yang and Sun in 2020. In their case, the data showed that both casual and hardcore participants obtained more points in the DDA level when compared to the level with quick progressive difficulty. The difference here is that their DDA system was more prone to lowering the difficulty, since it was dependent on the player losing health to do so (Yang and Sun, 2020). The following table displays the percentage increase of beginner and expert players' average score for both this and their research, the experienced skill level was omitted in this case because the other study only classified two skill levels that were Casual and Hardcore, which can be interpreted as Beginner and Expert respectively.

	Casual/Beginner	Hardcore/Expert
% inc. for Yang and Sun	318%	147%
% inc. For this Research	21.7%	15.2%

Table 5.1: This table displays the percentage increase of the score in the DDA level between this research and the one conducted by Yang and Sun in 2020(Yang and Sun, 2020).

We can see that the percentage increase for points gained in the DDA level is much greater in their research. The reason for this difference is because the DDA system utilised in their research was very lenient, since it reduced the difficulty of the level when the player took damage, which happened very often. This contrasts with the DDA system of this study, which lowered the difficulty much less frequently because it was based on analysing player performance.

By taking everything into account in the current section, this shows that a real-time dynamic challenge adjustment algorithm can have a positive impact on the player's performance, since from the results we can see that the participants in every skill level had more balanced game statistics in the DDA level. Beginner players benefitted the most from the DDA system, since the difficulty was adjusted to suit their skills, which in turn yielded better performance. Experienced and expert players also benefited from the 2nd phase but to a lesser extent, because a more appropriately difficult challenge was presented to their skill level without holding them back, and giving them more opportunities to obtain better performance which turned out to be the case.

5.2 Experience Affection

This segment focuses on the second research question of the hypothesis, which centers on the player's noticeability of the adjustment and how it affects their enjoyment, frustration or perception of game difficulty.

The initial point to look at is how the participants responded to the question where they were asked if they noticed any changes in the difficulty during gameplay. Only 1 participant out of the 15 responded with no, which means changes were detected by 93% of the participants. When inquired about how the difficulty adjustment affected their experience, the majority wrote that it improved their experience and felt that it was necessary, with one beginner stating that it was more enjoyable to play the game suited for their level of experience. Albeit there was a response left by an expert, which read that it would have been better if there was the option to choose either a DDA level or one with a static difficulty. The expert also suggested that the tutorial section might have been appropriate to use the DDA system, to determine what the player's difficulty should be.

For the question which asked if they thought the difficulty level was appropriate for their skill, the majority of the respondents preferred phase two since options 4 and 5 were selected the most which are the highest values, and with only two selecting 3. The first phase had a more varied outcome since more participants selected options 2 and 3, and less selected 5. This means that 86.7% of players found the 2nd phase to be more appropriate for their skill level, whilst for phase one that value is 60%. The result of this question differentiates when compared to the result of a similar inquiry presented in the research done by Paula Silva, Nascimento Silva, and Chaimowicz, which asked if a balanced environment was established, with only 27% agreeing. The reason for this considerable difference is because the game utilised for the study mentioned, is much more complex since it was a MOBA game which involves complex strategies and tactics, hence defeating higher skilled players was not developed within the AI mechanism they used. Whilst the game utilised for this study had a very direct design, with a fewer number of advanced strategies involved (Silva, Nascimento Silva and Chaimowicz, 2017). A direct comparison of both studies can be seen in the charts below.

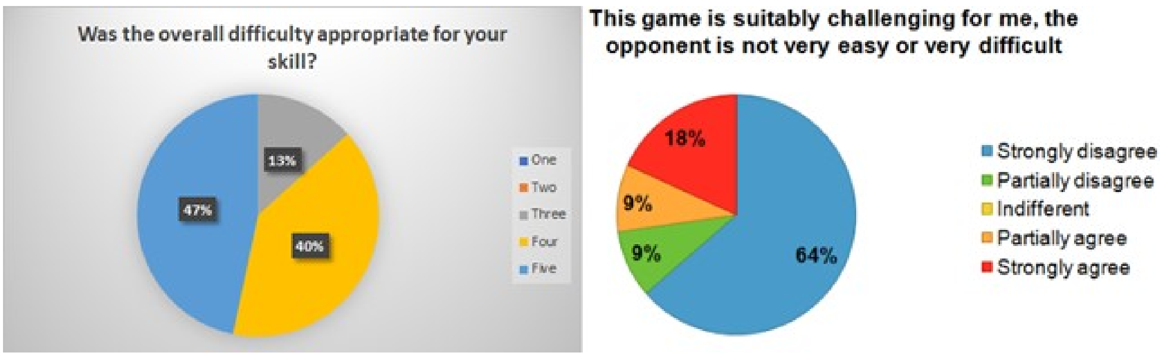

Figure 5.1: Both charts represent the question of difficulty reflection, left chart is from this research, right chart is from the study by Silva, Nascimento Silva and Chaimowicz in 2017 (Silva, Nascimento Silva and Chaimowicz, 2017).

It is important to note however, when asked to rate the overall difficulty, the 2nd phase was found to be slightly more difficult since fewer selected option 2 which means easy. The reason for this is because there were much more experienced and expert players than beginners, and since the DDA system made the game more difficult, the players were more inclined to select the higher values.

In the questionnaire, participants were also asked what the likelihood was of playing the game again, with the results being more favourable to the 2nd phase when compared with the 1st. 93.4% of the participants selected either option 4 or 5, except for one which selected 3. For the 1st phase however, the outcome was very different because 40% of the participants selected options 2 and 3, and option 4 was chosen less. This is a similar outcome to the result obtained by Paula Silva, Nascimento Silva, and Chaimowicz in their research which asked the same question, with a higher percentage of people in that study saying they would play the game with DDA again. The following graph demonstrates the difference between this study and their study (Silva, Nascimento Silva and Chaimowicz, 2017). The following charts compare the percentages of both this study and the aforementioned research respectively.

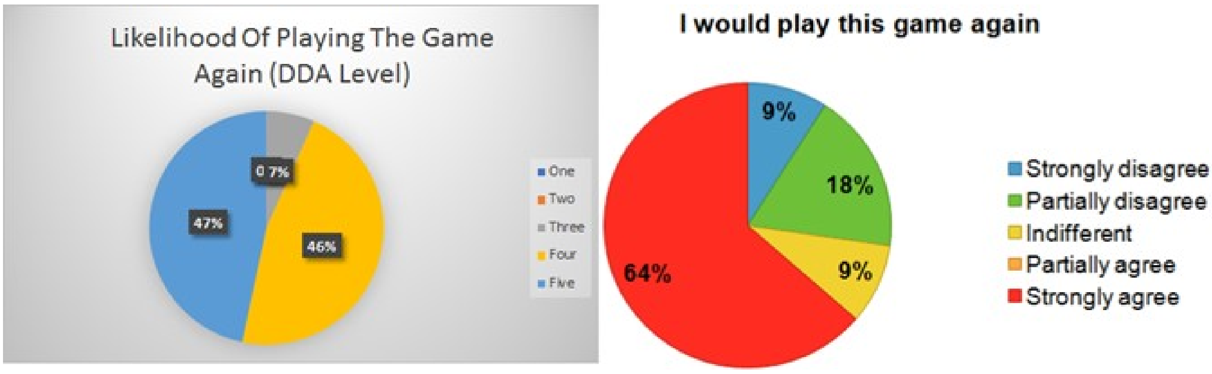

Figure 5.2: Both charts represent the question of returning to the game, left chart is from this research, right chart is from the study by Silva, Nascimento Silva and Chaimowicz in 2017 (Silva, Nascimento Silva and Chaimowicz, 2017).

The chart from this research shows that 93.4% would play the game again when compared to the 64% of the study done by Silva, Nascimento Silva and Chaimowicz in 2017 (Silva, Nascimento Silva and Chaimowicz, 2017).

By taking the results of this segment into consideration, it is signified that when participants notice a change in the difficulty of a level, their level of enjoyment can increase if the challenge is adjusted accordingly to their skill level. This is supported by the result that shows a higher percentage of participants that would play the DDA game again in the future. However, a participant's perception of the real time adjustment varies depending on their skill level, in the case of this study, beginner and experienced players found the DDA to improve their experience as they found the changes to be necessary for them. Whilst experts on the other hand, had a varied perception of the DDA system, since some of them preferred the difficulty to remain static as long as the challenge was appropriate for their skill. So overall, dynamic difficulty can make a positive impact on a player's overall experience, but this effect tends to diminish in higher levels of skill.

5.3 Level of Engagement

This section focuses on the third research question of the hypothesis, which is how the level of engagement is affected through dynamically difficult games. The best approach is to investigate the findings that are focused on immersion readings, heart rate measurements, and written comments for both phases, and from there on seeing how they contrast.

To start off, the results of the question which asked participants how immersed they felt varies depending on the phase. For beginners, it is an improvement, since 100% of them selected option 5 which is the highest, when compared to phase one 75% selected option 4 and 25% selected 5. This correlates with the results mentioned in the previous section, since beginner level players found the DDA level to be more enjoyable which enhanced their experience and performance. For experienced and expert players however, the result was more diverse in the second phase, with less choosing option 5 and more choosing 4, 3 or 2 when compared to the first phase. The reason for this inconsistency is because for some of the higher skilled players, the difficulty kept changing more often than others, one of the participants in fact wrote that because of this, the adjustments became very noticeable which caused a loss of immersion. Some of the other higher skilled players however stayed on the high levels of difficulty without too many changes occurring, some wrote in the questionnaire that since it became more difficult, the level became more immersive because more focus was required.

The immersion readings in this study when compared to the one mentioned section

1.4, also show a resemblance of players who encountered high levels of self-consciousness and awareness of time during the DDA test. The researchers stated that participants were consciously self-evaluating their performance during the test, which was a source of concern since both the immersion, and concentration were affected negatively because of this. This is similar to what happened in this research, when some of the higher skilled participants started to notice the adjustments, which disrupted their level of immersion.

In the examined heart rate data, we can see that that for each skill level both the total average and maximum average reading was higher in the 2nd phase. For total average, beginners' reading was increased by 6.5%, experienced players by 12.17%, and experts by 7.23%. In terms of maximum average heart rate, beginners rose by 1.79%, experienced players by 16.12%, and experts by 7.91%. This increase in percentage corresponds to the data discussed in the previous section which stated that participants overall found the difficulty in the 2nd phase to be slightly more difficult than in the 1st. In the case for beginners, the increase also correlates with their immersion reading to be higher in the 2nd phase, whilst for experienced and expert participants since the game was more adjusted to their skill level in phase two, then the challenge got greater which corresponds with their heart rate increase, especially for experienced participants. This means that for beginner players, the DDA system helped them increase the level of engagement during gameplay, which is indicated by the higher heart rate and immersion readings.

When we compare the biometric readings of the research done by Baldwin, Johnson and Wyeth in 2014 with this one, players that also went against opponents when there was a presence of dynamic difficulty also had the highest biometric readings, with the researchers stating that high readings were an indication of when the participant was being challenged, while lower readings indicated a reduced challenge (Baldwin, Johnson and Wyeth, 2014).

After analysing all the data related with this section, we can see that when a DDA system is integrated in a gaming environment, a positive impact can be made for a player's level of engagement. This is associated mainly however for end users who are classified as novices and are learning the game, because a challenge that is not suited for them can cause frustration which leads to loss of immersion. Hence, why a DDA system is able to adjust the difficulty accordingly and improve a beginner's experience especially in terms of immersion. For higher skilled players, a DDA's effect when it comes to positively effecting level of engagement varies. For players who are in an intermediate skill level with some experience, a DDA system has a higher chance of disrupting immersion because more adjustments might be needed if the player is having an inconsistent performance, this causes noticeability of the changes during gameplay were players lose focus and increase their self-awareness. For the experts, the effects DDA has on immersion is different depending on the variance of their performance, players that are performing well consistently and have the difficulty increased accordingly to their skill, then their concentration also increases which benefits immersion, as long as their performance does not drop significantly however.

5.4 Limitations and Possible Improvements

This study compares an adaptive DDA implementation in a game environment with one which does not have dynamic difficulty. It does not address however other popular DDA implementations such as player-oriented DDA. The main difference between adaptive DDA and player-oriented DDA is that adaptive allows for the difficulty to automatically either rise or fall depending on player performance, whilst player-oriented is when the difficulty is manually controlled by the player during gameplay. An example of research that utilised player-oriented DDA would be the one conducted by Ang and Mitchell in 2017 (Ang and Mitchell, 2017). However, this study specifically selected adaptive DDA in order to test how this type of system affects players that have different skill levels. This is so game designers can use this information to make an educated choice on their DDA strategies in their future game designs.

Another aspect to note would be that the participant pool contained an array of people with varying degrees of skill level, what could have been done differently is that the number of participants could have been equal for each skill level. However, due to limitations caused by the Covid-19 pandemic getting a higher number of participants in an organised manner was slightly unfeasible. If however for example there where 10 or more participants of each skill level for each phase, then a more detailed insight would have been obtained regarding the comparison of gaming levels with DDA and ones without.

Some of the participants suggested in the questionnaire that they would have preferred if the game included more gameplay depth such as different strategies, more mechanics and features, like sprinting, reload, weapons, better ambient sounds and so on. Another aspect mentioned by the participants was that the controls for throwing a grenade could have been improved because they felt it was too clunky. This no doubt had a negative effect on the overall immersion readings for both phases. Even though the game itself was not very basic and simple, it would have benefitted if it featured the aforementioned suggestions, since this would have improved the user experience and immersion.

Chapter 6

Conclusions and Recommendations

This chapter focuses on concluding the study by summarizing the key research findings that are in relation to the research aims and research questions, as well as the values and contribution thereof.

The presented work aimed to examine how a dynamic difficulty adjustment system can have a positive impact on end-users when implemented into a gaming environment. The approached method to investigate this was to develop an adaptive DDA system and implement it to a 3D shooter, after this a test was set up which was split into two separate phases, the first did not utilise the DDA system whilst the second one did. Participants that took part in both tests had their performance, difficulty perception, and immersion level analysed and documented.

The results indicate that an adaptive DDA implementation can contribute to the overall experience of end users, but its affection varies depending on the player and their individual skill level. Further findings show that beginner level players are the most who could benefit from this system, since after the test, an improvement of 21.7% was present in the performance category. The immersion readings for beginners were overall 25% higher in the 2nd phase, which meant that the difficulty was adjusted accordingly to their skill which made them increase their focus. Experienced and expert players did also show improvement in terms of performance, but not on the level of beginner players, since their average score increase after the test was around 15% for both skill levels. Their immersion readings however were lower in the DDA level, with experienced and expert players having 45% and 25% less immersion respectively. The reason for this drop was because for some of the higher skilled players, the difficulty kept changing more often than others, so the adjustments were more noticeable which increased their self-awareness.

The results also showed 93% of the participants noticed the adjustment during the level, which definitely contributed to the loss of immersion which happened to the experienced and expert players. The main reason for this happening was that the DDA system was designed to adjust the difficulty every 15 seconds if necessary depending on the player's performance. Research conducted for future dissertations could attempt to mitigate this issue by having multiple levels in a DDA gaming environment, where the system would adjust the difficulty for each level, rather than every set amount of time. This possible solution could assist in improving the immersion readings in future tests, since the difficulty adjustment between levels could be harder to detect, which might retain or reduce the loss of self consciousness.

In addition, the results also indicate that a DDA system that reads the performance of the player and adjusts it accordingly, could be also suitable for games as a guiding entity that would advise the players what difficulty level they should select. Doing this would benefit their enjoyment of the game since they would be informed beforehand which difficulty level is the most suitable for their skill level.

Given the presented results, it can be concluded that the presence of DDA can improve the overall performance of every player regardless of skill level. This study managed to achieve this because the DDA system developed was designed to lower or increase the difficulty multiple times and not just once (from very easy to very hard), hence an appropriate challenge was presented to every skill level. For immersion, it should be noted however that it can be negatively affected for players who would prefer the difficulty to remain static, since changes in the difficulty during a level can be very noticeable depending on the player's skill level.

Future studies could expand upon this research by modifying the adaptive DDA system utilised and enhance it by altering the artificial intelligence of enemy instances, instead of just changing their variable values. This would be for example a combination of the system applied in the research done by Paula Silva, Nascimento Silva, and Chaimowicz in 2017 and this research. This would no doubt give more detailed insight of DDA development and create more opportunities for gaming developers, which could generate more favourable results that support mainstream utilisation of dynamic difficulty adjustment systems.

References

Hunicke, R., 2005. The Case for Dynamic Difficulty Adjustment in Games. 6. Northwestern University IL.

Zohaib, M., 2018. Dynamic Difficulty Adjustment (DDA) in Computer Games: A Review. 6. Department of Computer Science, BMS College of Engineering, India.

Silva, M., Nascimento Silva, V. and Chaimowicz, L., 2017. Dynamic Difficulty Adjustment on MOBA Games. Department of Computer Science Universidade Federal de Minas Gerais (UFMG) Belo Horizonte, Brazil.

Baldwin, A., Johnson, D. and Wyeth, P., 2014. The Effect of Multiplayer Dynamic Difficulty Adjustment on the Player Experience of Video Games. Queensland University of Technology Science and Engineering Faculty Brisbane, Australia.

Yang, Z. and Sun, B., 2020. Hyper-Casual Endless Game Based Dynamic Difficulty Adjustment System For Players Replay Ability. Bachelors. School of Design and Arts Beijing Institute of Technology Beijing, China.

Ang, D. and Mitchell, A., 2017. Comparing Effects of Dynamic Difficulty Adjustment Systems on Video Game Experience. Bachelors. National University of Singapore.