Theorised Best Parent Optimisation: An Approach for Playstyle Creativity via Preference-Driven Evolutionary Content Generation

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Certificate of Original Authorship

I, Padraic Heaton, declare that this thesis is submitted in fulfilment of the requirements for the award of Master of Science (Research) in Computing Sciences, in the Faculty of Engineering and IT at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Padraic G. Heaton

Abstract

Discovering and delivering what players want in games is a constant struggle that begins during the development process and extends into post-production as developers try to improve their game. In item-driven games, player retention and engagement is traditionally founded upon the quality and variety of the items available. This is particularly apparent in First Person Shooter (FPS) games where items tend to entirely dictate the actions available to the player. To this end, developers have investigated the use of Procedural Content Generation (PCG) tools to quickly and efficiently create large amounts of content for their games. PCG has been traditionally controlled by generating outputs within very tight restrictions to ensure that all generated outputs function correctly and within the developer defined bounds. However, this directly contradicts the purpose of PCG item generation which is to create new and unique procedurally emergent items. To solve for this, new techniques have been developed leveraging the use of Genetic Algorithms to 'evolve' items that conform to design constraints but can remain novel and creative within those bounds. Further, if these design constraints are directly reflective of the current player's interactions with the game, items can be generated that empirically suit the player's game playing style; this is one example of Experience Driven Procedural Content Generation (EDPCG). Genetic Algorithms rely on the discovery of the best population member to pass their genetic code onto the next generation; finding a perfect solution using this method requires large population numbers and many generations to evolve. This is important when adapting these types of algorithms into the context of an FPS. All input data comes from the player's interactions with each generated item, requiring the system to be able to function effectively without the player sorting through thousands of items; in essence, requiring a genetic algorithm to remain effective with smaller generation numbers and population sizes. This thesis proposes a solution to this problem through creating a theoretically ideal best parent in addition to relying on the best parents from each generation to be used in creating the next. This is an effective solution for this use case as it can bypass the need for multiple generations by estimating the player's preferred weapon loadout generations before that combination could appear naturally.

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Chapter 1

Introduction

1.1 Overview and Aim

Static media, once experienced in it's entirety, lose some of their initial value as consumers discover, appreciate, experience and then move on to new content. Digital games, due to their inherently interactive and dynamic design, have a natural ability to extend this life cycle. Various tools native to the digital game format allow for content to become more specific, personalised and immersive. Some of these tools take form in the mechanics and abilities made available to the player, dictating what they are capable of within the game. In some games, these mechanics and abilities are contained within items that allow players themselves to determine what they can do by virtue of deciding which items they want to use. For this thesis, these games will be referred to as 'item-driven' games. In these types of games specifically, the need for variety has resulted in huge amounts of items that can seem impossible to sort through for the player to find what they're looking for, if it even exists in the first place. This 'sorting' would typically see the player stepping away from gameplay to inspect each item they have obtained, in comparison to what they are currently using, in order to determine if they would like to swap them. The more items given to the player, the more time this process takes away from actually playing the game. To this end, this research investigates developing, applying and validating techniques that will continuously supply consumers with new and empirically personalised content.

The overarching idea behind this project is to work towards a gameplay experience that automatically refreshes and personalises itself according to the player's perceived interests. The intended result is increased enjoyment, engagement and immersion in the user experience. More specifically, the research focuses on experimentation with techniques that produce game content at run-time, personalised to the player. This investigation will explore the field of Experience Driven Procedural Content Generation (EDPCG) (Yannakakis and Togelius, 2011) in conjunction with intuitive user-driven evolutionary preference classification.

This project focuses on the EDPCG of weapons in a First Person Shooter (FPS) context, using a genetic algorithm. For the purposes of this project, an FPS is defined as, "*A type of computer game in which the player aims and shoots at targets, and the graphics displayed are seen from the viewpoint of the shooter.*" ("Dictionary.com — Meanings & Definitions of English Words", 2024). Procedural Content Generation (PCG) is the automated creation of content according to strict parameters, traditionally featuring randomised components (Shaker et al., 2016). PCG systems are highly subjective and, as outlined by Shaker et al., 2016, can be applied to a wide range of content, such as environments, characters, items, or mechanics. An extension of this concept focuses on these strict parameters dynamically changing in response to data derived from the player experience; EDPCG. This technique is similarly subjective regarding the methodology of acquiring the data from the player and how that data influences the PCG system. For example, an essential form of EDPCG is the concept of a Dynamic Difficulty Adjustment (DDA) (Shaker et al., 2016) system, which is a system that analyses the aptitude of the player and automatically alters the difficulty of the game in accordance. The preferences of a player are ever evolving, and as such, investigation has been done surrounding the adaptation of content to certain defined parameters. As organisms in the real world adapt over many generations to their environments, this work aims to mirror this by adapting content to a defined set of rules (their environment); and what if these rules were directly informed by the player's interactions. Genetic algorithms are a technique inspired by Charles Darwin's theory of evolution, wherein a large population pool of generative results are sampled for the 'fittest' members, to be then used as the 'parents' for the subsequent generation of the following population pool (Mirjalili, 2019). The 'fittest' members in the population are determined by an applicable fitness function, which is the source of much subjectivity and exploration for research.

In deciding on this research focus, the question of, "*What constitutes a player's playing style in any game context that allows for customisation?*" was sought to be answered more broadly , with the conclusion being all capabilities that the player character has access to (which have been explicitly chosen by the user). For the context of this project, this will be defined as the finite amount of weapons equipped for use by the player as they represent interchangeable player abilities. The player traditionally has the choice of which weapons to use to achieve their goals, with each varied choice appealing towards different people; therefore demonstrating that the weapons they choose to use constitute their playing style. To build upon this idea, if weapons could act as a form of interchangeable active ability the player would be able to quickly build and change their playstyle through their weapon loadout. For the purposes of this thesis, a loadout (or weapon loadout) refers to the combination of items the player is using at one given time; the items that they have 'equipped' onto their in-game player character. These weapons could be represented by a combination of various components (gun type, projectile type, effect type, rarity, etc.), with each combination resulting in functionally distinct behaviour and therefore playing style. To summarise, this project aims to promote game adherence and playstyle creativity in players by generating a wide variety of functionally unique weapons, resulting in varied and emergent player capabilities catering towards potentially unknown player-specific niches.

1.2 Research Questions

RQ1: What impact does a genetic algorithm-based weapon item generation system have on a traditional First Person Shooter game, as compared to psuedo-random item generation?

This question serves to investigate the impact of using a genetic algorithm weapon generation system on the overall design of the game it's housed within. What qualities of the game itself need to change to facilitate this system? And, what qualities of the algorithm need to change to fit this genre? Answering this question will describe the game and algorithm attributes required by this integration.

RQ1.1: What system parameters and game context features result in the most positive feedback from users?

This question further examines the above integration between genetic algorithm weapon generation (RQ1) and the FPS genre by determining what parameters are important in achieving the desired results. For example, do players respond more positively to more or less random items? Or, do players want more or less weapons each generation? Answering this will provide a foundational understanding of how to apply this algorithm to a game in a real-world use case.

RQ2: How does the player experience differ using the experimental system when compared to a traditional First Person Shooter approach for generating weapons?

Using the prototype created in answering RQ1 and the general understanding gathered by RQ1.1, this question serves to provide a more holistic perspective of how this algorithm changes the player experience. In answering this question, a more nuanced understanding of this integration's effects will be gained. This opens up further discussion behind the reasons players may or may not prefer this experimental system, and what steps can be taken to improve it.

1.3 Objectives

In pursuit of answering the identified research questions, there are some objectives and outcomes that will be produced. These have been detailed in the Table 1.1, including which research questions these will aid in answering.

Table 1.1: Project Objectives & Outputs

		RQ1	**RQ1.1**	**RQ2**
1	Research existing solutions for this use case	✓		✓
2	Design the experimental item generation system	✓		
3	Create a functional digital game prototype	✓	✓	✓
4	Design an experiment to validate prototype		✓	✓
5	Collect a data set of user feedback		✓	✓
6	Create the thesis document itself	✓	✓	✓

The experimental system identified above is in reference to the genetic algorithm-based experience-driven procedural content generation system discussed in previous sections. This system will be developed and documented alongside the digital game prototype, with the resulting final iteration being used in focus group testing to generate the feedback data set. The prototype and the system will allow for parameter customisation and fine-tuning, allowing for different EDPCG methodologies to be tested and for the optimal settings to be documented. These findings will then be collated and synthesised into a final thesis.

1.4 Project Methodology

The steps toward achieving these objectives and answering the Research Questions are planned to occur over the course of two years. Each objective will be achieved in sequence, with the first step seeking to achieve Objective 1 through research and investigation of relevant publications to this project. This stage was housed within the University subject 'Research Foundations' (42670), wherein a Literature Review was output and adapted to become Chapter 2 of this thesis. Building on top of this foundation, Objective 2 was the next and most important step for the creation of this project. Taking into account similar solutions to this thesis' problem, this stage saw the initial conceptual design of the experimental algorithm to be explored further in this project.

During this time, further knowledge was gained by undertaking external courses as a part of the University subject 'Technology Research Methods' (32931). For this subject, courses were chosen focusing on experiment design, data collection, and game development to acquire the skills needed to effectively conduct this research. Once the algorithm had been designed to a satisfactory extent, Objective 3 was pursued by developing a game prototype and implementing the experimental algorithm. During this process, focus was shifted back and forth between development and algorithm design as new challenges were discovered and overcome, resulting in a combined exploration of both Objective 2 and 3. Once the game prototype had reached its final stages, Objective 4 became the priority in order to design an experiment to accurately validate the prototype and the algorithm within.

Finally, once the experiment had been designed and Objective 4 had been completed, participants were then recruited and the experiment conducted. Doing so worked towards achieving Objective 5 by collecting data directly from participants playing the game. In-game features were also included in the game prototype to automate some collection of data. Over the course of these two years, Objective 6 has been worked towards consistently. At each stage of this project, each completion of an objective was formalised and documented in this thesis. By the end of this project, all objectives were achieved and therefore answers were found for each one of the identified research questions.

1.5 Key Contributions

The key contributions from this project are the experimental item generation system (Theorised Best Parent Optimisation (TBPO)) which will be discussed further in Section 3.1, and its complementary implementation using Component Based Weapon Design which will be discussed further in Section 3.2. This project explores the overlap between evolutionary scripting and preference based item generation in the FPS genre. Findings from this project will further the academic knowledge surrounding applications of genetic algorithms as well as contextual features that promote their use. Game developers will similarly be able to gain further understanding into the use of PCG systems in their games such as this one. All stakeholders of this project will come to a fundamental understanding on the feasibility of a system like this, what features make it function optimally as well as what effect it has on the gameplay experience.

1.6 Significance

1.6.1 Relevance

The core problem that this project is attempting to address is universal; people will always be seeking new and refreshing content that they enjoy, and that applies to the medium of digital games. In games that do not feature dynamic content, once the player has experienced everything on offer there is inherently less value in continuing to play the game. A system similar to the proposed one will work towards the automatic renewal of existing content to maintain player interest for longer. Further, when selecting game content to consume, people will naturally gravitate towards games that facilitate their current mood and desired game-play style. The ability for a game to be playing style dynamic in this sense will allow a single digital game to react naturally to a user's desired experience by changing its key features without restricting the creativity that comes with diverse gameplay options. Such an ability will work towards overcoming the problem of unsupported niche playing styles in traditional games.

Further, the ability for a game to not only automatically create content but for that content to be personalised to the player allows development efforts to be shifted elsewhere. A large amount of time and energy goes into the creation and fine-tuning of game-play features, which would be dramatically reduced with the addition of this system. Thus, providing a game's development team with more time and resources to apply to other areas of the project. To this end, using a component combination based weapon system (e.g. Borderlands franchise (Gearbox Software, 2009)) a single new component would significantly increase the weapon, and therefore playstyle variety.

1.6.2 Novelty

In isolation, the concept of a genetic algorithm is not a novel idea, nor is the idea of experience-driven procedural content generation. However, the cross-over between these two disciplines has yet to be fully explored. Despite the niche of this concept combination, there has been previous work similar to this project. The main contribution that overlaps with this project is the article discussing the research and development around the game Galactic Arms Race (GAR) (E. Hastings and Stanley, 2010). This digital game featured a genetic algorithm-based weapon generation system that considered the frequency of the player's use of a given weapon. GAR differs from this project regarding the weapon generation system, and it's resulting item's functions afforded by the player when using a given weapon combination. Weapons produced in GAR functioned as follows: "*The genome in GAR is a special kind of neural network called a compositional pattern producing* *network (CPPN) that guides how particle weapons behave*" (E. Hastings and Stanley, 2010), essentially the weapons each fired a projectile wherein movement behaviour of that projectile is what has been generated. In opposition to this, this project is using the generation and use of weapons as vehicles to provide the player with abilities. With the intention of each weapon being functionally distinct from one another and applicable to different playing styles and different game-play situations. Secondly, the weapons are planned to be the sum of a combination of weapon components that make up the final product.

This project is further distinguished as it explores the effectiveness of such a system, experimenting with different parameters and settings to determine the optimal system makeup. As GAR (E. Hastings and Stanley, 2010) has demonstrated that a system like the proposed one is possible, GAR will become a core foundational work upon which this research will iterate on, to identify its use in a different game context (an FPS).

1.7 Thesis Structure

Chapter 1: Introduction

This chapter serves as an introduction to the important concepts for this project; being Item Generation, PCG and Genetic Algorithms. In addition to this, the key research questions, project objectives and the timeline in which they were achieved have also been discussed. The aim for this chapter is to set up the role that this project fulfills in its academic niche.

Chapter 2: Background

This chapter establishes the background and context that this research exists within, serving as the basis of understanding used to build the experimental system upon. This investigation has been presented in the form of a literature review, exploring key academic work relevant to this project and its wider fields of study. Any gaps in understanding and potential solutions have also been briefly discussed in order to identify areas where research could be conducted.

Chapter 3: Theorised Best Parent Optimisation: Design & Implementation

This chapter demonstrates the process behind and design of the experimental item generation algorithm and its accompanying prototype. Design decisions that influenced both the algorithm design and prototype design are discussed in this chapter, with both being integral to the overall function of this solution.

Chapter 4: Assessing Prototype Validity & Algorithm Outcomes

This chapter discusses the process behind validating the experimental algorithm through an experiment, taking the prototype (which utilises the experimental algorithm) and testing it with potential users. The experiment design, raw data collected and extrapolated findings/outcomes are the focus of this chapter.

Chapter 5: Conclusion

This chapter summarises all findings and reiterates all conclusions discovered, re-introducing key concepts and discussing the results and solutions discovered over the course of this project. Finally, it explores avenues any potential future work could explore, using this project's findings as a foundation.

Chapter 2

Background

2.1 Overview

Experience Driven Procedural Content Generation (EDPCG) is a field that aims to direct traditional Procedural Content Generation (PCG) systems towards a goal, with metrics derived from the player's experience (Yannakakis and Togelius, 2011). PCG is a technique that allows for the automated generation of game content. This technique is used to reduce development time and increase content variety by shifting the development focus from content creation towards algorithm optimisation. The specialised EDPCG field leverages the inherent ability of digital games to change in response to player input by expanding into the adaptation of certain game components. This has allowed for the development of automated systems that can detect, process and create game content in direct reference to the current experience of the player. To this end, the preferences of the player need to be identified in some manner, which is where a variety of solutions have been used. These solutions are diverse and each come with both benefits and drawbacks, but each work towards an empirically accurate model of the player so that content can be adapted specifically to them.

The intersection of EDPCG and real-time Preference Classification has yet to entirely overlap, but much work has been done towards this goal. Total immersion, engagement and enjoyment are all aspirations that all forms of media strive to achieve. As digital games are an ever evolving medium, they inherently allow for interactivity, updates and change; they have the unique ability to extend their life-cycle dramatically. PCG is a technique that has been widely used to facilitate this life-cycle extension, wherein it allows a game to generate play components at run-time, thus allowing for a theoretically infinite amount of new content (Shaker et al., 2016). This is achieved by using different algorithms that are all uniquely created for the game context. All of these algorithms find common ground in the fact that they aim to produce constrained and rule based random outputs. There is a huge amount of knowledge and discourse in these fields, requiring a strategy to locate and use the most specific and relevant resources for this project. As such, the following selection and categorisation of papers was necessary.

2.1.1 Paper Selection Criteria and Categorisation

A breakdown of each major field was performed in order to search for the specific areas that are relevant to this research; as a result, it was identified that the fields of Adaptive Games, Procedural Content Generation, and Evolutionary Content were the core foundational elements to be studied. From there, articles, conference proceedings and dissertations were found using a combination of the following organisations' databases: Association for Computing Machinery (ACM), SpringerLink Journals, and ProQuest. The core databases used for this review was ACM due to its specialisation into the Information Technology field and therefore its inclusion of all topical publications for investigation. SpringerLink Journals was leveraged to investigate targeted publications that fell outside the scope of ACM, as it encompasses a wider range of fields. These publications were included due to the scope of this review somewhat including psychology and behavioural studies due to the focus on human-computer interaction. Finally, ProQuest was largely used to discover foundational publications referenced by contemporary papers, so that the wider and original concepts are taken into account as well as more modern interpretations. These databases were chosen due to the breadth of publications available to be investigated, as well as the depth of search-ability granted through sophisticated indexing and the use of search strings.

The first part of the research process was to come up with a Search String, see Fig. 2.1, to use on the above platforms to acquire relevant existing work that should be included in the study. As relevancy is important to this paper, search results were only included if they were published during or after 2010. This was to focus the scope of this research on the most current and up to date research and to remove the need to sort through academic work that has become irrelevant many years after publication. However, pivotal papers that appear as foundational resources for this field have been included regardless of publication date. These limitations have been put in place to limit the amount of manual sorting required before a core relevant set of research can be evaluated.

(video games OR digital games) AND procedural content generation

AND personalization AND (evolutionary OR genetic)

Figure 2.1: Article Database Search String

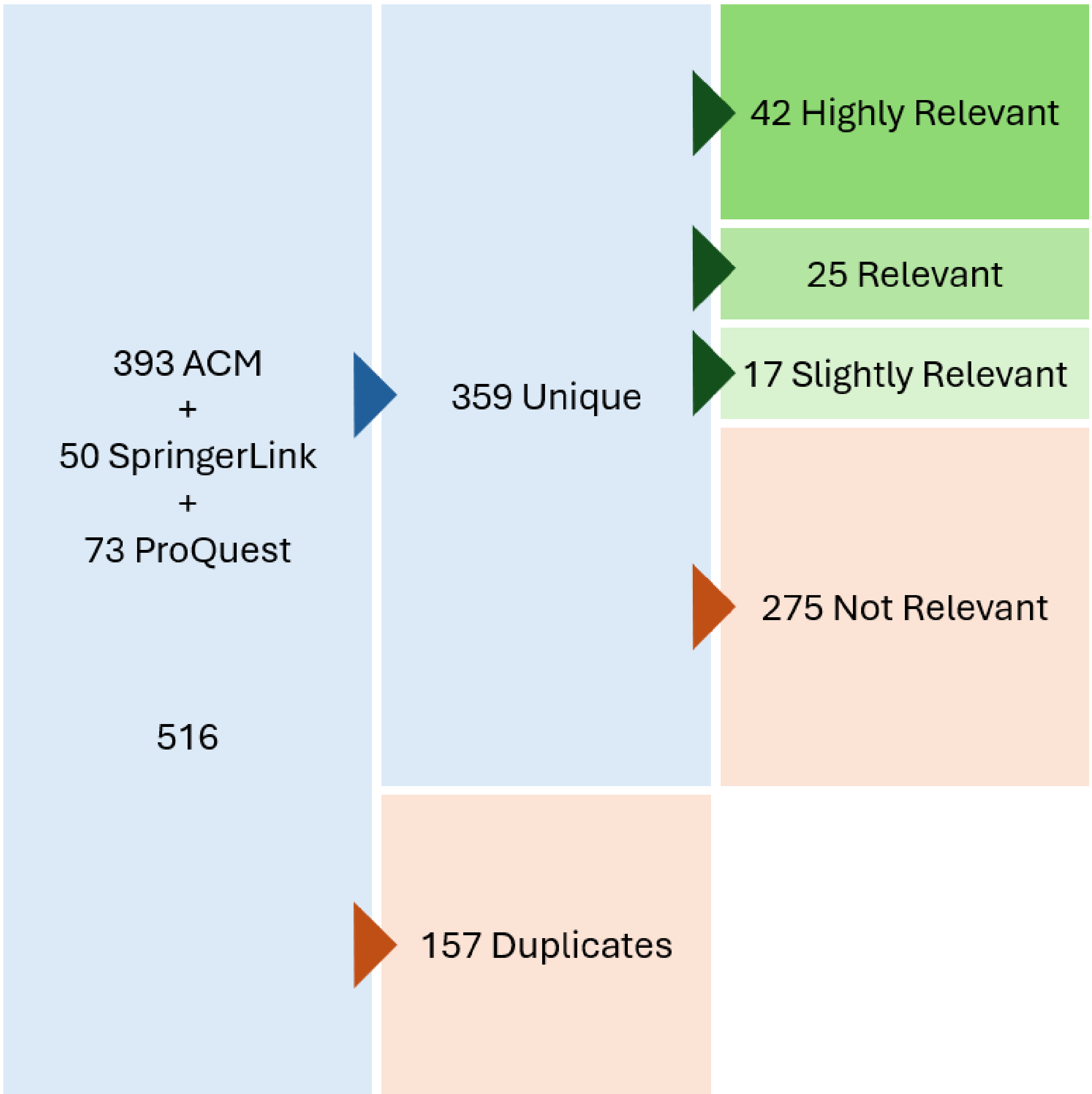

Figure 2.2: Article Exclusion Diagram

As described in Fig. 2.2, using the above search terms to search the identified databases resulted in 516 results which were then sorted through manually. This was done by a rudimentary paper title and abstract evaluation, wherein the title of each paper was measured against the target fields and a decision was made on its relevancy. These fields included EDPCG as well as the wider field of PCG, Adaptive Games, Dynamic Content Generation and Preference Classification. As the titles and abstracts are indicative summations of the content, any and all papers that did not appear to discuss the inner workings, applications or cross-over between these fields were eliminated. Further examination was performed on the core sections of each identified research paper (methodology, results and conclusion), to validate its inclusion in this paper. In this stage of the publication filtering, preference was given towards research that identified and/or explored the cross-over or interaction between core fields, with other papers being excluded. Following this preliminary manual sorting process, 84 research papers have been included as relevant to this research field. The final examination incurred a thorough review of all sections of each paper in order to holistically identify their research focus. In this final stage, preference was directed towards papers that specifically explored Experience Driven Procedural Content Generation and/or Evolutionary Content, special consideration was given to papers that explicitly explored the interaction between these two fields. The entire filtration process resulted in 42 papers deemed highly relevant to this work, 25 papers that are relevant to this work and 17 that are foundational but may fall in adjacent fields of study. Any academic work not included within this review is not by any means less quality than chosen work, just arbitrarily deemed not as relevant to this review in comparison to other similar work. Below I present the resulting review of the papers that have been selected.

2.2 Procedural Content Generation

Games can be broken into two distinct areas: the physical space, objects and components that are visually identifiable to the player, and the abstract rules, constraints and objectives imposed upon the physical space. Procedural Content Generation (PCG) is a field in which components of these two halves of game experiences are created automatically, without direct input from the developer (Shaker et al., 2016). Research has been conducted in order to discover ways to generate both game spaces and the rules that govern them. Said techniques can occur during development, where the developers use PCG to aid or speed up their design process, or it can occur during play (at the game run-time). The motivation behind incorporating systems like these into games can be broken down into three main objectives: decreasing development time, increasing content variety and overall reducing the repetitive nature of static games. This can be refreshing for players as the content variety can become theoretically infinite with most PCG systems resulting in millions of possible PCG outputs.

Figure 2.3: Procedural texture obtained with the Perlin method and its terrain representation (Gasch et al., 2020, Figure 2)

Coherent Noise functions (for example, Perlin Noise (Lagae et al., 2010), Simplex Noise, Worley Noise (Cozzi & Riccio, 2013)) are often used to achieve this as data points close together produce similar psuedo-random results, which can then be expressed as coherent procedural outputs. The most common use of PCG in conjunction with these noise functions is the generation of natural and organic appearing terrain, leveraging the gradual change in numerical output to reflect the height of terrain at a given point (see Fig. 2.3 for an example from Gasch et al. (2020)).

However, traditional PCG techniques suffer from the same reason that they succeed, they are defined by very strict rules in order to ensure that their results are playable experiences; these rules also often result in very similar results that become repetitive to the player over time. A common solution to this problem is to blend PCG techniques with a large quantity of developer-created assets that can reduce the chances of players encountering duplicate levels. Capasso-Ballesteros and de la Rosa-Rosero

(2021) demonstrated this solution by combining strict rule-based PCG algorithms with randomly selected developer curated content to create a coherent resulting experience. This was shown to be very effective at generating playable and enjoyable levels, but did exhibit a problem with content repetition; due to the strict rules and random selection, generated content became very similar and therefore repetitive over time. To counter this, approaches have been made to create PCG systems that mimic parts of the game design process that has become standard for developers, for example Dormans and Bakkes (2011) explored the use of generative grammars two generate both missions and spaces for their experience. Grammar based PCG systems aim to use simple replacement rules combined with a static starting point to generate a complex output, similar to a plant starting at the seed and logically growing and branching out into a complex shape. This was shown to be an effective strategy, with the focus being on the quality of the replacement rules to ensure that the final result was in a playable state. For the purposes of this paper, a playable state is defined as the state or quality of a game component to be experience in its entirety without error or failure.

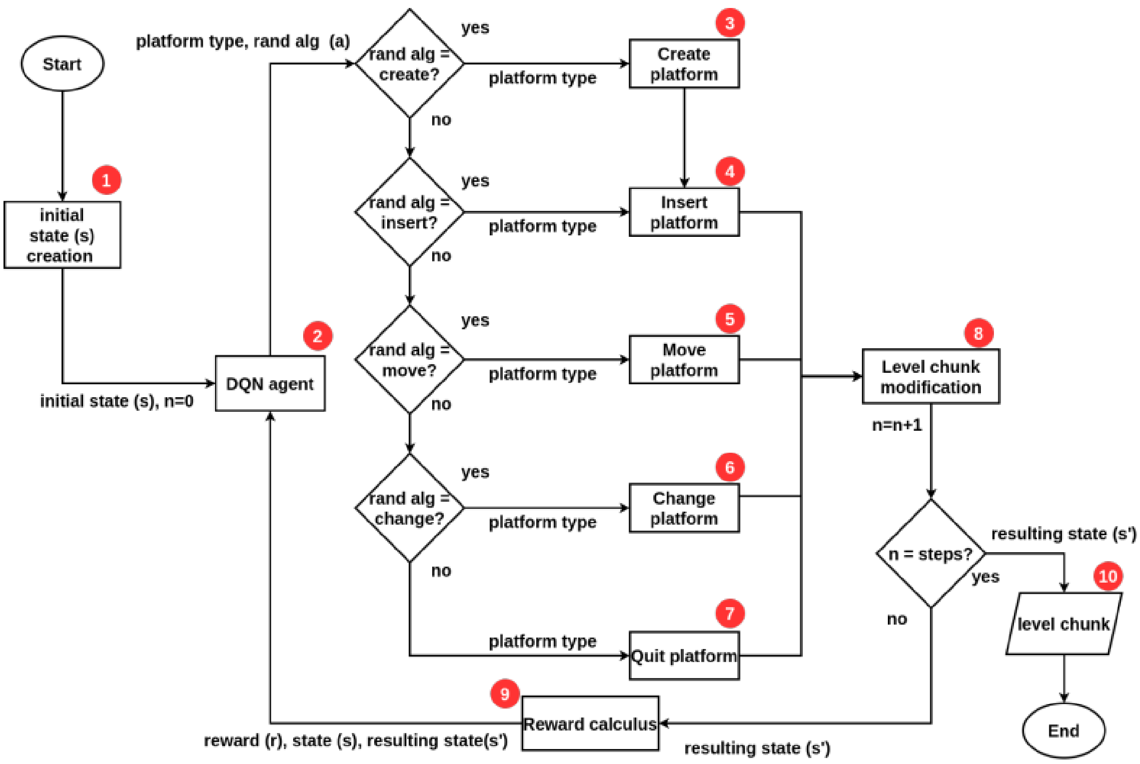

Figure 2.4: IORand flow chart diagram (Moreno-Armendáriz et al., 2022, Figure 4)

The use of grammar systems was extended by Moreno-Armendáriz et al. (2022) in which a hybridisation between a graph grammar-based PCG algorithm and reinforcement learning (Sutton & Barto, 1998) was found to be effective in producing coherent and novel levels. Graph grammar is a form of grammar systems wherein patterns found in branching graphs are replaced rather than a linear string, which is closer in proximity to how a game designer plans a level. The coupling between reinforcement learning and the graph grammar based system was proven to be effective, with the machine learning algorithm acting as a quality assurance mechanism to inform the PCG system. In this case, the AI assumed the role of a developer or player giving feedback to the system and tweaking parameters to conform to the generative goal, see Fig. 2.4 (Moreno-Armendáriz et al., 2022) for a more detailed overview of this process.

However, a common problem identified in each of these papers is the quality and novelty of the content generated by the procedural content generation system. Towards this end, much research and development has been conducted to rectify this issue. Capasso-Ballesteros and de la Rosa-Rosero (2021) and Moreno-Armendáriz et al. (2022) have created techniques for creating digital game levels that are coherent, intuitive and novel. These content generation systems aim to mimic how game developers design levels through a graph grammar-rewriting process. This process ensures that the resulting levels are both playable and novel, whilst also allowing for fine control of results thus eliminating the issue of repetitive content generation.

Moving away from generative game spaces, generative game objectives can also be effective for player retention in genres that rely heavily on this aspect. Zook et al. (2012) investigated the modelling of the player's skill level as an input into a mission generation algorithm to present the player with objectives that challenged the player appropriately. This was accomplished using a combinatorial approach in which developer defined missions were interwoven to create novel and engaging missions for the player. The challenge exhibited (and overcome) in this article was that of catering to both the player's skill level, the over-arching story of the game whilst having these missions be generative.

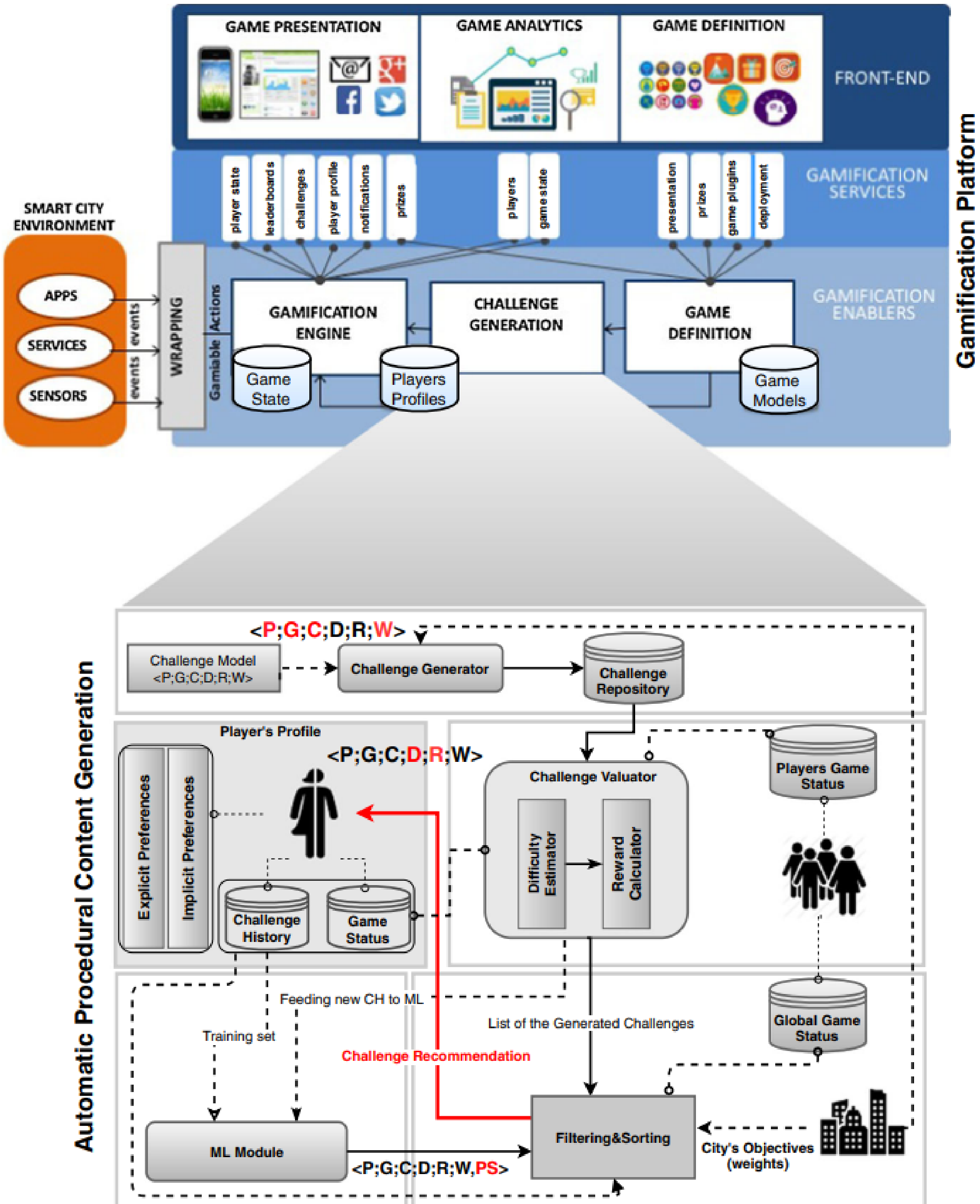

Figure 2.5: Conceptual view of the gamification platform and automatic procedural challenge generator framework (Khoshkangini et al., 2021, Figure 2)

Khoshkangini et al. (2021) built upon this research by implementing these systems into a Serious Game (Stănescu et al., 2019) to facilitate player exercise, and used these techniques to generate personalized challenges to the player in order to increase retention, engagement and performance. This prototype revolved around keeping the player physically active, thus the importance of including a system that promoted adherence. This PCG algorithm revolved around the recommendation of appropriate developer designed missions or challenges that were then adjusted to suit the aptitude of the player involved. The inputs to this system included all data available including personal goals, achievements, contextual cues, and exercise data collected by the game (see Fig. 2.5 (Khoshkangini et al., 2021)) for a more detailed overview of this generative process). This technique was proven to be effective at enhancing this gamified experience over a 12 week trial including over 400 active players, further reinforcing the value that systems like these bring to game contexts.

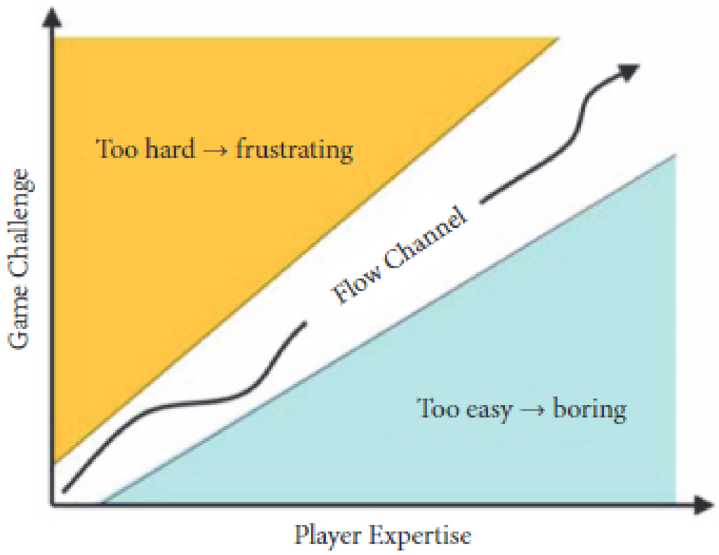

Figure 2.6: Flow channel concept proposed by Csikszentmihalyi (Zohaib, 2018, Figure 1)

The most basic an well-established incarnation of EDPCG is the concept of Dynamic Difficulty Adjustment (DDA) (Spronck et al., 2004); wherein a game system is put in place to alter the difficulty level of the game to match the calculated skill level of the player, based on a developer-defined difficulty heuristic calculation algorithm. The ultimate goal of this is to keep the player in the 'Flow' zone/channel/state (see Fig. 2.6 (Zohaib, 2018)), wherein the player does not find the game too challenging nor too easy. The heuristic calculation is where a lot of research has been conducted, in attempts to find the most efficient game play parameters that accurately reflect the current difficulty state of the game. Suaza et al. (2019) discusses a basic example where the differences in health levels from the player and their opponent can be used to accurately describe the current difficulty level of the match. DDA systems are important first steps but, in isolation, do not address the problem of player preference change, lack of new content, or immersion decay.

Adaptive Games is the wider field that encompasses both DDA and EDPCG, which revolves around digital games or experiences that have the ability to change depending on the user (Lopes & Bidarra, 2011). These types of games take into account features of the user to then alter the experience in a data driven way. The most basic form of an Adaptive Game system can be explained by DDA, to this end, Suaza et al. (2019) found that few data points (subjective to the game context) could accurately inform the input heuristic, in this case it was the difference between the player's and enemy's health level. It was found that the larger the difference between the health levels, the more difficult the experience was for the player, meaning that the difficulty could be effectively adjusted to consistently result in a fair match. However, traditional DDA systems suffer from the inability to adapt both quickly and effectively, resulting in some players losing interest and disengaging with the game before adaptation has become apparent. Arulraj (2010) sought to remedy this problem with the inclusion of machine learning both in the difficulty estimation and adjustment. This solution revolved around adding the concepts of dynamic weight clipping, differential learning and adrenaline rush (which are each different DDA system optimisation methods posited by Spronck et al. (2006)) into a traditional DDA system. Collectively, these additions allowed players to remain in a flow state by moving players between states of successive wins followed by being challenged.

Adaptive games can take many forms, with some working to overcome the player rather than to work with the player, a popular technique for this type of system is Dynamic Scripting (Spronck et al., 2006). This technique was first introduced by Spronck et al. (2006) wherein a system was described that an NPC opponent would adapt a strategy to overcome a human player over time. This was accomplished by the use of rule-bases that contained manually defined rules that were intelligently selected to be used by the opponent during a match, the probability of choosing these rules was changed in response to how they performed during the match. Policarpo et al. (2010) further explored this concept by applying it to a different game context, a first person shooter, in order to evaluate and generalise this technique beyond its first implementation. It was found that not only did the opposing AI agent generate a strategy to counter the player, but it also resulted in a more immersive and unpredictable game experience; thus becoming an overall more dynamic game for the player.

Although the most popular games do revolve around the inclusion of enemies and opponents, the field of adaptive games as a learning tool has also been investigated. Much of the knowledge used as the reference when developing systems like these comes from the field of psychology, in order to understand how a player will think and act when playing a game, to then adapt the experience towards that end. Kickmeier-Rust and Albert (2010) demonstrated the use of adaptive games in an educational context using a technique coined 'Micro-Adaptivity'. This describes the ability of a Serious Game (Stănescu et al., 2019) to cater towards the player in the same manner that a teacher would aid a student if they were struggling in class. Hints, motivational interventions, feedback and assessment clarification are all example of 'Micro-Adaptivity' and were shown to be effective at aiding students. However, it did also highlight the need for further work as technical and theoretical knowledge limiations resulted in a 'clunky' game experience and highlighted the need for more personalised interventions rather than general changes. This has been a common problem amongst systems like these, wherein the challenge of the entire experience will change in response to the player exhibiting difficulty whereas they were only finding one component of the experience difficult.

Figure 2.7: Path of Exile Passive Skill Tree (GrindingGearGames and Wilson, 2013)

As stated by Poeller et al. (2018), a player's interests are directly reflected in their choice of and behaviour in digital games they play. In games that do not feature a PCG system as part of its core process, they have often sought solutions that tend towards allowing for increased amounts of customisation, individualisation and freedom in modern digital games. A good example of this is the intense focus on customisation in the Action Role Playing Game 'Path of Exile' (GrindingGearGames & Wilson, 2013), which features a total of 454 active abilities and 1325 passive skills that players can combine to form countless amounts of play-styles (see Fig. 2.7). Such existing solutions have been shown to be effective in retaining a consistent player-base, but do feature inherent problems as these systems inherently result in the player being required to make a conscious choice to abandon one play-style, customisation or progress in favour of a different one.

2.3 Effect of EDPCG on the Player Experience

The motivation behind developers implementing systems like these are to increase immersion, engagement, enjoyment and interest in their players. Constant and Levieux (2019) investigated the effect of DDA systems on the confidence exhibited by the player, where it was hypothesised that DDA systems will lead to a beneficial form of overconfidence. As demonstrated in this thesis overconfidence, specifically in a game context, is not a detrimental emotion and allows players to take risks or experiment in an environment that has very little impact on their real-world life. Through a comparison between random difficulty levels and DDA-governed levels, results gathered through in-game questions showed that the inclusion of DDA systems does in fact result in high levels of beneficial overconfidence in players. Confidence in game contexts can be seen as a combination of immersion, engagement and enjoyment, thus demonstrating that DDA systems are effective towards meeting the goals of this field.

Engagement more specifically can be reflected in the retention of players, both during and between play-sessions. This metric is important when it comes to Serious Games, which are defined as "*(Experiences wherein) game-based methods and concepts and game technology are combined with other ICT technologies and research areas and applied to a broad spectrum of application domains ranging from training, simulation and education to sports and health or any other societal relevant topic or business area*" (Göbel et al., 2010). Mitsis et al. (2022) investigated this through implementing a system to recognise player engagement in an existing adaptive Serious Game to evaluate its success. During this project, heart-rate sensors were used in conjunction with game-play data to estimate engagement, retention and adherence to their product. At the conclusion of the study, it was found that PCG systems in this context were proven to be effective at maximising adherence to the game and working towards ensuring the extended use of the game.

Further, player motivation plays a large part in their desire to continue playing a game. Fostering a sense of intrinsic motivation is important in ensuring retention and adherence to the experience. Volkmar et al. (2019) analysed the effect of adaptive game design principles on the motivation exhibited by players compared to that of a game without an adaptive system. In this prototype, the achievements and rewards were adapted to the player. Through the use of a questionnaire following the trial, it was found that players who played the adaptive game exhibited higher levels of desire to return to the game-play experience in comparison to the non-adaptive game. In this experiment, the group that played the adaptive game felt intrinsically motivated to continue playing as they had more of a sense of achievement or progression, rather than simply intrinsically wanting to play the game. Intrinsic motivation is difficult to adapt towards as it is increasingly subjective and hard to automatically analyse in comparison to intrinsic motivation, however, a theoretical framework to achieve this would result in very high levels of player retention and engagement.

2.4 Preference Classification

The quality of any EDPCG system intrinsically hinges on the quality of the system's understanding of what the player actually wants out of the experience. An inaccurate preference classification will result in an experience that is either indifferent or destructive to the player experiencing it; for example, an inexperienced player could be given an extremely challenging level or a player that strongly dislikes puzzles could be given a level that solely features puzzles. Outside of games, much work has been performed to estimate products or features that a person would enjoy based on their previous interactions. Matrix Factorization is a popular preference estimation method used in the retail industry (Roy & Ding, 2021) to recommend products to consumers that are similar to products they have previously purchased or that other similar users have purchased. These tools have been proven to be extremely effective in that space, but have also begun to be adapted to the context of digital games. The foundation of understanding in this topic is based in Motive Disposition Theory, which (as identified by Poeller et al. (2018)) supports the assumption that a player's interactions with a game are a reflection of their inherent beliefs or motivations, and therefore can give an insight into their personality or preferences. Sifa et al. (2020) explored the use of Matrix Factorization to recommend select parts of an existing game to users based on their identified preferences, and found that that they were able to retain more players using this technique than compared to the previous handcrafted experience. This technique evaluates the content that you consume in order to construct an empirical persona that can be used to recommend new and unseen pieces of content.

Preference classification via recommender systems has existed for a long time, and thus its features have been researched extensively. Although this technique is traditionally used in the online retail industry, Sifa et al. (2020) and Khoshkangini et al. (2021) have begun to use these techniques to recommend game content to players. Both of these research projects have used instances of systems like these to automatically recommend abstract game content in the form of missions, objectives or challenges. Resulting analysis from both of these projects show a marked increase in player engagement and enjoyment, reinforcing the value of investigation into this field. Further towards the adaptation of intangible game features, Volkmar et al. (2019) investigated the generation of game achievements that align with the observed player's personality. This work used the BrainHex (Nacke et al., 2011) player types to classify players, then draw conclusions on what type of achievements they would find motivating, then finally adapt existing achievements towards those ends. This research demonstrated a similar increase in player engagement and was coupled with the automatic generation of content.

The seven identified player classifications, as according to Nacke et al. (2011), are as follows:

1. Seekers: value exploration and story in games
2. Survivors: value succeeding in challenging environments
3. Daredevils: value experiencing high-risk situations
4. Masterminds: value problem solving, strategising and puzzles
5. Conquerors: value overcoming challenges, with a focus on progressive skill increase
6. Socialisers: value social interaction, either with players or game story
7. Achievers: value completing challenges, with a desire to complete all challenges a game has to offer

Keeping an understanding of the broad spectrum of different players, and especially what parts of different games players derive enjoyment from is paramount to this field of study.

Matrix Factorization is a technique that usually requires a large amount of data to accurately make predictions, this is a problem in the context of games as they are a medium consumed for different time periods depending on both content quantity and player preference. To resolve this problem, the incorporation of Archetypal Analysis (Cutler & Breiman, 1994) has been shown to be effective by Javadi and Montanari (2020) wherein they performed the same function as Matrix Factorization using few data points in conjunction with Archetypal Analysis. This low data requirement is a result of Archetypal Analysis created an accentuated empirical persona based on your past interests, this is done by assuming that the content consumed first is representative of one's interests. This has been shown to allow for accurate content recommendations with little data points, whilst also allowing for refinement over time as more data becomes available.

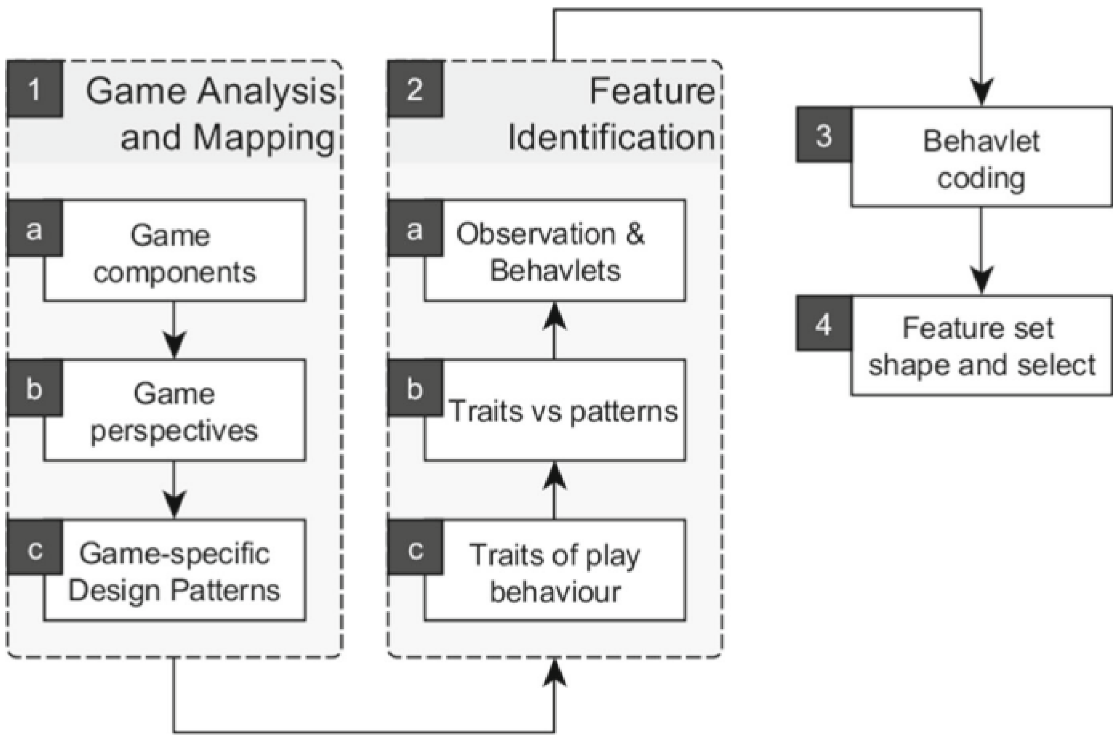

Figure 2.8: The four stages of theory-driven Behavlet extraction (Cowley and Charles, 2016, Figure 2)

An alternative approach that similarly solves the problem of large data requirements has been posited by Cowley and Charles (2016) wherein expert domain knowledge, psychological theory and game design were leveraged to construct 'Behavlets'. See Fig. 2.8 (Cowley & Charles, 2016) for the process of extracting these 'Behavlets' from a given digital game. These concepts are areas of play that can be directly interpreted as personality features of the player; where the choices, decisions and interactions of the player can be used to evaluate their behavioural preferences. As identified in this work, these areas of play ('Behavlets') exist in all games that allow for a degree of freedom, exemplified in the discovery of 139 'Behavlets' being found in the popular game Gears of War (Cliff Bleszinski et al., 2006). This is integral to future work in this field as it demonstrates that a player's in-game behaviour can be analysed to give an accurate model of their personality or preferences. In support of this idea, Bontchev et al. (2018) highlighted the importance of identifying a player's playing style in order to understand and cater experiences towards them. It was recognized that there are four main playing styles that act as a two dimensional spectrum in which all players reside, these extremes are: Competitor, Dreamer, Logician and Strategist. These styles were derived from Kolb's experiential learning theory, as this publications context of study was an educational game. However, these styles can be reflected in the wider gaming context as they depict how a person interacts and understands the world around them. To this end, Bontchev et al. (2018) verified the consistency of these playing styles through a large questionnaire wherein each of these styles were identified.

2.5 Genetic Algorithms

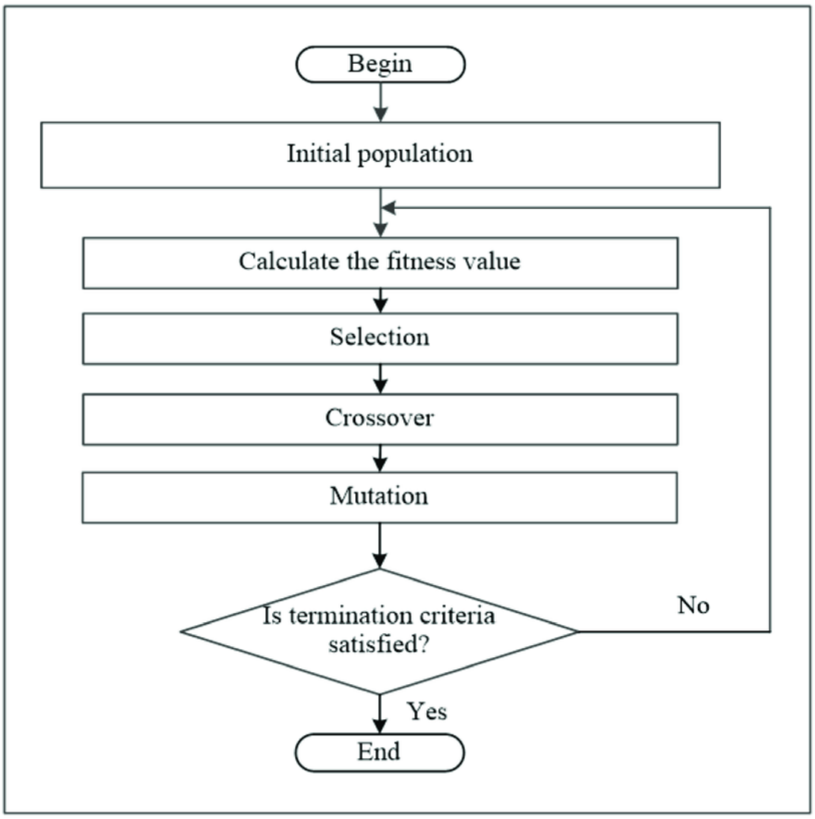

Figure 2.9: Flowchart of the standard genetic algorithm (Albadr et al., 2020, Figure 1)

Genetic algorithms are a type of generation algorithm that mimics the real-world process of evolution in order to generate solutions to a given problem. As demonstrated in Fig. 2.9, these algorithms follow a process of creating a population pool of possible solutions, assessing which solution is the best and then using the best solutions as a blueprint to create the next population (Mirjalili (2019), Albadr et al. (2020)). The solutions are usually named “members” of the population in reference to the biological counterpart. The members of the population are characterised by being a combination of genes, often represented as an array, that all work in conjunction with one another to produce a result. For example, if one was writing a genetic algorithm to generate a particular sentence, the sentence as a whole would be the population member with each character being a gene of that member. This array of genes is sometimes referred to as its genotype or DNA and specifically describes what characteristics that member can express. In some implementations, the genotype is different from the resulting physical expression of that population member. Different versions of one particular gene are referred to as its alleles. In the sentence generation example, the gene could be the first letter of the sentence, which would have 26 alleles of different letters it could be. A population member’s physical representation, or phenotype, is the resulting physical characteristics as dictated by the genotype. For example, if there was a system that generated colours, the genotype could be the hexadecimal value and the phenotype would be the resulting colour. The genetic algorithm itself simply manipulates this genotype, with a phenotype being implemented on a subjective basis if the use case calls for it.

The key characteristics that set genetic algorithms apart from random generation is the fitness function, mutation and crossover. The fitness function is how one defines the goal of the genetic algorithm; and more specifically acts as the assessor to determine how effective a given population member is at solving the intended problem. For example, if the goal of the genetic algorithm was to generate a sentence, the fitness function could take in a given population member (a sentence) and output how many characters are correct in that sentence. This allows for each member of the population member to be given a rating for how well they solve the given problem. This then leads into another important aspect of genetic algorithms which is crossover. This sees the two members with the highest fitness ratings being used to generate the following generation, with their genotypes being crossed over to create 'children'. When creating the next generation, a population members genes are randomly selected to be from either parent, as the parents have been evaluated as the best solutions from the previous generation. During this process, there is a small chance for a gene to be selected at random, not inheriting from either parent. This is called mutation, and is an important component as it allows for genes that were not present in the previous population to spontaneously appear. These newly introduced genes could result in better resulting population members and removes the possibility that the algorithm would not be able to find a good solution. This prevents an issue wherein specific genes that were not present in the first generation may never appear in subsequent generations.

Figure 2.10: GAR Gameplay Screenshot (E. J. Hastings et al., 2009, Figure 4)

These algorithms have been applied to Procedural Content Generation (PCG) solutions in video games. The most applicable example of this for this project is Galactic Arms Race (GAR) (E. Hastings & Stanley, 2010). This has been a foundational project for this one and saw an implementation of genetic algorithm based weapon generation for preference based weapons. An online multiplayer game prototype (see Fig. 2.10) was created as a part of this project and featured particle based weapons that evolved to suit a player's preferences. The genotype that was evolved in this project was the movement pattern of each projectile once it had been fired by the player. This produced many unique behaviour patterns and facilitated different player preferences. This implementation used usage statistics from each player to inform them of which weapons were preferred, and used that in place of a fitness function when determining the best parents to be crossed over when generating the new population.

A popular avenue for investigation has been into the generation of levels and puzzles using genetic algorithms to verify their integrity and to overall increase their quality. Pereira et al. (2021) investigated the ability of a genetic algorithm to evolve locked door dungeons in a 2D game. The algorithm manipulated and generated tree structure representations of dungeons until a valid configuration was found. These maps were then validated by playtesters who were unaware of the fact that the levels were computer generated and scored these levels higher than those that were handmade. Similarly to this, Viana et al. (2022) investigated the use of a two population genetic algorithm system to generate dungeon levels with barrier mechanics that impeded the player. Each time a level was generated a feasible (able to be completed) and an infeasible (unable to be completed) level is generated, with each evolving and adapting over time until they overlap. The feasible level aims to maximise the distribution of different rooms to promote exploration and the infeasible level aims to limit these aspects, once an overlap has been discovered it is used for the game. The result of this process is a level that can be completed but also features the maximum amount of exploration options for the player to play through.

Up until this point, a common problem was evident in that a genetic algorithm required a large number of iterations before an effective strategy could be found. Kop et al. (2015) posited a solution to this problem with the incorporation of an Artificial Intelligence (AI) technique, evolutionary or genetic scripting as well as reinforcement learning. This system allowed the agent to create effective strategies much quicker by leveraging the accurate adaptation from evolutionary scripting. The inclusion of these techniques was shown to resolve these issues and to accurately (and efficiently) prioritize rules from a fixed rule-base to be used by the AI agent. Furthering the idea of adapting AI opponents in games, Ripamonti et al. (2021) generalised and packaged a development ready approach for generating 'monsters' for a digital game. Entitled DRAGON (Diversity Regulated Adaptive Generator ONline) (Ripamonti et al., 2021), this system utilises a similar evolutionary/genetic approach to monster generation where a population of monsters is evaluated against a player preference based fitness function. As with all evolutionary programming solutions, the focus is on the quality of the fitness function as this informs the system of the target that needs to be reached. Ripamonti et al. (2021) demonstrated that this system was effective given a high quality of subjective fitness function that accurately informs the system of the player's preference towards any given monster. This implementation also exhibits online adaptation which means that the preference estimation and adaptation occurs during run-time (whilst the player is playing the game) rather than occurring during development time in order to create static assets for the final game (offline adaptation). This was further proven to be desirable in systems like these, as the adaptation algorithm can specifically respond to the player currently playing at the time, rather than attempting to predict the preference of future players that may play the game; which would require a level of domain knowledge that work in this field is trying to limit.

Much work has been performed in the adaptation of AI agents, which highlights the online adaptation of digital game spaces and objectives as an area meriting further investigation. Lara-Cabrera et al. (2014) has performed some work in this space, comparing different PCG algorithms for generating game levels for an Real-time Strategy game with the intent of creating both balanced and dynamic levels. The output of this work implemented a self-adaptive evolutionary algorithm that optimises a randomly generated map over time towards this end. It was shown that a system like this outperformed traditional handcrafted levels in both quality and development time, but also demonstrated an ability to 'over-fit' towards having balanced levels; resulting in a level wherein players could not reach each other, resulting in no winning or losing and therefore technically perfect game balance. This work further reinforces the importance of a well-defined fitness function for any implementation featuring evolutionary or genetic systems.

2.6 Game Item Generation

In a lot of games there is the idea of items or some form of progressive scaling of character power over time. With systems like these there have been different solutions for how these items are provided to the player, including when, where and how items (and therefore player power) become available. The most popular way for item loot systems to be implemented is using a technique termed for the thesis as Restricted Random Loot Table, in this case 'Loot' refers to in-game items that can be made available to the player. A system like this sees the creation of loot tables (see example in Table 2.1) that are applied to a certain loot source and is sampled whenever items should be produced. For example, an enemy in a game can be a source of loot that produces items when it is defeated. Which items are produced and in what quantity is dictated by the loot table assigned to that enemy. In the example given in Table 2.1 this particular enemy has a 50% chance to drop one or two health potions (quantity selected randomly) upon being defeated. This system is used in primarily in the Role-Playing Game (RPG) genre, such as in the Elder Scrolls Series (Bethesda Game Studios, 1994) and World of Warcraft (WoW) (Blizzard Entertainment, 2004).

Table 2.1: Example Loot Table

Item	Quantity Range	Drop Chance
Health Potion	1-2	50%
Gold Coins	10-20	50%
Normal Boots	1	25%
Legendary Sword	1	0.01%

This system allows developers full control over the availability of items in their game, by being able to dictate what is possible for players to obtain and at what rarity should those items be acquired. Each loot source in games like these refers to one loot table, but a loot table can be applied to many different loot sources. The in-game placement of these loot sources become a tool for the developers to dictate the pace of a game, and allow for full control over when and how players can attain item. This idea can be further extended by guaranteeing certain items for the player to obtain by applying a loot table with a single item at a 100% to be chosen. This is usually done when the item concerned is integral to the story or core mechanics of the game; resulting in there being a method to guarantee the acquisition of a certain item with no random chance of failing.

These restricted random loot tables are simply a method to select the items to be provided to the player, the statistics and parameters that govern the quality or function of these items can sometimes be generated at runtime. In most incarnations (namely in WoW, (Blizzard Entertainment, 2004)), this takes the form of each parameter for an item having a developer determined minimum and maximum which is randomly selected between when an item is generated. This PCG technique adds an additional level of random chance to each item wherein players receiving the same item could have a 'better' or 'worse' version of it. A difference between duplicate items gives some value to repeated results, whilst not punishing players that get a bad given value. No matter what the resulting parameters are for each item, the function remains the same and depending on the given minimum and maximum may or may not significantly effect the item quality. However, this does not increase the variety of items it simply introduces many small variations in existing items; remaining to rely on developers to introduce diversity and variety in the item system.

Figure 2.11: Borderlands 1: Shotgun Weapon Type Components (Gearbox Software, 2009)

Another common incarnation of PCG is the random selection of developer defined and created components to collectively result in a new output. An example of this is the reward system in the popular games franchise 'Borderlands' Gearbox Software (2009) wherein the weapons granted to the player consist of many different components, randomly chosen and combined to form the overall item. These components include but are not limited to: item rarity, weapon type, scope, magazine, manufacturer, abilities, elements, and attributes. More specifically, each weapon's statistics are derived from more modular components; these are the weapon's body, grip, magazine, barrel, sight and accessory (see Fig. 2.11). Systems like these randomly select components from a large pool of possibilities and pieces them together to result in the eventual output, which artificially increases the amount of content in the game simply by the vast quantity of possible combinations.

2.7 Discussion

Experience Driven Procedural Content Generation (EDPCG) is a field that is been rapidly expanding, founded on the motivation to extend the life-cycle of digital games by leveraging their interactive nature to adapt specifically to the player. Each different instance of systems like these all consist of two halves in one form or another, first the system must form an estimation of the player based on data automatically collected, then the system must compare this player model to both the current state of the game and the developer's vision in order to then adapt the experience. In its most basic form, Dynamic Difficulty Adjustment (DDA), the system first estimates the skill level or game-play aptitude of the player, then compares the identified skill heuristic against the desired difficulty level set out by the developer, then finally adapts the difficulty of the game to bring the player's skill level closer to the intended difficulty level. Each of the components of EDPCG systems warrant targeted research seeing as they are inherently complex.

Preference Classification, the first EDPCG system step, exhibits complexity as it aims to objectify a subjective concept; it aims to take a person's likes, dislikes or interests and categorise them into matrices or tables. This estimation can range from determining the skill level of the player (DDA Systems) to aiming to accurately predict the content that a user would enjoy consuming. Traditional algorithms for achieving the latter, such as Matrix Factorisation, rely on large data sets and extended interaction from the user in order to gain a better understanding of the things they enjoy. This has its benefits, as more accurate persona depictions (and therefore content recommendations) can be made, however, it also requires an extensive time period prior to achieving this comprehensive and data-driven model of the user. Approaches have been made to alleviate the large data requirement, through tools such as Archetypal Analysis which put more value on early data points that do rely on user assumptions but have been proven to be effective at constructing accurate empirical personas with little data. Regardless of the technology or technique that is used to classify the preferences, personality or interests of the user, the benefit is becomes evident in how that is acted upon.

EDPCG uses the estimated and classified personal features as the input for a generative content algorithm. The way these function and the outputs they provide are entirely subjective to the use case, thus requiring bespoke innovation in each context without a 'one size fits all' type solution. These PCG algorithms have become more popular in modern times as they aim to replace some of the content development time through the automatic generation of game components either prior to release or during run-time (whilst the player is playing or loading the game experience). Any of the features of games can be procedurally generated, but research has been split into two categories: generating the tangible and visual spaces or elements of a game (such as the level, items, enemies, aesthetics), and generating the abstract rules that govern how a game is played (such as missions, objectives or constraints placed upon a game). Despite the target of procedural generation, each of these systems has to overcome the eventual problem of content repetition. Traditional PCG systems are intrinsically required to produce similar outputs so that developers can ensure that the output results in a coherent play experience for the user.

This has been a main focus of research in the field of PCG, aiming to determine generative solutions that are random enough to keep players engaged (i.e. not viewing and playing similar content over and over again) whilst also making sure that the end result is playable, coherent and overall exhibits assured quality. These innovative solutions all take inspiration from the design process that game developers enter into when creating each component of games. For generative space algorithms, grammar-based graph rewriting systems appear to be the most holistic solution to this problem. This technique is defined by the definition of nodes and connections visualised as a graph, that is representative of a conceptual game level layout. The starting point, or axiom, is then acted upon by rewriting rules that replace patterns with different patterns, allowing for complex outputs to be constructed by simple rules. These rules also ensure a coherent and playable experience, whilst also providing organic and varied outputs to the user.

As identified in this chapter, there is a notable gap in the application of sophisticated preference classification algorithms as inputs to an advanced procedural content generation algorithm. A theoretical system that can achieve this would be able to construct digital game spaces that are specific and personalised to the player currently experiencing them. It can be strongly argued that game spaces are more pertinent towards a player's choice to remain engaged and immersed in an experience in comparison to the abstract concepts such as missions or objectives. However, with this inherent gain comes a large challenge of understanding how to automatically link these two systems into a congruent result.

There has been a large amount of research, development and industry validation surrounding the generation of game content that specifically adheres to the player's preferences. These techniques fall under the concept of EDPCG and require two core parts to function, the identification of player preferences and the subsequent generation of applicable solutions. As investigated in the game Galactic Arms Race (GAR) (E. Hastings & Stanley, 2010), genetic algorithms can function as accurate methods to estimate a player's preferences over time in order to generate weapons that conform to their observed gameplay style. An overlap between ideas brought up in the wider field of Preference Classification and evolutionary algorithms could produce quicker and more accurate results and serves as an area that could be investigated. Further, the application of evolutionary algorithms towards preference classification has not been fully explored with gaps present in the use of this concept in game genres other than that of GAR.

2.8 Identified Gaps & Potential Solutions

After concluding this literature review of EDPCG, its effects, Preference Classification, Genetic Algorithms and Game Item Generation as a whole, there are some gaps in the current academic understanding that warrant further investigation. The most relevant gap for this project is the description of a more generalised solution for genetic algorithm driven preference based game item generation, beyond the context already established by GAR (E. Hastings & Stanley, 2010). Building on top of the findings in E. Hastings and Stanley (2010), there remains the following questions:

1. What would a system like this look like in a different game genre?
2. Could a system like this work in a single-player context, using data gathered only from one player?
3. What game features and algorithm features need to change to facilitate the use of this solution?
4. Does this solution remain effective given these context changes?

This project sets out to provide answers for these questions through the application and adaptation of the item generation system featured in GAR (E. Hastings & Stanley, 2010) within a First Person Shooter (FPS). To this end, given that this new context is single-player rather than online multi-player there requires a solution that can leverage the benefits of an evolutionary algorithm without the required population sizes and generation iterations. Such optimisations have yet to be explored, especially towards creating preference based outputs wherein the core of the algorithm revolves around the player and their interactions with the game.

Further, the effects on gameplay and the player experience of EDPCG solutions in traditional games has yet to be fully documented. EDPCG is still very niche in commercial games due to it still being a relatively novel concept, resulting in there being limited understanding on the way its use would change player opinion. This question will be partially explored in this project as the scope is limited to its application and effect on a stereotypical game in the First Person Shooter genre. To support this, opinions will be gathered in interviews with experiment participants on the theoretical application of this system on different genres. Different game genres are enjoyed by different audiences for different reasons, therefore a universal solution would be difficult to define. A further understanding of the effects of using this system in an FPS game would work towards defining key transferable concepts that could be used when applying this knowledge to a different game genre.

Finally, the final identified gap is the use of a more sophisticated preference classification or estimation technique in a digital game, for use in generating personalised content. This particular gap falls outside the scope for this project, but would be interesting to investigate in any future work in this field. Techniques such as Matrix Factorisation and Archetypal Analysis have been proven to be effective in different use cases for identifying what pieces of content a user prefers. This could be leveraged to generate or recommend content in a digital game that aligns with a player's preferences.

Chapter 3

Theorised Best Parent Optimisation: Design & Implementation

The main contribution of this thesis is the design of this algorithm, Theorised Best Parent Optimisation (TBPO). The concept behind this algorithm was conceptually inspired by a core idea behind Archetypal Analysis (Cutler and Breiman, 1994) wherein an individual's observed data is accentuated in order to estimate what archetype they fall under. This is an optimisation technique that has been used in the Preference Classification method of Matrix Factorization (Javadi and Montanari, 2020). As such, this idea could be applied to a genetic algorithm based generation strategy as an optimisation method. Genetic algorithms rely on large quantities, often thousands, of generations and population size in order to find the optimal gene sequence that fits a given fitness function. In applying a genetic algorithm to preference determinism in a First Person Shooter (FPS) game, it is very difficult to design for this quantity of generations nor population size. In this prototype (Section 3.2), there is one generation of weapons created each wave and only around 15-20 weapons per generation. This has been done so that the player can effectively operate as the fitness function in this algorithm. A player's actions in a game are a direct reflection of their personality (Poeller et al., 2018), and in this context their decisions with what weapons to use and how they use them directly control the fitness function. As such, a solution that allowed a player to effectively sort through the entire generated population without losing interest or becoming overwhelmed was required.

During initial investigation it was found that the component based weapons would fundamentally allow for a genetic algorithm based generation system, this will be expanded upon in section 3.2. During initial internal testing, with a few weapon components implemented, it was observed that players were showing preference towards items due to the presence of a small part of the weapon combination rather than its entirety. Players seemed to enjoy a weapon simply due to it being a particular weapon base type, or having a certain effect or behaving a certain way due to the present modifiers. This is decidedly different to organisms in traditional genetic algorithm solutions where the entire gene sequence is integral its validity and fitness. Treating the entire weapon as preferred may mislead the designed system to believe the player prefers parts of the weapon they may actually dislike. For this solution, there needed to be a way to decouple the gene sequences and attempt to determine which particular parts of each weapon the player prefers.

The following sections in this chapter will explore the algorithm design in isolation, before being adapted to a digital game prototype. For this particular solution there are key algorithm features that divert from a traditional genetic algorithm and key gameplay features that divert from a traditional FPS game, both sets of novel features are integral to the overall function of this solution. The primary purpose of the prototype created is to be used as an experimentation tool to validate the effectiveness of the algorithm described as it functions within the context of the game.

3.1 Algorithm Design

The foundation of this algorithm is, as the name implies, to construct a theoretically optimal parent to be used as one of the parents during the crossover process. This process applies in this context due to the component based weapon design being observed resulting in players preferring (and thus influencing the fitness of each weapon) weapons based on the presence of particular components. The purpose of this algorithm is, in part, to allow for a player's perceived favoured parts of a weapon to persist whilst the other components change. Over time as the player reaffirms their preference with each particular component of a weapon, the optimal configuration will be discovered.

3.1.1 Overview

The core of this algorithm follows the known process of genetic algorithm based generation, with the notable replacement of one parent during crossover with a theorised optimal parent. The construction of this theoretical parent comes about simply due to the prevalence of particular alleles (versions of a gene) in all weapons collected by the player. As described below, this parent's gene structure is determined a gene at a time, randomly picking from a list of all observed alleles of that type. The more a player chooses to use a certain weapon, the more often this allele will appear in the list and thus increase its likelihood of being selected as that gene's allele. This process if repeated for each gene in the sequence. This theoretical parent is then crossed over with an existing gene sequence that has been identified as having the highest fitness value. One critical genre deviation to identify before proceeding is how reloading functions in this game. Weapons reload very slowly and automatically only after it has run out of ammunition. This process can be sped up by the player going out of their way to interact with a reload station, to immediately use the weapon again. For the purposes of this paper, the metric 'Weapon reloaded' refers to these instances of manual reloading as opposed to the automatic process tracked by the 'Weapon clip emptied' metric.

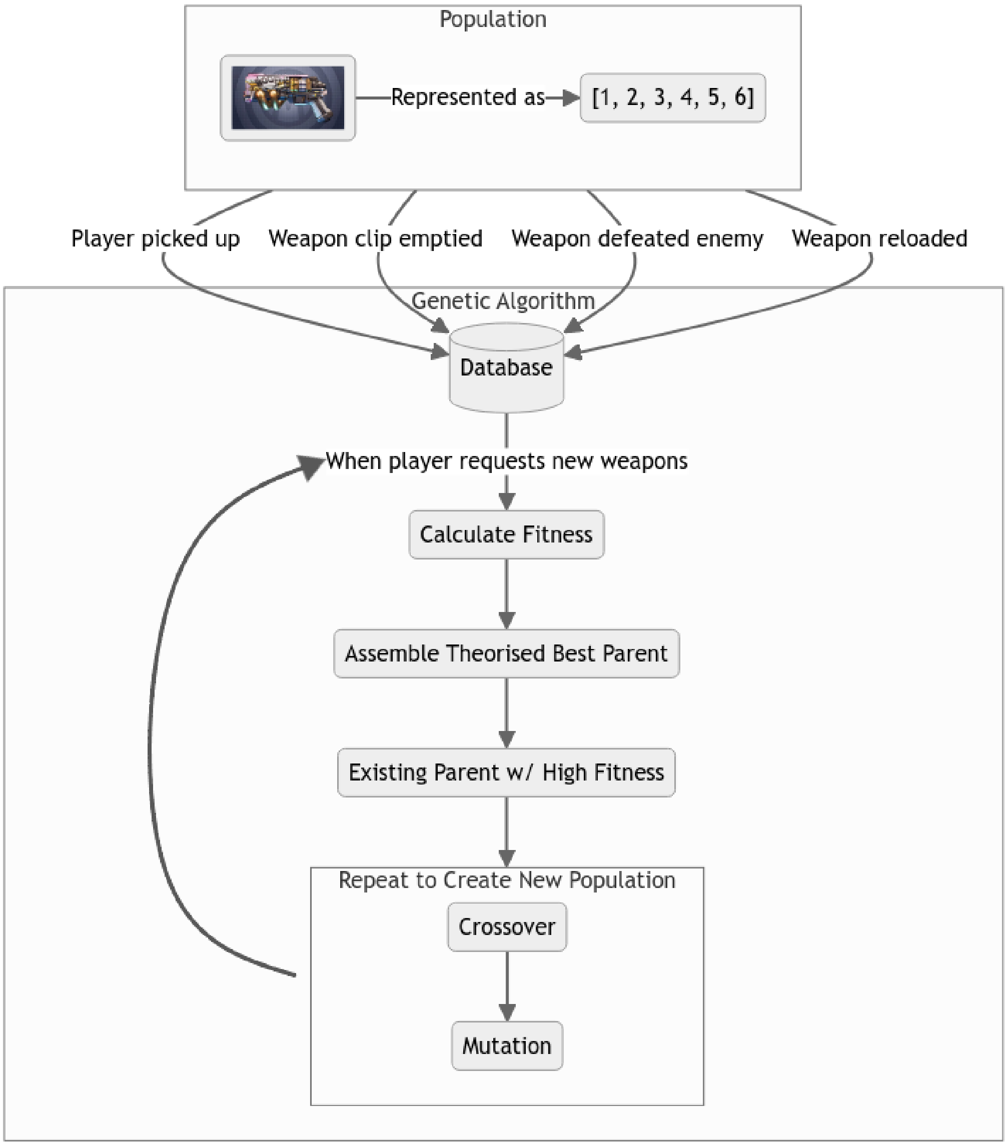

Figure 3.1: Theorised Best Parent Optimisation Process Diagram *(weapon graphic depicts TNTina from Borderlands 3)*

3.1.1.1 Algorithm Flow

The step by step explanation of the process found in Fig. 3.1 is as follows:

1. Each weapon is represented as an array of integers (Fig. 3.6), which each referring to a specific component of the corresponding type (Appendix A.1)

2. If there are insufficient data points, as specified by the developer, a random weapon is generated

3. Once a player picks up a weapon, it is entered into a database and its usage

is tracked. A weapon being picked up is the largest influence on its fitness as without being picked up it cannot be selected. This usage metrics collected are as follows:

   (a) Amount of times the weapon's clip has been emptied

   (b) Amount of times the weapon has defeated an enemy

   (c) Amount of times the weapon has been reloaded

4. If there are sufficient data points, each tracked weapon calculates its fitness by summing up the normalised values of each of its tracked metrics, see Fig. 3.2

5. For the first parent used in crossover, construct the gene sequence one gene at a time. For each gene, create an array of all alleles of that gene from each observed weapon in the database and choose randomly from that array. This will inherently give higher weight to alleles that are more common for that gene. Repeat this until a full genome sequence has been constructed consisting of the most popular alleles for each gene

6. Perform crossover using this created parent gene sequence and another parent selected from the database that has the highest fitness value, including a given mutation rate. Repeat this until the entire new generation of weapons has been generated

7. Assemble the phenotype representations of these weapons and present them to the player

$$\sum_{i=0}^{n} f(x_i)$$

$$f(x) = x/y$$

x = This object's metric

y = The maximum value of this metric from all objects in pool

n = The total number of metrics

Figure 3.2: Normalised Metric Fitness Formula

3.1.2 Minimum Data Points Threshold

Generating items that align with player's interests is a difficult task due to the subjective and dynamic nature of a player's interests. When a player plays a game for the first time, they enter into an exploratory period where they are rapidly familiarising themselves with the game and what they are capable of. This phase, sometimes referred to as the 'early game', is an extremely important period of time where variety and diversity is key. For the player to come to educated decisions regarding what they prefer in a game, they must first understand what their options are. Data collected during this phase may not be reflective of a player's preferences as they would be exploring different playstyles to observe how it makes them feel. Further an item recommendation and creation system such as this would not be effective until it has enough data points to make assumptions on what the player would like. Because of this, a minimum data point threshold was incorporated into this algorithm design. Until the player has equipped and used a defined number of weapons, all items would be generated completely randomly. This increases the chance that the player will be exposed to a weapon, or simply a particular component, that they prefer so that they can make more informed decisions as the game progresses. The quality of all player decisions, and therefore the fitness function of this genetic algorithm, hinges upon their fundamental understanding of what the game can offer.

3.1.3 Stacking Novelty Chance

As highlighted above, there is a large importance on the player's exploration of different playstyles and weapon loadouts. The minimum data point threshold partially solves this problem by addressing the early-game exploratory period but does not allow for flexibility past this threshold. Once this has been reached, the player's options will only further be restricted as they continue to be presented with similar items, removing some of their ability to explore different gameplay options as the game continues. One method to combat this is to incorporate a small chance for the algorithm to be skipped and a weapon to be generated completely randomly. This builds upon the idea of mutation that is already present in the genetic algorithm used for this project but allowing for the entire gene structure to be assembled randomly instead of a single gene. Mutation gives a genetic algorithm the ability for a potentially beneficial allele to become present in the population even if it was not present in the previous population; therefore this would only further allow for potentially beneficial combinations to be introduced to the population. As players continue playing a game and they become experienced using their selected weapons, they may want to change their playstyle to refresh the experience. Having a chance of generating a random weapon each generation allows for players to remain able to use a gene combination (weapon) that may not have been present in the previous population.

Given the importance of a function like this, affordances have been made to ensure that this happens consistently. The basis of this chance remains random, however every time that a weapon is generated and does not generate randomly, the novelty chance (chance to create a random weapon) increases by a given amount. When the novelty chance check succeeds and a random weapon is created, this chance is reset to its default value. This feature acts as a 'failsafe' to ensure that mutation will always occur as the chance for generating an entirely unique weapon increases until it does occur. This allows the developer to control how often this chance should be triggered, whilst also ensuring that it does eventually occur. For example, one could set the default novelty chance to a low number or zero and the novelty increment to a low number to promote the preference based algorithm and potentially only have few random weapons per generation. Incorporating this aims to cater towards the dynamic and subjective nature of a player's preferences as they change over the course of playing a game.

3.1.4 Required Context to Function

The core design of this algorithm, including its supplemental features, have been designed specifically for this use case; a preference based weapon generation system in a digital game. As such, this algorithm can only function properly given that specific context features are present in the game. The main defining contextual feature is that the output organism's (member produced by the genetic algorithm) fitness or aptitude should be hinged upon the presence of one or more genes rather than the sequence as a whole. The core of this theorised best parent optimisation is to allow for favoured genes to remain present in the population whilst the other genes in the combination change around them.

Another required contextual feature is that there are no outputs that are incorrect, wrong or otherwise unusable. The component based weapon grammar ensures that any weapon produced can function, with its fitness directly depending on the player experiencing it. Within this system, there are no objectively optimal outputs and each potential combination could theoretically be perfect for a particular player. As such, for this algorithm to function correctly, all outputs must be functional to some extent as to not deny potentially emergent playstyles. Further, incorrect or randomised outputs (in this context) could result in the player exploring a subjectively new playstyle that they enjoy. Diversity, exploration, creativity and flexibility are just as important as constructing the perfect item for a player, in this context.

This function of this algorithm assumes that the player is functioning in place of a fitness function, and as such the outputs need to be able to be easily envisioned and worked toward by the player. For example, in the case of an FPS game, the abilities of a generated item must be able to be easily identified and / or imagined. In this example, for the sake of the player being able to easily sort through a newly generated generation of weapons, each weapons' function must be able to be understood quickly and efficiently. Similar to any other fitness function optimisation strategies to speed up processing of genetic algorithms, any design techniques that allow for player to intuitively understand the function of a generated item speeds up the process of this algorithm. In this context, as the weapons function comes from a sequential application of its components, once the player understands a component in isolation they can intuitively understand how it would work in different combinations. Over time, the player will build a good understanding and only become quicker at sorting through new generations of weapons, thus the efficiency of the fitness function increases.

Finally, in this given iteration of the algorithm the assumption is that allele occurrence equals preference by the player. The theorised best parent is assembled using an iterative weighted random selection process to determine each gene in its sequence. This relies on the assumption that the more a player picks up and uses a weapon, the more they prefer those specific alleles. Potential, and more sophisticated, methods of determining preferred components will be discussed in Section 5.3, but in this algorithm's current iteration occurrence must equal preference.

3.2 Testbed Game Design

This project was intended to be built upon the work explored by E. Hastings and Stanley (2010) using their prototype 'Galactic Arms Race' (GAR), iterated upon and adapted to a First Person Shooter (FPS) genre. GAR first proposed their concept of generating weapons as the game is being played, using a technique they named Content-Generating Neuroevolution of Augmenting Topologies (cgNEAT). The intricacies of their algorithm implementation in comparison to this projects' has been discussed in Chapter 3.1. For the purposes of this thesis, GAR (E. Hastings & Stanley, 2010) will be used as an example, and a point of comparison to highlight the novelty of the Theorised Best Parent Optimisation (TBPO) approach as it is the most similar work currently available.

The game prototype for this project, titled “Bootstrapped”, was created to be at its core a standard game that conforms to many of the FPS stereotypes. The core gameplay loop revolves around the player attaining items in the form of various weapons, and using those weapons to combat seemingly endless waves of enemies. The primary purpose of this prototype was to be used as an experimental tool to test the effectiveness of the weapon generation algorithm, rather than to be released and distributed outside of this project. Within this context, the game was designed with emphasis on being intuitive to pick up and play quickly, engaging the player in the core loop quickly, and to allow the player to be exposed to many different weapons. The main design pressure that influenced these decisions was the condensed time frame in which the experiments were to be delivered. For the purposes of this project, it is planned that each participant would only play for 40 minutes maximum. As a result, the entire gameplay life cycle was stripped down so that the player could experience every part of the game within that time frame.

3.2.1 Game Description

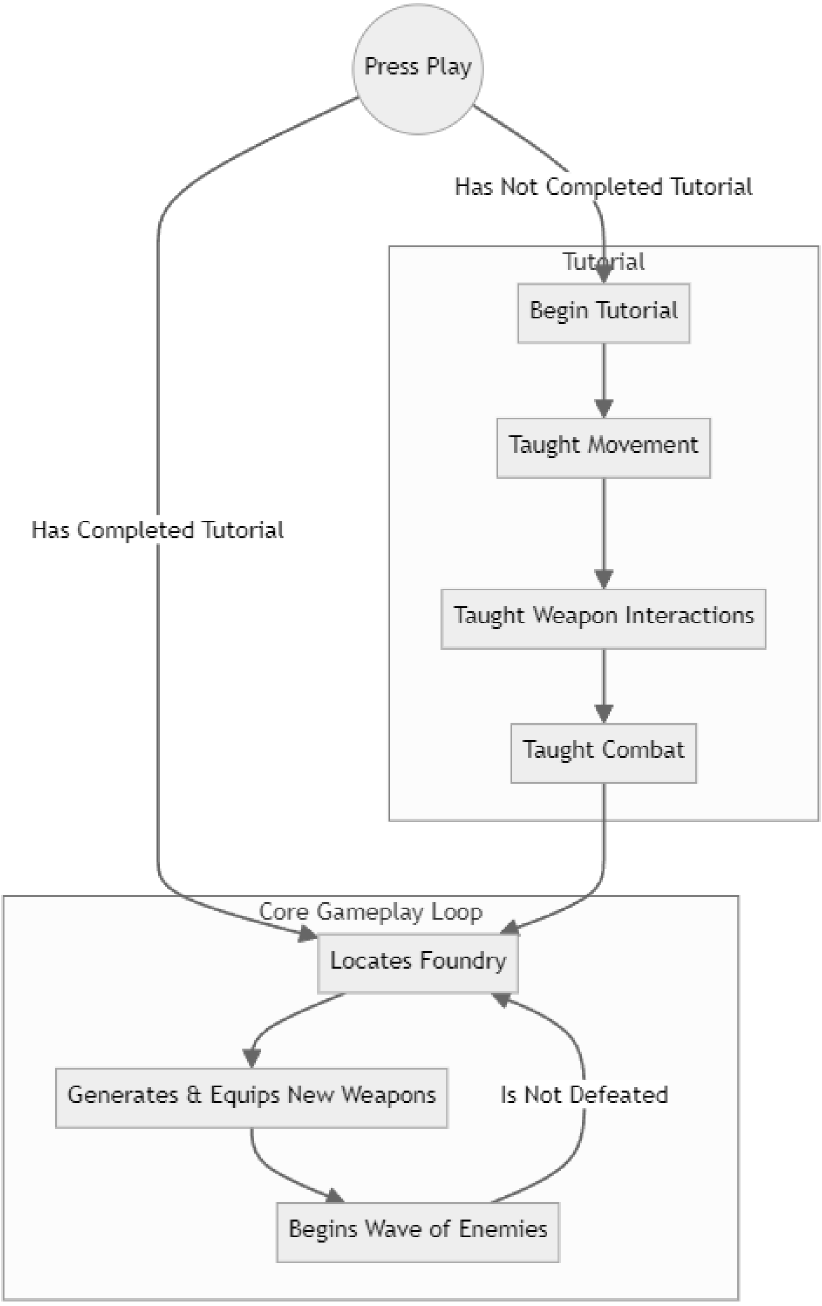

Figure 3.3: Game Prototype:"Bootstrapped", Gameplay Loop Diagram

As demonstrated in Fig. 3.3, the game prototype followed the traditional flow of first educating the player on specifics of playing the game through a tutorial, followed by the core game loop. Although the game does feature a tutorial, part of the inclusion criteria for this experiment stipulates that players must already have an understanding of how traditional FPS games are controlled and experienced. As mentioned previously, this prototype conforms closely to these genre stereotypes, allowing for the included tutorial to essentially serve to introduce the player to the new mechanics specific to this gameplay context. As shown in Fig. 3.4, this game uses a lot of design conventions from traditional FPS games to get new players up to speed quickly.

Figure 3.4: Game Prototype: “Bootstrapped”, Screenshot of Gameplay

To break down the formal elements of the gameplay prototype, the overall objective of the game is for the player to defeat all enemies in the given wave and progress onto the next wave. They are required to do this by picking up weapons they perceive as useful and/or enjoyable to defeat the increasing number of enemies in creative ways. If they do not defeat all the enemies and they are defeated themselves, they must restart the gameplay loop from the beginning. There are no other lose conditions for the game, the player may defeat the enemies however they would like. However, there is a built-in timer in each enemy that will cause them to destroy themselves after a fixed period of time; this is to ensure that the experimental session will be completed within a timely manner, see more about this in the below section. The procedure the player must follow consists of first generating and selecting from a range of weapons to use against the enemies, the player then triggers the beginning of the wave when desired. As mentioned previously, the only form of conflict in this game is the enemies combating the player, there are no timers or other lose conditions that the player is competing with. If the player defeats all enemies they win that round and begin the game loop again, there is no definitive end to the game and it can be played endlessly, infinitely increasing in difficulty.

3.2.2 Notable Design Characteristics

The vast majority of this game's design philosophy mirrors stereotypes of the First Person Shooter (FPS) genre. As mentioned previously this was done to speed up the skill acquisition process for new players, as part of the experiment inclusion criteria was experience with other FPS games. However, there are a few notable design choices that were made during the development of this prototype that move away from these stereotypes. These choices were made for a variety of reasons mainly centering on making the experience function better as a clinical experiment and simplifying the experience to allow for efficient mastery over the game mechanics. These choices are as follows:

1) Gameplay Loop Broken into Phases

The gameplay loop has been broken into a combat phase and a spending phase. During the combat phase, the player cannot get new weapons and must defeat all enemies with the weapons they have selected. This phase ends when the player has defeated all enemies. The spending phase is when the player uses all collected currency to generate weapons from the Foundry, and to select which weapons they would like to bring into the next wave. This phase is ended when the player triggers the next wave.

This distinction has been made so that the player has time to sort through and select which weapons they would like to use for the next wave, without the pressure of fighting off enemies at the same time. This allows the player to make much more educated and thoughtful decisions on the weapons they use, resulting in better tracked metrics and therefore better overall weapon recommendations. Overall, this choice lets the player focus on the task at hand and removes the overhead of multitasking.

2) Player Triggers Enemy Waves

For the next wave to begin, the player must manually trigger it to occur. This has been decided so that the player is able to elect when they are ready and prepared to begin the next wave of enemies. This allows players as much time as required for them to get their weapon selection ready, and to mentally prepare to face enemies. This is integral to the overall function of the algorithm as the player's decisions essentially are the fitness function for this genetic algorithm. If the player makes better, more educated and thought out decisions, the algorithm can make better inferences as to their preferences. This feature is integral to ensure that the data collected and acted upon is of the highest quality possible.

3) Hold Multiple Weapons at Once

Due to the complexity of the weapons generated in this game, they tend to have very niche use cases or otherwise lack some of the functionality provided by other weapons. This has been done intentionally so that there are a diverse range of options for a wide range players to be able to find something they enjoy. To somewhat avoid players having to make difficult decisions in the case that they come across multiple preferred weapons, the player is able to hold up to three different weapons. One weapon can be active at a time, but the player is able to quickly switch between any held weapons during gameplay. As described, this has been done for gameplay reasons but it also provides the generation algorithm with more data to construct preference based weapons. The generation algorithm takes into account which weapons the player uses and how they use them to interact with the game, allowing the player to do this simultaneously with multiple weapons allows more data points quicker than only allowing one weapon to be used at a time.

4) Weapons are Generated by the Foundry

The only way the player can generate more weapons to be used is by interacting with the Foundry, which is located at the centre of the map near where the player spawns. This has been decided so that all generated weapons are located in the same place, at the same time allowing the player to more easily sort through all weapons and select the ones they want to use. From an algorithm design point of view, this also mimics the population pool of traditional genetic algorithms rather than generating one weapon at a time.

5) Weapons Can't be Frequently Reloaded

This design choice was both difficult and important. Weapon reloading is an integral part of many games within the First Person Shooter genre, therefore the removal of that constitutes a removal of a core foundational feature. The way that reloading functions in this game is that all weapons slowly reload after all ammunition has been exhausted, or when the player interacts with reload stations around the map. This was done to encourage play style exploration, and to make the use of a weapon more strategic. With the weapon only allowing for a limited amount of consistent uses, the player must choose wisely when and where to use them. Further, this inclusion adds meaning to duplicate generated weapons as it now represents more uses of a favoured weapon. This design choice promotes play style exploration (which is fundamental to the aim of this project), suppresses the impact of potential over-fitting, creates an inherently more strategic gameplay loop and adds to the overall mood of the game.

6) Large, Static Map Design

As this game has been designed to function in an experiment, all variables that could be controlled have been controlled. One notable distinction of this is the level design of the main game level the players spend the most time in does not change. At the beginning of this project, the levels were randomly generated in order to retain a sense of exploration and to keep things renewed over the course of the experiment. This was changed to a static design to keep gameplay variables the same between different participants and between different gameplay sessions of the same participant. A particularly 'good' or 'bad' generated level may incorrectly skew the results observing the player experience.

7) Built In Enemy Expiry Timer

This was implemented into the game for two reasons, error prevention and experiment timeliness. The system used for the enemy navigation in the game was Unity's built-in NavMesh system which is prone to bugs when random enemy placement is used. As a result some enemies would be spawned in places unreachable by the player resulting in a soft-lock state wherein the player would not be able to complete the wave and would have to restart the game. This, combined with wanting to ensure that each experiment would complete in a timely manner regardless of player skill, resulted in this feature being added. The way this functioned was that each enemy begins a timer when they are spawned into the game and once it expires, they are automatically defeated.

8) All Weapons Firing Physics-Based Projectiles

This project builds upon the work of Galactic Arms Race (GAR, IJsselsteijn et al., 2013), in this game the pattern that each projectile follows when fired is evolved to create different behaviours in discovered weapons. Using this as a foundation, the projectiles in this game prototype are entirely physics based and use the modifiers to alter their behaviour in unique ways. Each projectile modifier either applied different forces to the projectile, altered the size, the final damage that the projectile did, or otherwise changed some parameter of the projectile. As a result, with each modifier being applied sequentially, each modifier would be able to function entirely independent of the presence of other modifiers - thus avoiding potential errors or cases where modifiers would not work in conjunction with one another . This is a notable departure from traditional FPS games wherein the majority of weapons have instantaneous (or almost) travel times on their projectiles. This was an important distinction to make in this project so that any number of projectile modifiers could be created with the knowledge that each could influence the rigid-body physics in combination with any other. For example, if the modifiers placed on the projectiles increased its speed, moved it upwards or towards something, it would all be able to function in conjunction with each-other as they each simply apply a specific force to the projectile. This is just one example of how the projectile modifiers can modify behaviour, having them be physics based intrinsically allowed for this.

3.2.3 Component Based Weapon Design

One of the use case features required by a genetic algorithm is the ability to represent the output being generated as a string of numbers that form the virtual DNA that is used for evolution. These DNA strings are what is actually used for generation, with all algorithmic manipulation and mutation changing what numbers are in each position. This representation is called the population member's (in this context, item's) genotype which is then translated into a corresponding physical representation known as its phenotype. See Fig. 3.5 for an example for how one generation of weapons is presented to the player in the created game prototype, mimicking genre stereotypes of items being dropped on the ground.

Figure 3.5: Game Prototype: "Bootstrapped", One Generation of Weapons

For this prototype, the desired outputs are various weapons to be used by the player. In this context, the weapon itself is the phenotype and has been constructed based on a genotype. Each of the integers in the weapon's genotype sequence represents a different aspect of the weapon to be constructed, as described in Fig. 3.6 and these are then presented to the player as shown in Fig. 3.7. For a brief list of each component available to each weapon, see Table 3.1, a more detailed description of each component can be found in Appendix A.1. When a weapon is generated, either using a random generation method or this project's bespoke generation, all that is created and manipulated is the weapon's genome sequence. This is then used as the blueprint to produce the resulting weapon with the specified components and behaviour, combining each component in the sequence defined by this genotype; creating the weapon's phenotype.

Table 3.1: Game Prototype: "Bootstrapped", Weapon Component Summary (for more, see Appendix A.1)

Base	Effect	Additive Delay	Modifier Count	Modifier		
Pistol	Fire	0s	1	Anti Grav	Bouncy	Condense
Shotgun	Knockback	0.25s	2	Curve	Expand	Explosive
Sniper Rifle	Magnetize	0.5s	3	Featherweight	Frictionless	Heavyweight
Submachine Gun	Weapon Jam	0.75s	4	Homing	Lob	Orbital
Machine Gun	Fear	1s		Piercing	Platform	Preserved
	Ice			Rebound	Snowball	Spiral
				Sticky	Velocity Boost	Volatile

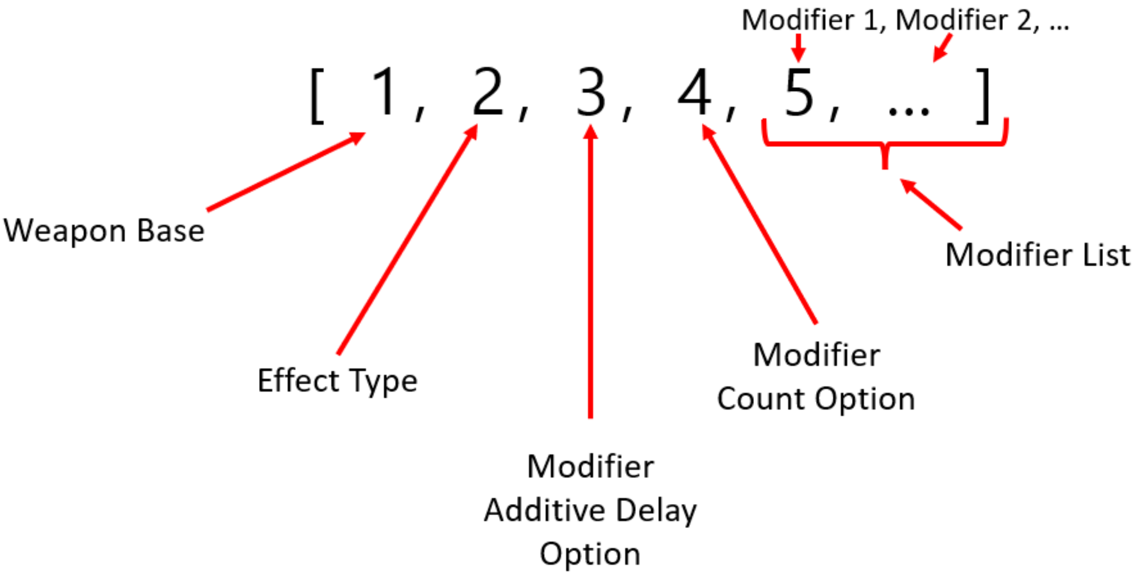

Figure 3.6: Game Prototype: "Bootstrapped", Weapon Genome Description

Figure 3.7: Game Prototype: "Bootstrapped", Weapon Component Presentation

This weapon design was inspired by how weapons functioned and evolved in Galactic Arms Race (E. Hastings and Stanley, 2010), where the each weapon's points of difference came about due to how their projectiles moved and behaved. In GAR, the movement pattern of the projectiles were the target of their evolutionary algorithm (cgNEAT), and the flexibility of this system resulted in extremely varied behaviour and therefore use cases for each generated weapon. This served as some of the inspiration behind the modularity of Bootstrapped's weapons as a system like this could not only leverage a genetic algorithm but also produce sufficiently varied content. In adapting this to an FPS options were explored that mirrored the component attachment system in popular shooter games such as Call of Duty series (Treyarch et al., 2003), Battlefield series (DICE and Johan Persson, 2002), Fallout series (Tim Cain et al., 1997), and the Borderlands series (Gearbox Software, 2009).

This was important from a design point of view as it enabled players to quickly understand how each component operates in isolation, facilitating an intuitive ability to imagine how components could function together in unseen combinations. For example, if the player understands how the 'Knockback' weapon effect type functions it can be assumed how it would function when applied to a different base weapon type; despite the player not being explicitly exposed to this combination. This quality is intended to foster the creativity of the player, discovering different components and intuitively understanding the potential of different weapon combinations. As the core of the preference based generation system revolves around how the player uses and interacts with weapons (see Chapter 3.1), it was important for players to understand how weapons functioned without needing to equip and test them. Once the player becomes familiar with what weapon combinations are available, it is planned for them to only pick up and use desired items; thus further influencing the preference estimation.

The overall design of which the weapons were assembled and functioned follows a grammar based method. This method ensures that any generated combination of weapon components will result in a functioning item. As each base weapon type works with each effect type, additive delay option, etc. there are no possibilities in which a non-functional weapon could be created. This aids the project in error prevention and allowing for emergent playstyles to come about as a result of a combination of components that was not initially designed for. This promotes the games ability to cater to previously unknown playstyles, broadening the scope of players that will find a preferred weapon in this game,

Further, this fundamental design of the weapons allowed a genetic algorithm (or a similar algorithm in the case of this project) to be applied to this game prototype. Traditional FPS games that treat weapons as whole packages would not be able to incorporate a genetic algorithm to generate them. As a genetic algorithm operates entirely on the manipulation of an array of numbers, the weapons required to be able to be represented as such. This allowed for some compartmentalisation of complexity as all generative algorithms were concerned about were the gene sequences of each weapon rather than their specific phenotypic representations (weapon base type, effect type, etc.). This allowed various generation techniques to be easily incorporated and built upon.

Another benefit of this type of weapon design is the ease of which new components can be developed and integrated into the game prototype. Each of the components can be essentially designed in isolation, with the development team ensuring that it functions properly in isolation. Once this has been confirmed, it is almost guaranteed that it will function in unique and interesting ways when combined with other components. This is a direct result of how the weapons themselves operate, with each component affecting each subsequent one when a weapon is used. The weapon base type influences how many projectiles are fired, how frequently and how much base damage they do. The projectile modifiers then influence the behaviour of the projectile once they have been applied (given the additive delay), and then they simply apply the given effect type to any enemies collided with. This effect then performs a defined function on the enemy once applied. This logical flow of component activation allows for the functions of widely diverse weapons to remain predictable and emergent, even when new combinations are discovered.

Finally, to justify the use of an algorithm like this there needs to be a large sample size of possible weapons to be found. If there were a small number of possible weapons, the player would easily be able to discover all options and select the one they prefer without the need for a preference based generation algorithm; random generation would suffice. Weapons generated using this methodology incorporate a huge variety of options, promoting playstyle variety and creativity but making it impossible for a player to sort through all possible options. As the project currently stands, there are 30,630,600 possible combinations of weapons (see Fig. 3.8 for formula) given the following parameters: 5 weapon base options, 6 effect type options, 21 projectile modifier options, 5 additive delay options and 4 modifier count options. The addition of any new component in this game's weapon system results in a substantial increase in options available to the player, allowing for an exponential increase in playstyles catered for with more component development.

$$(n_w * n_e * n_d) * \sum_{i=1}^{n_c} n_m^i$$

n_w = The amount of weapon base options

n_e = The amount of effect type options

n_m = The amount of projectile modifier options

n_d = The amount of additive delay options

n_c = The amount of modifier count options

Figure 3.8: Possible Weapon Combination Count Formula

For this prototype, it was important to use tools that provided the right amount of both structure and flexibility to quickly implement a standard FPS game whilst also being able to develop the experimental item generation. To this end, the Unity game engine was chosen due to its approachability and ease of development experience. Whilst this engine was used, various development tools were imported and created to facilitate development, these included level design tools, data structure editing tools and input system tools. The entirety of the game, including some of the listed tools, were developed primarily using the C# programming language using the VS Code text editor.

3.2.4 In-Game Data Collection

As a part of the EDPCG weapon generation system, there were a number of metrics that had to be recorded (see Chapter 3.1) regarding how the player interacts with the game. As a result the game leveraged an event driven design pattern to record a variety of different player actions to be used for the weapon generation and to act as an event log for further analysis. All recorded events were logged and saved locally in a .CSV file. This was created automatically and saved only on the computer that was running the game during the experiment. The file's title is the ID of the participant currently playing and it contains a record of events that have occurred during that particular playing session.

This was incorporated as part of the prototype primarily as a bug detection tool, and secondarily as a means to go back and piece together a player experience if anything highly notable occurred. As this game remains in its prototype phase, it was important to have a record of in-game events in the case that an error occurs so that it can be found and resolved.

3.3 Initial Empirical Evaluations

During the development process of this game prototype there was some internal, white-box, testing that occurred to ensure the quality of the game was sufficient for an experiment. Following this, as experiments began to take place, there were some parts of the game and parameters of the generation algorithm that changed. These changes were the direct result of feedback from the participants and observations by the researcher present. All changes were made following consultation with the project team and each new version was exposed to a different group of participants (see Fig. 4.2 for the breakdown of which participants played each version of the game). These changes were not only incorporated to facilitate smoother and more manageable experiments, but to also aid in answering the RQ1.1 of this project. This question aims to determine which parameters of the algorithm, and context features of a game would work the best together to produce the most optimal results. Each distinct version of the prototype, entitled defining the difference compared to the original version, are as follows:

Version 1) Original, Untested by Participants

This is the original game version as described and shown in this Chapter, and uses the corresponding parameters in Table 3.2.

Version 2) Playtime Reduced, Mutation and Novelty Chance Increased

The first two experimental sessions resulted in a number of minor changes to the game prototype and the parameters used in the algorithm. Some of these changes revolved around minor bug fixes to ensure that the game progressed smoothly and there were no issues during the experimental session. There were some parts of the game where participants needed to restart the process, so these were either removed or amended to prevent this from happening in future sessions. The main change in this version came from the decrease to the gameplay time, and the reduction of both mutation and novelty chances. The playtime resulted from the first two experiments running overtime, limiting the amount of time remaining to properly conduct the interview. As a result, the duration of each gameplay session was reduced from 15 minutes to 10 minutes. Further, it was reported by participants that they felt the weapons were not specific enough to their playstyle resulting in the reduction of the mutation and novelty chances. The novelty chance was reduced to zero with a slight increase to the novelty increment resulting in behaviour that would guarantee preference based weapons to be generated before introducing a chance of random weapons.

Version 3) Complexity Reduced, Playtime Reduced, Mutation and Novelty Chance Increased

Over the course of the majority of experimental sessions, it was observed and reported by participants that they did not feel like they had enough time to understand the options available to them in the game. As a result, in addition to the changes in Version 2, the amount of modifiers a weapon could potentially have was reduced. This was done to reduce the amount of weapon options available to the player in the hopes that they would be able to more easily experience or otherwise intuitively understand the options available to them; thus being able to make more informed decisions without a similar increase in playing time.

Table 3.2: Changed Parameters for Each Game Version

Version	Mutation Rate	Min. Data Points	Novelty Chance	Novelty Increment	Modifier Amt.	Session Length
1	20%	10	10%	10%	4	15
2	25%	10	0%	15%	4	10
3	30%	10	25%	10%	2	10

3.4 Working Towards a Validation

As this prototype is the primary tool for evaluating the experimental algorithm, it has been specifically designed to provide insight into this project's research questions (see Section 1.2). This prototype has been designed so that various generation methods can be swapped in and out in order to identify differences between traditional random item generation and TBPO generation; as well as allowing for different generation parameters to be easily changed. This quality of the prototype directly allows for all of the research questions to be explored and discussed.

RQ1 has been explored throughout this chapter as innovations have been made on both traditional genetic algorithms and FPS game genre stereotypes. RQ1.1 has been facilitated by the prototype design allowing for different parameters of the TBPO solution to be tested in order to determine which set results in the most positive feedback from users. Finally, RQ2 can be explored as the game automatically switches between a random generation method and the bespoke TBPO generation method over the course of the experimental session. The following chapter will discuss how an experimental session was constructed around this prototype, including all methodology conducted, results gathered and conclusions drawn.

Chapter 4

Assessing Prototype Validity & Algorithm Outcomes

The basis of this project is aiming to improve the in-game experience of constructing a specific game playing style from found items, comparing traditional methods to this project's targeted item generation techniques. As discussed in Chapter 3.2, the prototype was created so that different item generation techniques could be swapped in and out depending on developer defined requirements; allowing the player to directly test the exact same game using either traditional (random) item generation or this project's bespoke item generation. This allowed all other variables within the game itself to be controlled with only the generation methods dynamically changing, thus any notable differences in player opinion can most likely be attributed to the different generation methods.

4.1 Recruitment

This project's intended effects on the game experience are not limited to a specific niche of game player. However, for the purposes of this experiment, participants were required to meet certain inclusion criteria to participate (Fig. 4.1. In addition to this, participants were asked to provide their full name and contact email address for ease of scheduling experiment bookings. The inclusion criteria was chosen to specifically include those who would not be harmed by their participation as well as those who would be able to effectively assess the game's mechanics. As a part of this criteria, those who suffer from a history of epilepsy and/or issues related to or exacerbated by extended computer usage were excluded from this study in the remote chance that their participation would cause them harm. It was specified that all participants must have some experience with video games and the FPS genre so that they would be able to intuitively pick up and play the prototype. The prototype was intentionally designed to conform to stereotypes of the FPS genre so that experienced players could entirely focus on the procedural item generation mechanics. All other inclusion criteria simply ensured that each participant were physically and cognitively able to contribute to this research study. In its entirety, the inclusion criteria was not restrictive as a broad range of diverse perspectives would only aid in drawing conclusions from this project.

To be a part of this research study, you must meet the following criteria. If one or more of these criteria do not apply to you, you unfortunately cannot be a part of this research study.

- *I am familiar with video games and the First Person Shooter (FPS) genre*
- *I am fluent in English*
- *I have not contributed to the development of this project*
- *I am over the age of 18*
- *I am able to give consent*
- *I am able to travel into the UTS Ultimo Campus*
- *I have no pre-existing conditions related to or exacerbated by extended computer usage*
- *I have no medical history of epilepsy*

Figure 4.1: Experiment Participant Inclusion Criteria

Recruitment advertisements were posted in online forums were those who fit the inclusion criteria would be likely to see it. These included University of Technology Sydney (UTS) alumni and games industry networks. These recruitment posts invited potential participants to complete an Expression of Interest form (hosted on Google Forms), which forced users to manually confirm that each individual selection criteria applies to them before allowing them to submit the form. After an adequate sample size has been reached in expressions of interest, each participant was emailed thanking them for their interest and inviting them to book a research session at a time that suits them.

4.1.1 Participant Response

In response to the recruitment flyers that went out to online forums, there were 27 expression of interest forms completed. Those recruited were followed up by an email thanking them for their interest and inviting experiment bookings to be made. These then converted into 18 total experiment bookings with participants. Each of these bookings were successfully conducted, with all relevant data being collected with consent from the participant. The remaining 9 participants that did not make a booking by the closure date of the experiment sessions were excluded from the study and all records of their details were deleted. The 18 participants that did progress to participating in the experimental sessions were each assigned a random, unique, two digit identification number. This number is referred to by all collected data points (In-game data, questionnaire data and interview recording data), and simply serves to relate the data together and to serve as a means to refer to each individual result in this thesis. Participants were kept anonymous for the duration of this study, no personal details have been divulged nor included in this thesis.

Due to the subjective project hypothesis and the qualitative nature of the data to be collected, 18 participants is sufficient. This study is investigating the effects of a preference based weapon generation system, aiming to understand what impacts this system has on the player experience. As such, the results gathered from these participants reached the saturation threshold where participants began reporting similar results with little to no further insights being gathered as more experiments were conducted.

Further, different groups of participants were exposed to different versions of the game prototype. The particular characteristics of these different versions has been discussed in the 'Design Evolution' section in Section 3.2. The distribution of how many participants were exposed to each game version can be seen in Fig. 4.2.

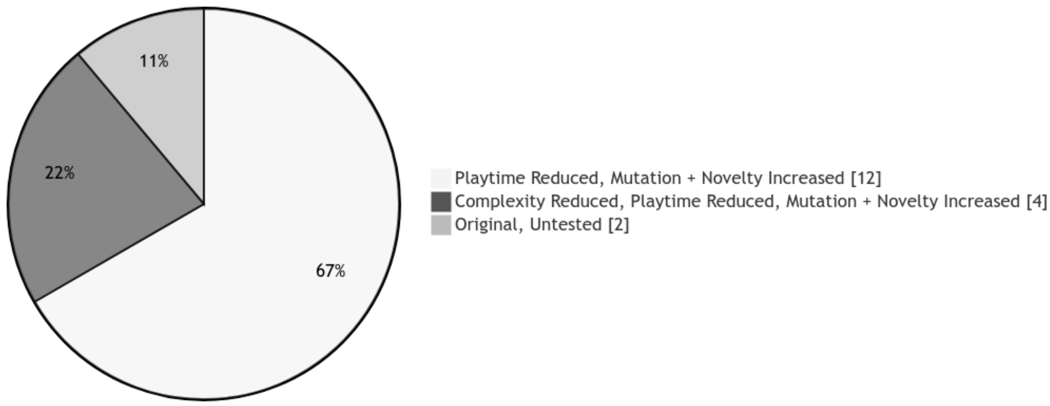

Figure 4.2: Participant Prototype Version Distribution

In total, the following participants (referred to by ID number) played each corresponding version:

- Original, Untested (2):
  - 31, 35
- Playtime Reduced, Mutation + Novelty Increased (12):
  - 25, 49, 98, 36, 88, 87, 34, 56, 96, 18, 82, 97
- Complexity Reduced, Playtime Reduced, Mutation + Novelty Increased (4):
  - 24, 27, 47, 72

4.2 Experimental Design

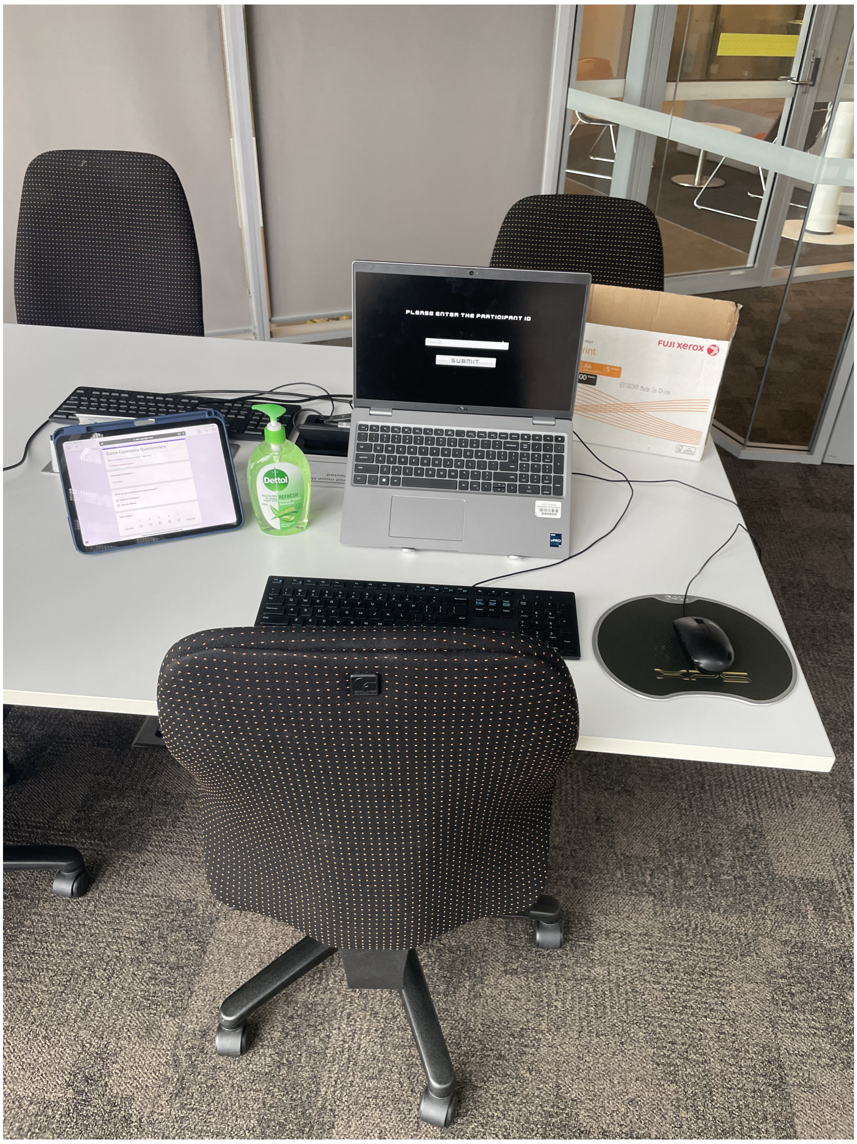

Figure 4.3: Prototype Experiment Hardware Setup

All experiments were held in a booked meeting room at the University of Technology Sydney (UTS) Ultimo Campus, within the Faculty of Engineering and IT (FEIT) Building 11. All experiments were completed in a face to face mode, with one participant in a session at a time. Each were conducted using the same hardware setup (see Fig. 4.3) and within the same environment.

The experimental process (Fig. 4.4) for each participant began once the room has been prepared, including setting up the hardware to be used and disinfecting any high touch surfaces. The participant is then read aloud the information sheet and invited to complete the consent form (see Appendix B.1) if they agree to all terms and inclusion criteria. Once this has been completed the participant is then invited to play through the in-game tutorial that will teach the player the fundamental mechanics used to play this game prototype. Following this the player will then play through the game twice, first with all items being randomly generated and second with the game using this project's bespoke method to give the player preference-based weapons. During the entirety of the gameplay process, the research assistant remains a silent observer answering any questions the player might have regarding the game but not stepping in, assisting or otherwise skewing the participant's experience. This was important as part of this experiment was to assess the ability of the game to foster creativity and exploration in the player's experience, which would have been hampered if the player was simply informed of all playstyle possibilities.

4.3 Outcome Measures

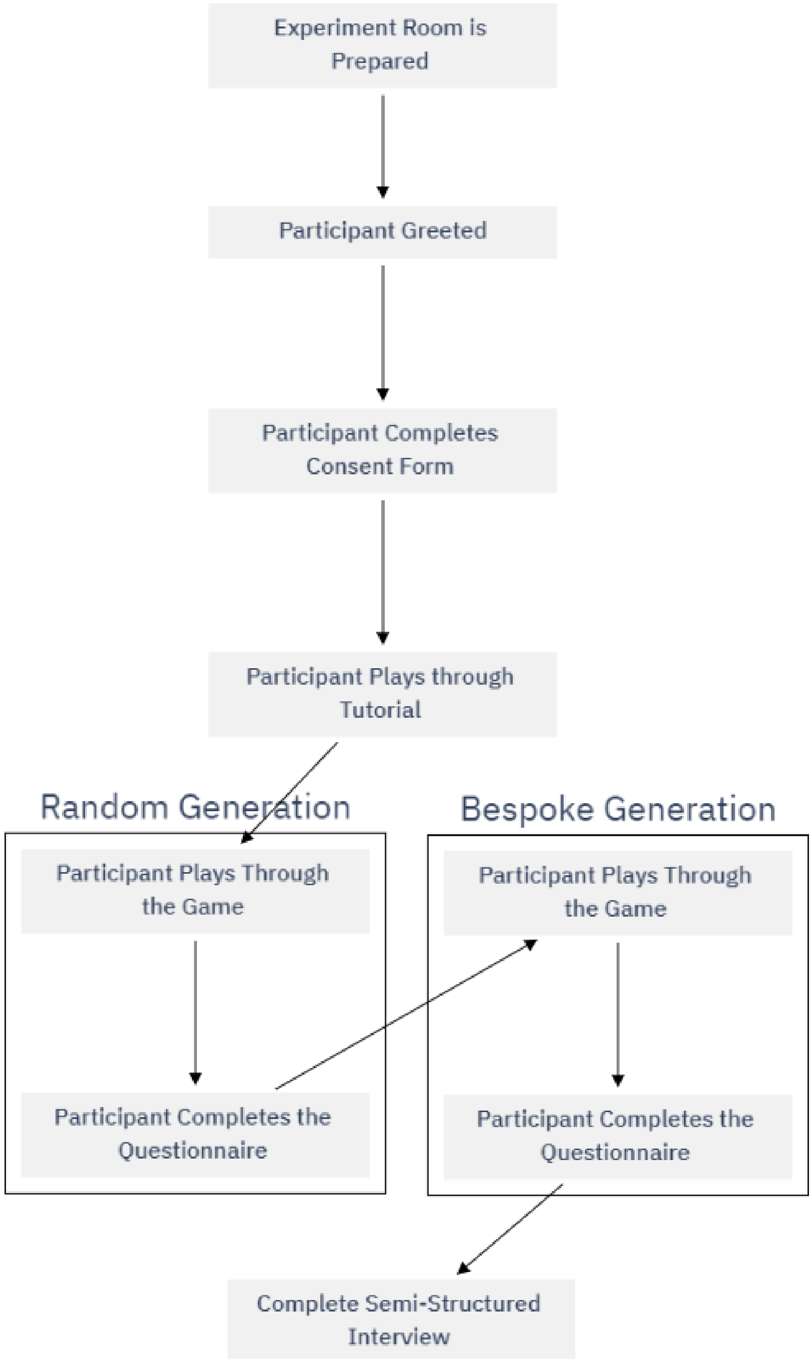

Figure 4.4: Experimental Process Diagram

The overall structure of this experiment revolves around comparing and contrasting random item generation to this project's bespoke generation method, in order to gauge what impact it has on the player experience. To this end, the experiment was designed to first expose the player to the gameplay loop (see Fig. 3.3) using random item generation to establish a control to compare against. As demonstrated in Fig. 4.4, the player completed a questionnaire after each play session which allowed them to be directly contrasted with each other; this will be discussed further in the following section.

As demonstrated in Fig. 4.4, the overall process for each experimental session aimed to produce relevant and useful data to assess the effect of this algorithm. Each experiment begun by resetting the room, disinfecting all hardware and high-touch locations, and then inviting the participant in. Following this the participant had as much time as they needed to read and complete the consent form before interacting with the game prototype. The first stage of the game prototype was the tutorial which aims to teach the player the fundamentals of the game and allow some time for them to acclimate to the controls and mechanics of the game; to this end, the tutorial does not have a time restriction. The following stage of the game sees the player playing for a short amount of time whilst all weapons are generated using a traditional random method. After this, the player is invited to complete a questionnaire (this will be discussed further below) and then invited to play the same experience again. During this second round, the game is instead using this project's Theorised Best Parent Optimisation (TBPO) algorithm to generate the weapons. Following this the player completes the same questionnaire again, to allow for comparison between the sessions, and is then invited to complete a semi-structured interview with the researcher.

4.3.1 Game Experience Questionnaire (GEQ)

As this project is a comparative study, it was important to have some sort of tool that allowed for a level of contrast between the two generation methods. As such, the Game Experience Questionnaire (GEQ) (Poels et al., 2007) was administered to participants after they had experienced each game session. There were four main points of reasoning behind using this particular questionnaire, the ease of analysis and comparison, the ease of administering, the broad range of experience facets analysed and its common use in similar studies in this field. In a follow up article written by the same authors (IJsselsteijn et al., 2013), a guide was provided for analysing the questionnaire results. This guide allowed the results from each questionnaire module to be converted into heuristics representing ratings of different facets of the player's experience. For this experiment, the Core Module was presented to players after each gameplay session. This module, as described by Poels et al., 2007, can provide heuristics reflecting competence, sensory and imaginative immersion, flow, tension or annoyance, challenge, negative affects (boredom, dislike, etc.), and positive effects (fun, enjoyment, etc.).

The ability to easily and quickly turn the raw questionnaire results data into usable heuristics greatly sped up the analytical process. In the experiment, the test was administered using an online recreation of the GEQ Core Module on Google Forms. This was done to easily allow for data gathering as all results were automatically exported to a spreadsheet which could be analysed. As all data was automatically converted into a spreadsheet as well as the analysis methods being simple functions, analysis became almost automatic. Further, as the analysis outputted multiple different heuristics, it allowed for different aspects of the player experience to be contrasted between the two gameplay sessions. As discussed in Fig. 3.3, the player was asked to complete this same questionnaire on two occasions, both occurring after they had played a version of the game; with the only differences being which item generation technique was used (random, or bespoke). This resulted in two sets of data for each participant evaluating their experiences with the same game using two different generation methods, allowing any highlighted differences in any heuristic to be linked back to the change in item generation technique.

As stated before, another reason behind using a questionnaire was the ease of which it could be administered to participants without adversely interrupting the game flow. The questionnaire was planned to be presented at two intervals during the experimental process, one midway through and one at the end of the game-playing portion. On average it is estimated to only take a few minutes to complete in its entirety, with all questions not requiring too much mental investment to complete. Too lengthy of a process would have negatively affected the experiment, skewing the player perspective negatively in regards to the second play session. Further the breadth of analysis this questionnaire provided allowed for more granularity when evaluating which aspects were affected as a result of the changing item generation technique. Keeping the scope for this analysis larger than anticipated allows for potential unintended effects to be captured and recorded. This questionnaire has seen use in various similar studies that assess the subjective qualities of changes to a game experience: Caroux et al., 2023, Wang et al., 2023, Pallavicini and Pepe, 2019, and Xu et al., 2020.

All the benefits of the GEQ listed above assume that the questionnaire itself can output valid and usable results to found an opinion on. This has been brought into question by a few research papers (Johnson et al., 2018, Law et al., 2018, Brühlmann and Schmid, 2015) which identify some areas of the questionnaire that could be improved, and might not produce accurate heuristics. It has been shown that despite the widespread use of this questionnaire, it is evident that the outputted heuristics may not be reflective of their intention. The main foundational error that has been made in the creation of the GEQ is that it is not backed up by peer reviewed studies. It has not been empirically validated and appears to have been constructed using a process termed a rational-theoretical approach, which saw the questionnaire developers creating questionnaire items based on subjective understanding of the subject matter. As mentioned by Johnson et al., 2018 and Brühlmann and Schmid, 2015, the heuristics outputted by the GEQ may not actually measure what they intend to. However, Brühlmann and Schmid, 2015 supports that despite the subjectivity of the GEQ it can still be used as a valid predictor of player enjoyment and commercial success. Seeing as the heuristics themselves may be somewhat inaccurate, the questionnaire can still be used to gauge overall player experience when viewing the heuristics holistically. This is sufficient for the purposes of this project as the intention is to gauge the extent to which the player's experience as a whole is impacted by the bespoke generation system.

According to Johnson et al., 2018, there remain a few metrics that have empirical support, these are: flow, immersion, competence, and positive affect. These metrics are the most applicable to this study as the questionnaire serves to identify any broad effects on the gameplay experience as a result of the changing item generation methodology. Despite the inaccuracies in the specific heuristics, a holistic difference in the game experience would become evident when comparing GEQ results between the two gameplay sessions. The questionnaire is administered directly following the gameplay session (as specified by IJsselsteijn et al., 2013 and reinforced by Johnson et al., 2018).

As the quality of this questionnaire and its results are in question, it has been supplemented by a semi-structured interview. This interview will serve as the primary mechanism to gain insight from each participant, with the data gathered by the questionnaire providing insights on the prototype as a whole. The effectiveness of this questionnaire within this specific context will be outlined in Chapter 4.4, where data will be compared with interview responses.

4.3.2 Semi-Structured Interview

As mentioned previously, the questionnaire results were supplemented by a semi-structured interview with each participant at the end of their experimental session (see the list of questions below). Due to this project's subjective outcomes, it was important to explore each individual participant's experience without the restriction of a rigid interview. During the game playing portion of the experiment, the researcher observes the participant playing the game and brings up any relevant questions during the interview, in addition to the standard questions). Further, any points of note brought up by the participant can be delved into to gain further understanding of their experience. This flexibility allows for a greater understanding of subjective experiences whilst still providing a structure to inspire participants to reflect on their session.

The questions prepared before the interview were as follows:

1. What was your favourite, or most memorable, weapon combination?
   (a) What made it so enjoyable?
2. Was there a specific weapon combination you were looking for, but could not find?
3. Did you prefer the prototype before or after the mid-playtest questionnaire?
   (a) What do you think made you prefer one over the other?
4. Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons that it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games (Borderlands, Diablo, Destiny, etc.)?
   (a) Do you think that it would have a different effect on the early game experience compared to the late game experience?
5. Are there any further comments or feedback on this session or the game prototype?

Each question in the interview aimed to identify the player's opinion of different aspects of the game prototype. Questions 1 and 2 specifically targeted the player's experience with the weapons generated by the game. These questions aimed to assess the effectiveness of the modular component weapon design and the accuracy of the preference based generation respectively. These questions also function to give an insight into the player's engagement with the game, as those immersed in the game would be more likely to easily remember particular combinations they had or were searching for. Question 3 was aimed at assessing the non intrusiveness and broad experience effects of the bespoke item generation method. The intention with this question is to observe if players completely preferred either generation technique, or noticed a difference at all. The bespoke item generation system should not be noticed by the player, but should make the play feel as if their luck is increasing in regards to getting desired weapons. Question 4 reveals to the participant that the game was, in part, trying to provide them with weapons their preferred and challenges them to give their opinion on a system like this. The sub-question here aims to shift their perspective away from a game prototype and to imagine the effects a perfectly implemented system like this would have on games they are familiar with. Finally, Question 5 as well as any other questions injected as a result of observations during the experiment serve to give the participant the opportunity to voice any concerns or ideas they have in regard to this project.

4.4 Findings

4.4.1 Game Experience Questionnaire (GEQ)

The first component of the results collected was the participants' responses to the Core Module of the Game Experience Questionnaire (GEQ) (IJsselsteijn et al., 2013). As shown in Fig. 4.5, there were some minor observed differences in results when comparing responses after the player has played the game using random weapon generation (first) and the theorised best parent optimisation generation (second). Although all metrics remained similar across the two sessions, as players progressed from the first session to the second Competence, Tension, Negative and Positive Affects appeared to increase with Immersion, Flow and Challenge decreasing.

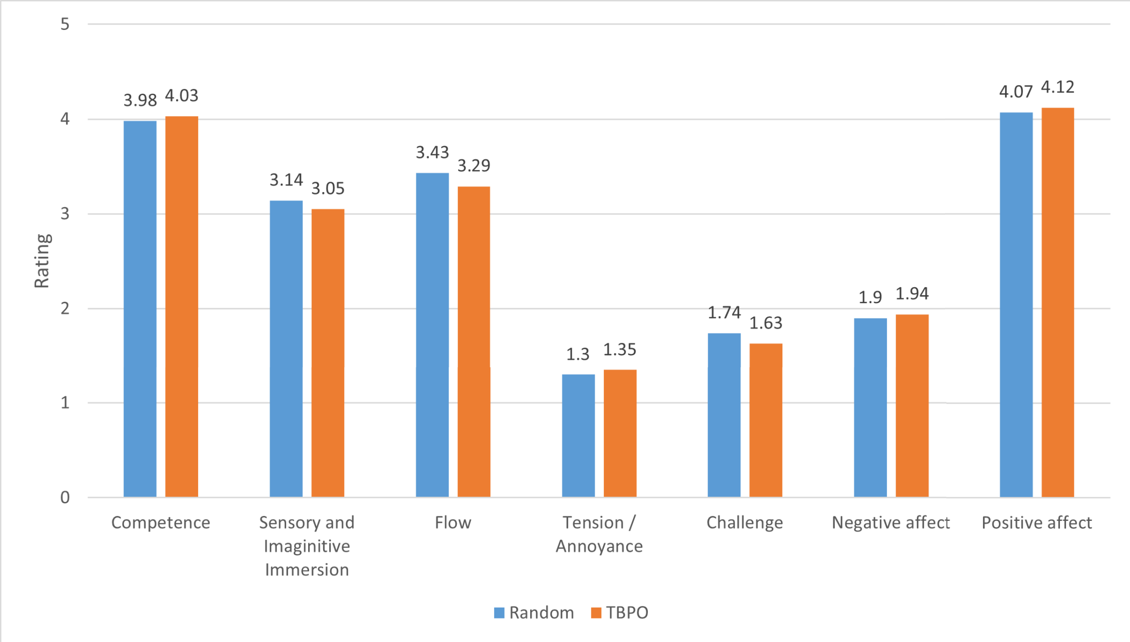

Figure 4.5: Game Experience Questionnaire (Core Module) Mean Outputted Heuristics for All Game Versions

Table 4.1: Game Experience Questionnaire (Core Module) Data Ranges

Game Ver.	**Gen Method**	**Heuristic**	**Min**	**Max**	**Avg.**
1	Random (Session 1)	Competence	3.8	5	4.4
		Sensory & Imaginative Immersion	2	2.33	2.17
		Flow	2	3.2	2.6
		Tension/Annoyance	1	2.33	1.67
		Challenge	1	1	1
		Negative Affects	2.5	4	3.25
		Positive Affects	3	4.4	3.7
1	TBPO (Session 2)	Competence	3.4	4.8	4.1
		Sensory & Imaginative Immersion	1.83	2.5	2.17
		Flow	2.4	2.8	2.6
		Tension/Annoyance	1.33	3	2.17
		Challenge	1	1.6	1.3
		Negative Affects	2.5	3.75	3.13
		Positive Affects	2.8	3.6	3.2
2	Random (Session 1)	Competence	3.2	5	3.83
		Sensory & Imaginative Immersion	2.33	4	3.15
		Flow	2.2	4.4	3.5
		Tension/Annoyance	1	2	1.28
		Challenge	1	2.8	1.78
		Negative Affects	1.5	2.5	1.81
		Positive Affects	2.8	5	4.05
2	TBPO (Session 2)	Competence	2.6	4.6	3.82
		Sensory & Imaginative Immersion	1.33	4.5	3.03
		Flow	1.8	4.2	3.28
		Tension/Annoyance	1	3.33	1.31
		Challenge	1	2.2	1.65
		Negative Affects	1.25	4.25	1.98
		Positive Affects	2.8	4.8	4.12
3	Random (Session 1)	Competence	3.8	4.8	4.2
		Sensory & Imaginative Immersion	2.83	4.33	3.58
		Flow	3	4.4	3.65
		Tension/Annoyance	1	1.67	1.17
		Challenge	1.4	3.2	2
		Negative Affects	1	2.5	1.5
		Positive Affects	3.8	4.8	4.3
3	TBPO (Session 2)	Competence	4.4	4.8	4.65
		Sensory & Imaginative Immersion	2.67	4.67	3.55
		Flow	2.8	5	3.65
		Tension/Annoyance	1	1.33	1.08
		Challenge	1.2	3.4	1.75
		Negative Affects	1	1.5	1.25
		Positive Affects	4	5	4.6

Across all game versions, all that changes between the observed game sessions is the item generation method used when the player requests a new batch of items (see Section 3.2 for how this works). As alluded to by the data in Table 4.1, this is not a significant gameplay change, resulting in the similarly small change in the data collected between the two different gameplay sessions across all game versions. However, this does result in any consistent heuristic differences across all players of the same game version being worthy of note. As a result of this, the purpose of the questionnaire data is primarily to compare the effects of different algorithm parameters across different versions of the game; and to denote any unintended significant impacts on gameplay as a result of the presence of this algorithm.

Table 4.1 explores the data gathered by the GEQ, comparing the ranges of the outputted heuristics across the different versions of the game. As discussed in Section 3.3, the different versions of the game denote different parameters for the Theorised Best Parent Optimisation (TBPO) algorithm. Observation of data surrounding the player experience of those exposed to different algorithm parameters works towards answering Objective 4 and Research Question 1.1.

The data gathered using Game Version 1 (Table 4.1) outputted some mixed heuristics with only Competence and Positive Affects scoring highly. Most outputted heuristics remained similar across the two versions with only the Positive Affect metric reducing from 3.7 to 3.2 when comparing the first and second gameplay session. During these trials Immersion, Tension and Challenge scored relatively low with Flow and Negative Affects outputting average results. These remaining heuristics did not change significantly when comparing the two gameplay sessions.

The data gathered using Game Version 2 (Table 4.1) saw some more positive heuristics being derived from the questionnaire data when compared to Game Version 1. During these trials Competence, Flow and Positive Affects scored relatively highly with this remaining true across both gameplay sessions. Immersion scored higher than Game Version 1 on average raising from 2.17 to 3.15 when compared to this version of the game. Tension and Challenge remained scoring relatively low, with Negative Affects also being reduced in this version of the game.

The data gathered using Game Version 3 (Table 4.1) outputted the most encouraging results with Competence, Immersion, Flow and Positive Affects scoring highly whilst Tension, Challenge and Negative Affects scoring relatively low. However, these heuristics remained relatively similar between the two gameplay sessions.

4.4.2 Semi-Structured Interview Observations

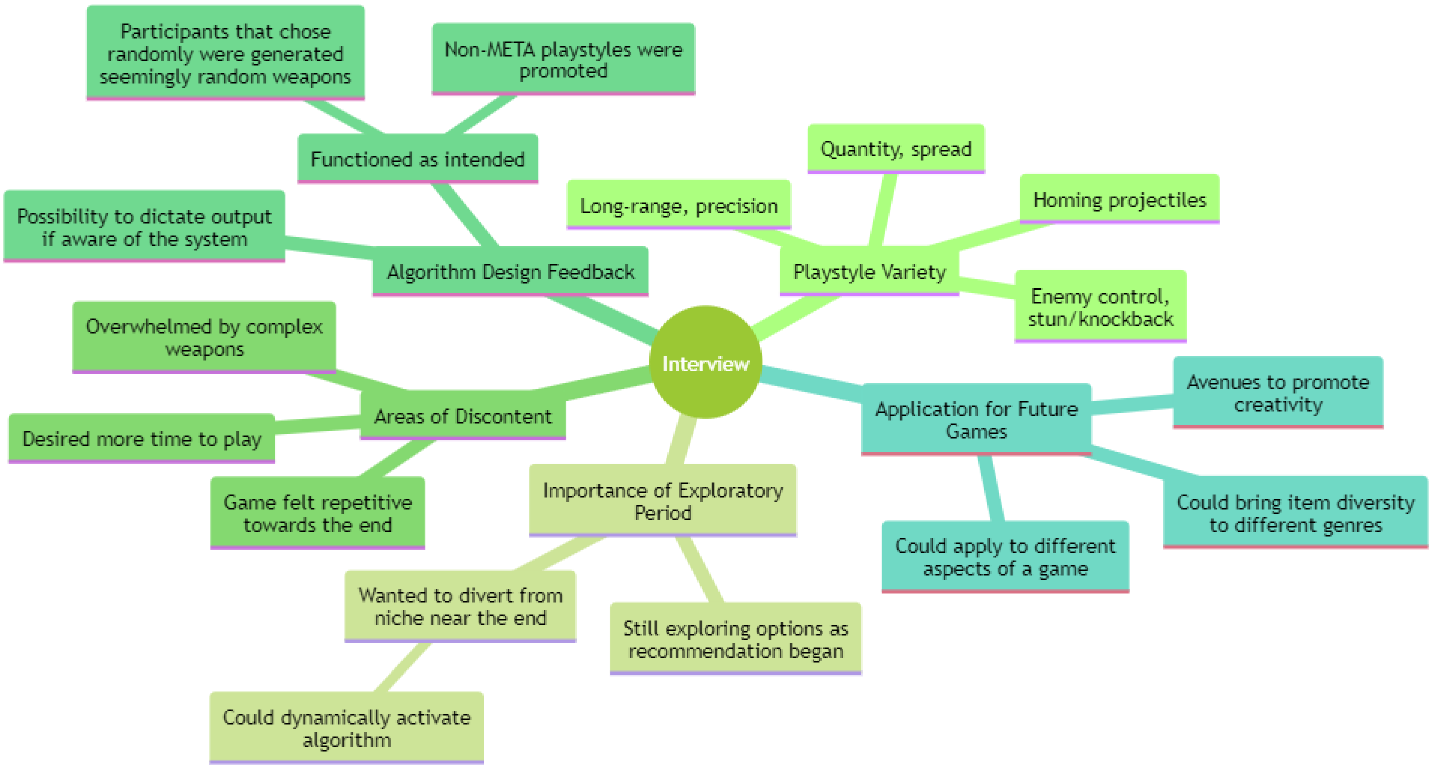

Figure 4.6: Semi-Structured Interview Findings Overview

Research Question 2 to stipulates a subjective output based on the effect on the player experience as a result of this algorithm's use. To this end, the majority of findings for this project need to come directly from the opinions of participants; thus requiring the use of this semi-structured interview. As discussed earlier, this format was chosen to allow for comparable results between participants through the standardised questions with the freedom to delve further into some given answers if required. These interviews were conducted one on one, with a researcher and the participant, immediately following the gameplay session. Please see Fig. 4.6 for a compilation and categorisation of common feedback from participants performed after the interviews .

4.4.2.1 Playstyle Variety

Many diverse playstyles were observed over the course of the experiments, demonstrating that the game needed to respond to a wide variety of preferences. As observed during the semi-structured interviews, there were four main playstyle categories reported. These observed playstyles were as follows:

- Those preferring to remain in one place, using long range weapons like the sniper rifle and preferring modifiers that made projectiles more predictable and do more damage - such as anti-gravity, velocity boost, lightweight, etc.
- Those preferring to control enemies in order to have an easier experience, using a variety of weapons that featured effect types such as shock, ice, haunt or knockback. These players preferred to stop enemies from functioning so they could strategise without being threatened.
- Those preferring to leverage the weapons and modifiers to cover the map with projectiles. Favouring quantity and size over anything else, these players preferred shotguns or SMGs that featured modifiers such as expand, snowball and volatile.
- Those preferring the automatic accuracy of the homing projectile modifier. Players in this category preferred to combine this with weapons such as machine gun, SMGs and shotguns that could output many projectiles that could each seek out enemies around corners to safely defeat them.

4.4.2.2 Gameplay Session Preference

As highlighted in the Game Experience Questionnaire results, opinions on each gameplay session did not seem to change. When asked in the interview, participants reported different results on which gameplay session they preferred, either featuring random generation or TBPO generation. It is important to note that this question was asked to participants immediately prior to revealing that the second gameplay session featured a preference based weapon generation. 7 participants stated that they preferred the first gameplay session, with 11 participants preferring the second gameplay session.

There were differing opinions on why each participant preferred each gameplay session. Participants who preferred the game prior to the mid-playtest questionnaire mainly reported that it was due to the game becoming repetitive as the experiment session went on. On the other hand, players who preferred the second gameplay session attributed it to having more understanding of the game and therefore feeling more in control of what was happening. One participant, 56, noted that they felt the quality of weapons being generated increased in the second gameplay session but could not determine why.

Despite all participants voicing a preference on which session they preferred, some participants did not observe a tangible difference in the gameplay. Participants 27 and 49 mentioned that they were not aware of any differences betweent the two sessions and, upon revealing the generation method changes, further reported that they did not notice the weapons being tailored to them. This could have been a result of them using a wide range of weapons during the early stages of gameplay, resulting in the generation algorithm similarly producing seemingly random results.

4.4.2.3 Importance of the Exploratory Period

All participants, to differing extents, discussed the importance of the exploratory period that occurs at the beginning of playing any new game; where the player is excited and desires to discover what the game has to offer. This exploratory period was observed with variable amounts of time across each participant. This comment was often combined with reports that the generated weapons were too heavily influenced by early-game decisions, resulting in preference based weapons being too similar to each other.

In discussion during the interview, some participants brought up the possibility of the preference based generation algorithm being intelligently activated rather than always active. These were mainly posited in response to players mentioning that early game decisions held too much strength over the preference based weapons once they begun being generated. All participants who discussed this idea desired for there to be more weight given to weapons picked up more recently, as they made those decisions more in line with their current desires. As the game progressed, the players preferences began extremely variable as they explored the options available to them and refined over time towards a certain playstyle. As a result of the algorithm tracking data from the beginning of the game, early-game decisions that may not align with the players current preferences given weight to be selected by the algorithm.

One solution to this issue discussed was to pair this system with a form of playstyle niche detection system that can turn on or off the preference based weapon generation system depending on if the player is seeming to target a specific niche. Another potential solution discussed was to apply a weighted selection to the weapons considered for the algorithm, greatly preferring weapons picked up more recently whilst also not discarding early-game decisions that could be informative. The final potential solution brought up was to confine this algorithm to a certain mechanic or feature in the game that specifically produces preference based items with the rest of the game producing randomised items. This would allow the player to have control over whether or not they would like to pursue their observed playstyle or leverage the variety given by randomised items.

4.4.2.4 Areas of Discontent

Some participants, namely 25 and 56, noted that they would have preferred more time to play the game. These participants mentioned that they did not believe they had enough time to fully experience all options available to them, and consequentially did not believe that the algorithm had enough time to accurately gauge their preferences. This seemingly came about due to a combination of the large weapon variety and the limited duration of each gameplay session.

The vast amount of options available and the complex design of the weapons resulted in some participants feeling overwhelmed when tasked to sort through and select weapons each wave iteration. Participants who reported this finding overlapped with those that wished for more time to experience the game prototype. Similar to this, some participants reported that they did not put much thought into their decisions on which weapon to pick up. In this case, favoured components were determined and weapons selected on their presence rather than the combination as a whole. These participants also did not appear to have a playstyle or desired weapon combination sought after during the gameplay session.

Over the course of both gameplay sessions, many participants reported that the game became repetitive. This feeling mainly centered around the core gameplay loop remaining basic with the game level, enemy variety and player mechanics being static. This sentiment was also brought up in regards to the observed lack of variety of the weapons produced in the second phase of gameplay as weapons became more and more preference based.

4.4.2.5 Algorithm Design Feedback

The TBPO generation algorithm seemed to produce similar results to the players decisions in the early game. Participants that exhibited a comparatively larger desire to explore their options were given similarly seemingly random weapons in the second half of gameplay. Conversely, players that were more able to quickly determine a preferred playstyle or weapon combination were given more specific weapons in the second phase of the experimental session.

There were some interesting points discussed during the interview process wherein concerns were raised regarding a system like this being intentionally influenced or manipulated towards a particular end goal. As noted by some participants, this would only be a possibility given that the player is aware that this system is in the game, and is currently governing the type of items they are receiving. 27 mentioned that observing or hearing about friends or online influencers could cause the player to abandon their current preferences in favour of theirs. Further it was highlighted by 25 that, in some cases, a player that favours an objectively 'bad' or unoptimised weapon may only be given similar items despite the game becoming more difficult; requiring more applicable META (Most Effective Tactic Available) weapons. Similar to this, it was also brought up that a player who is aware of what the META is for the particular game would be able to intentionally skew the algorithm into providing them with these over-powered weapons.

The power of the weapons directly came from the components they consisted of. Some participants favoured weapons entirely due to the presence of a particular component rather than due to how the weapon functions as a whole sequence of components. This preference implied that each different component of a weapon influenced the fitness (player preference) at different levels. It could have been insightful to ask each participant which component they felt had the most impact to them.

Some participants were aware during the experiment that their preferences may not align with other players, and would definitely oppose the META for the game. 47 identified that they intentionally opted for a loadout that they found less effective but enjoyable to use, and appreciated the presence of the TBPO algorithm to support that decision. They posited that the weapons they were favouring would be harder to find or more rare in a similar game that did not feature a generation algorithm such as this.

4.4.2.6 Application for Future Games

In discussions with the participants, there were some ideas brought up to apply this sort of preference based algorithm to different aspects of a game's design. Ideas were brought up to apply this to features such as the level generation, enemy design or behaviour, and potentially mission or objective design. Although these discussions brought up how similar issues present in the current implementation surrounding misaligned inputs (preferences) and outputs (weapons) becoming present in more features of the game, given this expansion.

The very nature of this algorithm is to remove the grind from loot based games, to shortcut the gameplay loop of trying and failing to get desired weapons so the player can progress through the game. It was identified by some participants that this system would eliminate some of the gratification that comes from the journey towards obtaining particular items. Although not enjoyable in the moment, it was discussed that the more time someone invests in attaining something, the more enjoyable it is when they finally get it. Similarly, it was discussed that there is a lot of value in these types of games with strategising how to use weapons that may not be preferred or optimal. 'Making do with what you've got' becomes a key part of these games, which allows players to discover new and interesting playstyles that they might not have initially believed they would enjoy. Both of these aspects would be removed given a perfect implementation of this system.

Interesting further developments to this algorithm were posited during these interviews that mainly focused around further promoting variety whilst remaining to produce preference based weapons. 49 mentioned that it would be interesting to have a select few weapons per population generated that intentionally opposed or otherwise did not align with player interests. This would be done to simulate the experience of acquiring and 'making do with' weapons that may not be historically preferred but could ultimately become a player's favoured option.

4.5 Discussion

4.5.1 Impact of Preference Based Generation Compared to Random

The player experience of playing the game prototype was not significantly impacted or changed by the addition of a preference based weapon generation system. As shown in Fig. 4.5, the average result from each given heuristic at most shifted by 0.14 (Flow), let alone changing a whole ranking in any category. As discussed in the above Observations, when comparing the first gameplay session (Random generation) to the second gameplay session (TBPO generation) the first heuristic to change was Competence. This measurement increased on average by 0.05 across all participants which reflects the expected outcome of players' understanding of the game growing as they experienced and played more. This could also encompass the feeling that the game became easier over time, resulting in the observed decrease by 0.11 in Challenge. Sensory and Imaginative Immersion decreased by 0.09 when players transitioned to the second gameplay session. This has been a similarly reported effect in the interviews as players felt that they could quickly experience all the game had to offer, resulting in further gameplay feeling repetitive. This sentiment also somewhat explains the changes in Flow (decreasing by 0.14) and Tension / Annoyance (increased by 0.05). Although minor changes in the results given in the questionnaire, players expressed desire in the interviews for more gameplay features to retain player interest for longer. These subtle changes in questionnaire responses reflect that the gameplay prototype could have been more engaging to play, but overall suggests that the presence of the algorithm does not change the experience significantly. One detriment of this system, as discussed with participants, is that it could become too controlling or otherwise dictate the gameplay too much in one direction or another; as observed by these results this is not the case.

In discussion with participants in the interviews, there were differing opinions on which gameplay session was preferred, with a range of different reasons why each may have been preferred. Those who preferred the first gameplay session, with random item generation, did so because they enjoyed the variety given by the randomly generated items and/or felt that they game became too repetitive in their opinion as time went on. The lack of variety given by the TBPO algorithm is an ongoing balancing act when it comes to any preference based generation, where too strong of a rule base results in too similar outputs whilst too rules that are too weak result in pseudo-random behaviour. This is similarly influenced by the prior actions of the player before the algorithm becomes active; players that begin the game by only using weapons of similar characteristics will mainly be presented with such similar weapons. Conversely, players that embrace and explore the variety presented in the first gameplay session will be presented with more varied outputs in the second session, when the algorithm becomes active. The most optimal scenario for the function of this algorithm is where players spend time exploring their options in the beginning of the game, and then refine their playstyle as time progresses.

Those who preferred the second gameplay session did so because they felt that their understanding of the game grew, that they had discovered a playstyle that they were able to pursue, felt that it was more challenging or even felt that the variety presented was better. As part of the participant inclusion criteria (Fig. 4.1), all participants had experience with playing First Person Shooter (FPS) games on the computer. This suggested that the required understanding that grew over the course of the experiment surrounded the function of the weapons, as all other game systems were standard across traditional FPS games. The required complexity of the weapons generated was necessary in allowing for the large variety, but was observed that it confused players. As shown by the players that preferred the game as they progressed into the second gameplay phase, those who came to understand the weapon system were more able to come to intelligent decisions regarding their loadout thus resulting in a more positive experience. Finally, there were some participants that were specifically enjoying the playstyle brought on by a particular weapon component and appreciated that the algorithm presented them with that component amongst different combinations. This speaks to a core concept promoted by this algorithm in that components are valued at different weights when determining the theorised best parent (Chapter 3.1), which has specifically promoted the gameplay experience of these participants.

4.5.2 Importance of an Exploratory Period

Most participants discussed or brought up the importance of having more time at the start of the experiment to build their understanding of how the game works and what options are available to them. There was some confusion when it came to how the weapons functioned, especially when it came to the projectile modifiers. If players had more time to become accustomed to the weapon system this would have impacted the gameplay experience less and less. As mentioned in the Limitations section, the time pressure was a necessary requirement imposed on participants to conform to the experiment schedule. In Chapter 3.1 it is mentioned that the player and their selections act as the fitness function to determine which weapons are preferred. The more time the player has to play the game, the more understanding they have of its mechanics, increasing the quality of their decisions when it comes to selecting weapons and therefore increasing the effectiveness of the fitness function for this genetic algorithm.

When a player begins experiencing a new game, they often are unsure of what they would like to get out of it. As a result, many decisions made early on in the game may not be reflective of their eventual preferred way to play once they understand what that may be. Many participants discussed this concept and proposed some methods to offset this impact on the quality of the algorithm outputs. All of these solutions discussed lessened or removed the impact of early game decisions being taken into account when selecting which weapons should be used as parents for generating each new generation.

These solutions included applying a weighted selection to the population pool to have weapons picked up and used more recently to have more of an impact on new weapons produced. This would further allow the system to keep up with a player's changing preferences as early game decisions would have less of an impact on the player's overall empirical preference model. Importantly, this solution does not entirely remove the influence of items selected towards the start of the game, which could be an important characteristic of a further implementation of this system. Despite players changing their preferences as their understanding of the game grows, initial instincual feelings towards different weapon types may speak towards a player's more foundational preferences and it may be beneficial to keep these in mind when assessing a player's current opinions.

Another solution entailed the activation of this system occurring during gameplay either after a certain amount of time or after it has been detected that a player has found a niche to be explored. This was the solution opted for in this current prototype as the player first experiences the games tutorial and the main game level whilst the game produces weapons at random, before then activating the system in the second gameplay session. A minor difference that could have improved the system, as brought up in discussion with participants, would be to disregard data collected before the system became active. This idea revolves around the assumption that the player spends the first defined period of time exploring their options and only after that time would their decisions be considered important and indicative enough to draw conclusions from.

The final solution posited revolved around having a mechanic or feature in the game that specifically used this new generation technique, with the rest of the game remaining to generate weapons using traditional techniques.

4.5.3 Adherence of Prototype to Different Playstyles

As mentioned in the above Observations, there were a variety of playstyles demonstrated during the experiments. Throughout the accompanying interviews it was reported that players who were leaning towards a certain niche playstyle did feel that the Theorised Best Parent Optimisation algorithm was able to support them. The overall design of the weapons in the prototype allowed for a wide range of playstyles to emerge and be facilitated through the unique interactions between all components of the weapon.

In the observations section, four main playstyle categories were identified but there were much more diverse loadouts that came about during the experimentation. The process of playstyle identification and the subsequent weapon creation / acquisition is entirely facilitated by the component based weapon design combined with the TBPO algorithm. Each component in and of itself adheres to different ways of playing the game, for example the sniper rifle weapon base type inherently lends itself towards a more controlled and long-range playstyle for players. Players that align with this category and use more and more sniper rifles will then 'lock' in that specific version of the weapon base component whilst the other components change around them, as a result of the TBPO algorithm. When constructing the theoretical parent to be used, the popularity of favoured component types influence the resulting gene sequence at different weights meaning that favoured genes or gene combinations stay present in future generations. This coherence between the weapon design and the algorithm allow for these playstyles to remain visible in future generations with the mutation and novelty rates promoting diversity within that niche.

This quality of the prototype reinforced the playstyle of players that admittedly favoured weapons and loadouts that could be unpopular. In games where weapons are static or feature more restricted PCG, players that are seeking these niche playstyles may not have been able to progress to the level they could in this prototype. Unique interactions between components produced emergent behaviour and had the ability to create weapons or mechanics that were unintended by developers. These emergent behaviours have been observed aligning themselves with some participants' playstyles in this experiment. These players appreciated the presence of this algorithm as they could, knowingly or unknowingly, influence it towards generating specific weapon combinations that they found enjoyable or interesting.

4.5.4 Opinions on Outputted Weapons

There were different opinions on the weapons outputted by the generation system, with insights being gathered on the weapon design itself and the accuracy of the preference based generation. Some participants did not intuitively understand the function of the weapons, mainly with the projectiles being entirely physics based. As identified in Chapter 3.2, this is a departure from most traditional FPS games wherein bullets travel instantaneously from weapon to target, colloquially known as "hitscan". For most participants this took some getting used to, especially given how the projectile modifiers would interact with the projectiles to produce unique behaviour. This unique behaviour, when understood by the player, is what allowed for niche playstyles to come about. When not understood by the player, this created confusion and a disconnect between the player and the game as they felt they could not accurately control what was happening; this is when immersion would decrease.

However, over time players would become more accustomed to how the game functioned as well as how the combination of components on a weapon would influence its behaviour. Based on observations by the research assistant, this point would often occur at a similar time to when that participant's exploratory period would finish. At this point, when players could understand and leverage the combinations, their enjoyment of outputted weapon seemed to increase. When asked about some specific components of the weapons, there were differing opinions on the quality of particular modifiers and weapon types. For example, the Platform projectile modifier (see Appendix A.1) was a point of contention with some participants enjoying the unique effect it provided, some leveraging it to reach areas inaccessible to enemies, and some participants outright denying any weapons that featured it. Overall, the majority of players eventually were able to find a weapon with a particular sequence of components that aligned with their interests.

4.5.5 Theorised Effect on Similar Games

When asked what effect a system such as the one created in this project would have on games of a similar genre a range of interesting points were brought up. Comparisons were made mainly to game series Borderlands (Gearbox Software, 2009) which featured a similar methodology for assembling its weapons, and served as a core inspiration for this prototype (as discussed in Chapter 3.2). Many participants discussed the source of enjoyment and engagement in the Borderlands game series as well as most other games that are founded on random loot acquisition. This source comes from the journey towards achieving a desired item, increasing the satisfaction of obtaining the item based on how much time investment the player had put in to acquiring it. The TBPO algorithm or other similar preference based item generation, especially a perfect implementation of it, aims to remove this journey by initially rewarding the player with what their end goal may be. This brings into question what players truly prefer, which is ever changing and remains dynamic over the course of the player playing a game. Further, many players do not know what they may enjoy with another source of enjoyment in these games coming from making use of weapons or items that may not have been historically preferred at all. It was discussed that acquiring new weapons that do not align with your playstyle may in fact stimulate new preferences and serve to shift your focus in a new direction. In this case, any data forming an empirical model of player preferences would be inaccurate as they have now shifted their preferences to an opposing playstyle. Given this idea, it is sometimes hard for players to know for certain which items they would prefer, let alone for there to be an algorithm that could calculate this. In future implementations it would be important to keep this in mind, and could be interesting to implement some sort of system that ensured part of the generated items were novel or even in opposition of what the player's identified playstyle may be.

Finally, given that the gameplay loop of this genre revolves around playing scenarios over and over again until the player acquires the items they prefer (named 'grind' or 'grinding'), it was posited that this system may find more application in different genres. The wide range of variety that the random loot-based games are built around is difficult to bring to other genres given the required 'grind' to experience them all. A system like this that inherently aims to remove the 'grind' would allow for games of different genres to benefit from having a wide variety of procedural items. This could be applied to any games that do not feature 'grinding' for items as a core part of their gameplay loop and would provide them with the ability to have emergent game mechanics, cater towards a larger target market and provide a refreshing way for players to experience the game.

4.6 Key Takeaways

This investigation has shown that the Theorised Best Parent Optimisation (TBPO) algorithm has been effective at producing weapons that align with the given player's preferences. Research Question 2 asks, "How does the player experience differ using the experimental system when compared to a traditional First Person Shooter approach for generating weapons? ". This data demonstrates that the inclusion of this algorithm was beneficial to the player experience in its effectiveness to navigate the wide array of possible weapon combinations; particularly as opposed to purely random item generation.

In attempts to answer the more specific RQ1.1, it has been shown that the final iteration of the algorithm parameters (Version 3) resulted in the most positive feedback from players surveyed using the Game Experience Questionnaire (GEQ). Moving forward, any future implementations of this algorithms should take inspiration from the parameters used here and the reasons behind those settings.

Overall, based on the responses in the semi-structured interview, the majority of participants were observed preferring the gameplay session featuring the TBPO algorithm. In conjunction with the GEQ response data, this shows that the presence of this algorithm enables players to successfully find the items they prefer without it changing the game's features or mechanics.

More specifically to this prototype's implementation, participants seemed satisfied with the variety of weapons available to them as well as with the algorithm's ability to provide targeted selections. As discussed in the interviews with participants, this is due to the component based design of the weapons allowing for new and unique combinations to be produced; and thus produce weapons that function in unique ways. This ability allows this system to be flexible and dynamic enough to cater for a wider array of playstyles than it otherwise would be able to. This has been a key consideration given the function of this algorithm and serves to partially answer Research Question 1 by defining some design constraints on games that feature this system.

In any future work featuring the TBPO algorithm, care needs to be taken to preserve the ability of the player to explore their options. In item-driven games, where mechanic diversity comes from the items, it is extremely important to encourage the player in exploring these given items. As discussed prior, there are a variety of methods to ensure this at an algorithm mechanic level that either centre around incorporating a level of controlled randomness into the process or otherwise lessening the influence of the recommendations. The most optimal solution would find a balance between an empirically defined 'perfect weapon', whilst still providing the player with a variety of options at each stage of the process.

There are opportunities for this algorithm to be applied to different game genres in order to share the benefits of item-driven game mechanics with reduced levels of it accompanying challenges. Item-driven games allow for an inherent level of customisation and diversity to be made available to the player, but also usually requires 'grind' for a player to achieve these benefits. With random item distribution, players must 'roll the dice' many times over in order to randomly get the item they want. This algorithm inherently reduces this need and would allow other game genres to include item systems with wide diversity without the need to change their gameplay directions to allow for this 'grind'.

Chapter 5

Conclusion

5.1 Answering the Research Questions

This project set out to investigate the ability of the Theorised Best Parent Optimisation (TBPO) algorithm in a First Person Shooter (FPS) game to resolve problems surrounding content engagement and the player experience. In item-driven games, mechanic functionality is encapsulated within the items that allow players to customise their playing experience by choosing which items to use. To cater to wider ranges of audiences, commercial games have worked towards dramatically increasing the variety and diversity of these items. This produces a problem wherein the player naturally cannot effectively navigate this space to find the items they prefer, given its size and the traditional use of random item distribution. To this end, an algorithmic solution to circumvent the reliance on manual item discovery has been shown to be effective in this use case.

In investigating a solution for this problem, key research questions were derived to test if an applicable solution was found. From these questions, the important objectives and outputs (Table 1.1) were determined and achieved according to the project timeline. The first step in this process was to investigate existing relevant knowledge in applicable fields in order to create a foundation for this project (Chapter 2). Following this, a potential solution was theorised and then implemented into a digital game prototype (Chapter 3). Finally, the prototype featuring the TBPO algorithm was exposed with different generation parameters to different groups of participants under scientific experiment conditions (Chapter 4).

RQ1: *What impact does a genetic algorithm-based weapon item generation system have on a traditional First Person Shooter game, as compared to psuedo-random item generation?*

The inclusion of this algorithm into any item-driven game does not alter the fundamental game experience for the player. Instead, its presence in a game context will result in the player naturally receiving more targeted and specific items that they have been observed preferring. Part of the function of this algorithm relies on the fact that players are unaware that this system is in place, and is influencing the items that they are receiving. It has been reported that, when comparing a player's experience between random item generation and TBPO item generation that the latter results in a more positive and immersive player experience. Although notably the system, in its current state, performs the best given a player that enters the game experience with a high level of domain knowledge as they can more quickly make educated and accurate decisions on which items they prefer. This is simply the result of this algorithm's reliance on the player and their actions to directly inform the quality, or 'fitness', of the items generated.

This algorithm relies on the fact that the game it exists in using a component based system as the foundation of their items, or another way to express and manipulate items as a sequence of numbers. As this algorithm's core is that of a genetic algorithm, it relies on the ability to cross over and mutate particular parts of each population member which would not be possible given a different approach to items in a game. Therefore, if one desired to implement this algorithm into a game it would only be able to operate on items featuring interchangeable components that each can work with each other.

RQ1.1: *What system parameters and game context features result in the most positive feedback from users?*

As a part of the experimentation with the created prototype, three different sets of algorithm parameters were tested amongst different groups of participants. Amongst these three versions of the game, Version 3 resulted in the most positive and encouraging feedback when looking at the Game Experience Questionnaire (GEQ) data. The parameters for this version featured comparatively less control over the weapons produced with various avenues of controlled random selection to retain item variety in each generation (see Table 3.2 for specific parameters).

This was an important distinction to make as it was reported that the main contributing factor towards enjoyment in this prototype's game genre is the variety available to the player coupled with the journey toward achieving the 'perfect weapon'. As a result, a balance must be found where the player is given weapons that their data suggests they prefer as well as allowing them to find new and unseen options. People are dynamic by nature, preferences change as new information becomes available and these algorithm parameters worked towards catering these changing needs; this phase of gameplay has been called the 'Exploratory Period' in this thesis. To this end, care must be taken to ensure that the content recommendations of this algorithm are not too forceful in limiting the options available to the player; such an effect would be counter-intuitive to the overall goal of this project.

RQ2: *How does the player experience differ using the experimental system when compared to a traditional First Person Shooter approach for generating weapons?*

When observing the changes in the moment-to-moment core gameplay experience between randomised and TBPO generation methods, there was a sentiment that preferred weapons simply "appeared to be being found more frequently". This has been echoed by the GEQ data as there was no observable gameplay change given the presence of this algorithm, combined with the semi-structured interview responses noting that they felt they could more easily find preferred weapons in the gameplay session featuring TBPO. For game developers, this algorithm is more complex than a random generation solution and would therefore require more time and effort to implement into a game for production. Further, games that feature random item distribution usually centre around this concept by incorporating 'grind' as a core part of their gameplay loop. 'Grind' is the repeated experience of one game section by the player in order to acquire an item that has a small chance of being provided to the player. Given a perfect implementation of TBPO, this 'grind' would be negated and would force game developers to pivot their gameplay loop in a different direction.

However, as reported by some participants in the interviews, this 'grind' is part of what makes these item-driven games so popular and so satisfying to play, with the length of the journey making the reward feel more meaningful to the player. For TBPO applications that remain in this genre, care needs to be taken to allow for players to still undertake this journey toward an ultimate goal of finding their desired item or combination of items. This can be accomplished by a balance between randomised and TBPO generation, where benefits of both methods can create a game product that is satisfying without becoming frustrating.

Ultimately, a balance between controlled generation (TBPO) and chaotic generation (Random) would produce the best results in this use case. Where this balance can be found varies between use cases. Algorithm parameters can be tweaked to fine tune how much of the item generation is influenced by either generation method. If that does not suffice, there are some further additions discussed below that aim to alleviate these potential shortcomings.

5.2 Limitations

Over the course of this project, there have been a few limitations that could be avoided or mitigated in any future work. Some of these are a result of the limited time and scope of the project, as well as the capacity for a sole researcher to conduct all necessary steps to achieving the objectives and answering the research questions. The identified limitations in regards to the algorithm, game prototype and experiment design are as follows:

1) Time and Researcher Capacity

As this project has been completed as part of a research degree, there was a strict time limit imposed for all objectives to be completed within. This inherently restricted to the depth and breadth of investigation into this project's problem and its solution. Further, this research was entirely conducted by a sole researcher, with continued supervision from full time academics. Similar to the time restraint, this imposed further constraints in terms of what was realistically possible to achieve. As with any form of research, more time and resources to investigate the problem would serve a more holistic solution but is difficult to achieve whilst doing a research degree.

2) Experimental Session Length

Many, myself included, felt that the experiment was not long enough. Some participants wanted to experience more of the game, either in general or specifically prior to the preference based generation beginning. The length was an imposed requirement to ensure maximum accessibility for participants and researchers to be able to conduct the session in a timely manner. As the algorithm bases its assumptions of off data collected over a period of time, more time equals more data and more data equals more accurate results. Even though this optimisation aims to decrease the requirement of data to make somewhat accurate outputs, more data would always help results.

3) Overall Prototype Simplicity

The prototype was not a complicated game. The core gameplay loop consisted of: Generate Weapons, Select Desired Weapons, Start Wave, Defeat Enemies, Repeat. All aspects aside from the weapons themselves were static. This was done to keep as many variables as possible controlled, with the only changing variables between the two gameplay sessions being the weapon generation methodology. This was important as otherwise results may be skewed with other environmental or mechanic changes secondary to the research focus (the weapons) resulting in positive or negative results.

4) Weapon Design Complexity

Some participants felt that the weapons were not intuitive to understand. This was not the case for all participants but it should be noted that some participants felt this way. As mentioned in Chapter 3.2, this complexity came about mainly as a means to exponentially increase the weapon variety in the game - thus justifying the use of a search algorithm such as the one used.

5) Reliance on Player Skill for Optimal Results

As discussed throughout this thesis, using the Theorised Best Parent Optimisation (TBPO) algorithm sees the player themselves functioning in place of a traditional fitness function. To this end, the quality of the player's decisions in-game intrinsically dictate the quality of the outputs produced by this algorithm. Therefore, players that come into the experience with more knowledge and have the ability to make more informed decisions with what weapons they prefer produce better outputs from the algorithm. Conversely, players that are new to the genre and are exploring their options see the algorithm produce pseudo-random results. This was somewhat addressed by the inclusion of a tutorial to educate players that need it, so that they were more aware of how the game operates and what aspects they might prefer or not.

6) Assumption that Occurrence equals Preference

For determining the theorised best parent, it was assumed that components the player picked more often were ones that were preferred by the player; taking only this single metric, occurrence, as the deciding factor in assembling the best parent. This was the chosen methodology due to the simplicity of its implementation allowing for quick integration into the game, and therefore allowing more time to ensure it was error free for the eventual experimentation. There are a multitude of different solutions for this particular limitation which are discussed in the section below.

5.3 Future Work

After completing this thesis' project, there have been some areas identified could have been explored but were not due to time and capacity constraints. The experimental algorithm, Theorised Best Parent Optimisation (TBPO), functioned properly and was able to output weapons that aligned with player's preferences, however there is some room for exploration.

The first area that could have been further explored was the methodology behind the construction of the 'Theorised Best Parent'. The way that this currently functions (as discussed in Section 3.1) is by assembling a DNA sequence based on the most prevalent allele (a version of a given gene) for each given gene. When considering the dynamic and changing nature of a player's preferences, the current methodology leaves room for a more agile solution. A more nuanced solution for this could take into account the 'fitness' scores of the items rather than simply looking for the allele that occurs most often. To this end, another solution could value weapons chosen more recently by the player higher than earlier decisions to more mirror a player's ever evolving and changing preferences.

The next area of investigation builds off of the sentiment to further promote playstyle exploration and creativity by expanding the understanding of 'what is preferred by players'. As established in the semi-structured interviews with participants, some of the fun in item-driven First Person Shooter (FPS) games is derived from 'making do with what you've got' and the overall journey towards finding the perfect weapon. This could be promoted at an algorithm level in a few ways, the first of which could simply be an increased novelty chance. Another way this could be solved is by intentionally generating part of the population to oppose the understood preferences of the player. This would present the player with contradictory, but potentially preferred options to facilitate exploration in what could be a better direction. However, this would require a high level of domain knowledge on the developer's side of things to understand what components of a weapon are in opposition of each other. Finally, the last potential solution to this problem would be the dynamic activation of this algorithm when it is identified that the player has put themselves into a playstyle niche. This would call for an additional 'nice detection' system that would be able to turn on the TBPO algorithm when the player is delving into niche options, and subsequently turn it off (and back to Randomised generation) when the player begins to explore other options. Ultimately, the optimal solution would require more work to theorise and validate the given addition to this algorithm.

Given more time, it would have been interesting to explore the application of this algorithm in a more complete prototype digital game in combination with a more involved experimental process with participants. For example, a prototype that featured more aspects of the weapons being determined by its components would allow for a much wider range of weapons outputted. This would have expanded the ability of the game to cater towards niche playstyles, and would have made it more apparent that the algorithm was functioning optimally if the correct weapons were recommended to the correct player.

Further, a more involved validation experiment would have further tested the ability of this algorithm to perform its function. Due to the scope of this project, the experiment was required to be completed in a timely manner. This is not reflective of the true experience as a consumer of video games, and the function of this algorithm and prototype in that context has yet to be explored. A more asynchronous experiment wherein participants were invited to play the prototype as much as they would like, at home, over a longer period of time would allow for a much more nuanced understanding of the algorithm and its effects in a use case more similar to that of commercial games. Finally, this would allow for the algorithm to have much more user data for the TBPO algorithm to draw more complete and accurate assumptions and estimations on the player's preferences.

This project has been an interesting investigation into the ability of a genetic algorithm to generate preference based items in an FPS game. Over the course of this project, the traditional genetic algorithm has itself been adapted to this use case in order to become an appropriate solution. Built upon an understanding of the academic work that came before, a new incarnation of an evolutionary algorithm was designed, implemented and then validated with participants. Although already an exciting addition to the understanding in these fields, there is always more that can be done to create the best game experience possible.

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Appendix A

Game Prototype Details

A.1 Prototype Weapon Component List

Weapon Base:

- Pistol: *low ammunition count, fast reload time, manual firing mode, fires single projectile, average base damage*
- Shotgun: *low ammunition count, average reload time, manual firing mode, fires many projectiles at once, low base damage*
- Sniper Rifle: *very low ammunition count, average reload time, manual firing mode, fires single projectile, high base damage*
- Submachine Gun: *average ammunition count, average reload time, fast automatic firing mode, fires single projectile, low base damage*
- Machine Gun: *average ammunition count, slow reload time, average automatic firing mode, fires single projectile, average base damage*

Effect Types:

- Fire: *applys weapon base damage incrementally over a duration*
- Knockback: *knocks the entity away from projectile, velocity based on damage*
- Magnetize: *knocks the entity towards projectile, velocity based on damage*
- Weapon Jam: *disables entity's ability to fire projectiles for a duration*
- Fear: *forces entity to run away for a duration*
- Ice: *slows entity movement speed for a duration*

Projectile Modifiers:

- Anti Grav: *Sets the gravity modifier for this projectile to zero*
- Bouncy: *Adds an event listener to the projectile that applies force in the complementary direction on collision*
- Condense: *Reduces size of the projectile, and increases the damage multiplier*

- Curve: *Continuously applies acceleration left or right (selected at random on application) of the projectile's forward direction*
- Expand: *Increases size of the projectile, and decreases the damage multiplier*
- Explosive: *Adds a listener to the projectile that triggers it's detonation function on collision with a surface*
- Featherweight: *Reduces the gravity multiplier of the projectile, and reduces the damage multiplier*
- Frictionless: *Reduces the friction parameter on the projectile's physical material*
- Heavyweight: *Increases the gravity multiplier of the projectile, and increases the damage multiplier*
- Homing: *On application, searches for an enemy in range until one is found. Once found, applies continuous force towards that enemy*
- Lob: *On application, applies a large impulse force in the world up direction*
- Orbital: *Applies a continuous force towards and around the player*
- Piercing: *Adds a 'life' to the projectile meaning on colliding with an enemy, so that instead of being deleted it detonates and passes through to potentially detonate again*
- Platform: *Adds a listener to the projectile that spawns a platform at the projectile's location on detonation - platform size is based on projectile size*
- Preserved: *Increases the lifespan of the projectile, increasing the time it lives before automatically detonating*
- Rebound: *Adds a 'life' to the projectile and a listener to the projectile that applies a force towards a secondary enemy upon collision with a primary enemy*
- Snowball: *Upon application slightly reduces size and damage multiplier, however slowly increases size and damage over the lifetime of the projectile*
- Spiral: *Applies a continuous force to the projectile, with the force's direction rotating around the projectile's forward vector*
- Sticky: *Adds a listener to the projectile that freezes it's physics when it collides with an obstacle*
- Velocity Boost: *Upon application, applies a large force in the forward vector of the projectile*
- Volatile: *Over the lifetime of the projectile, randomly increases and decreases both the size and damage multiplier*

Modifier Additive Delay Options:

- 0 Seconds
- $\frac{1}{4}$ Second
- $\frac{1}{2}$ Second

- $\frac{3}{4}$ Second
- 1 Second

Modifier Amount Options:

- 1
- 2
- 3
- 4

Appendix B

Experiment Resources

B.1 Participant Information and Consent Sheet

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

PARTICIPANT INFORMATION SHEET

Assessing the Effects of a Playstyle-Driven Evolutionary Game Content Generation System

UTS HREC APPROVAL NUMBER: ETH23-8557

WHO IS DOING THE RESEARCH?
My name is Padraic Heaton, and I am a student at UTS. My supervisor is Dr. Jaime Garcia, who can be contacted at jaime.garcia@uts.edu.au.

WHAT IS THIS RESEARCH ABOUT?
This research aims to discover how the experimental, preference-based game content generation system affects the game playing experience in direct comparison to traditional generation methods.

FUNDING
There has been no funding allocated to this project, it is being completed as a part of a Masters of Computer Science (Research).

WHY HAVE I BEEN ASKED?
You have been invited to participate in this study because you are familiar with video games and the First Person Shooter genre, you are fluent in English, you are not a part of the research project, you are over the age of 18 and able to give consent, you are able to travel in to the UTS Ultimo campus, and you have no medical history of epilepsy.

IF I SAY YES, WHAT WILL IT INVOLVE?
If you decide to participate, I will invite you to participate in a one hour long experimental session taking place at the University of Technology Sydney. During this session you will be playing a gameplay prototype created as part of this research project for around 40 minutes. Halfway through this 40-minute gameplay session, you will be invited to complete a short in-game questionnaire on your experiences thus far. Following the gameplay session, you will then be invited to complete a semi-structured interview with the researcher regarding your opinions on the game prototype as a whole.

As a part of this process, the final semi-structured interview (taking place in the last 10 minutes of the experimental session) will have its audio recorded. This will be done to allow more natural conversation and will be transcribed at a later date.

At no point during your participation in this project will your personal details be shared nor associated with any data collected. Following your completion of this form you will be assigned a participant ID that will identify any gameplay, questionnaire or interview data generated from your participation. This assigned ID will only serve as a way to identify which data points relate to each other, and it will not be used to identify any of your personal details.

ARE THERE ANY RISKS/INCONVENIENCE?
Yes, there are some minor risks and inconveniences associated with your participation with this project. They mainly revolve around the extended use of a computer combined with the travel risks associated with getting to the University of Technology Sydney. These risks include discomfort for being seated and using a computer for an extended period, eye strain from looking at a screen for an extended period, discomfort or embarrassment from being watched whilst playing a game you are unfamiliar with.

DO I GET PAID FOR PARTICIPATION?
No. You will not be paid as a result of your participation with this research project. All participation will be undertaken voluntarily, with no expectation of reimbursement from the researchers or their associated university.

Participant information and consent form - version, date *Page 1 of 3*

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

DO I HAVE TO SAY YES?
Participation in this study is voluntary. It is completely up to you whether or not you decide to take part.

WHAT WILL HAPPEN IF I SAY NO?
If you decide not to participate, it will not affect your relationship with the researchers or the University of Technology Sydney. If you wish to withdraw from the study once it has started, you can do so at any time without having to give a reason, by contacting Padraic Heaton at padraic.g.heaton@student.uts.edu.au.

If you withdraw from the study following your participation, all recorded data associated with your participant ID will be erased. This would include any and all gameplay data, questionnaire responses, interview data, audio recordings as well as any transcripts resulting from these recordings.

CONFIDENTIALITY
By signing the consent form, you consent to the research team collecting and using personal information about you for the research project. All this information will be treated confidentially. Following your completion of this form you will be assigned a participant ID. Any and all referral to data generated as a part of your participation will be associated with this ID, and not with your name nor email address. As a result, all data is anonymous with the ID serving as a method to identify which data points are linked together.

There will be one digital document that relates your details (name and email address) to your given participant ID, which will be stored securely within the researcher's University of Technology Sydney OneDrive file storage. This file will only be able to be accessed by the researcher and will never be shared with other third parties. Following the conclusion of all experiments, this document will be erased resulting in all recorded data being unable to identify you or any of your personal details.

Your information will only be used for the purpose of this research project, and it will only be disclosed elsewhere with your permission, except as required by law.

We plan to discuss and publish the results as a part of the thesis output of the research project associated with this experiment. As mentioned previously, any and all results discussed in this thesis will not refer to or be able to reveal any of your personal details.

WHAT IF I HAVE CONCERNS OR A COMPLAINT?
If you have concerns about the research that you think I or my supervisor can help you with, please feel free to contact us with the following details:

RESEARCHER:
Mr. Padraic Heaton – padraic.g.heaton@student.uts.edu.au

SUPERVISOR:
Dr. Jaime Garcia – jaime.garcia@uts.edu.au

You will be given a copy of this form to keep.

NOTE:
This study has been approved by the University of Technology Sydney Human Research Ethics Committee [UTS HREC]. If you have any concerns or complaints about any aspect of the conduct of this research, please contact the Ethics Secretariat on ph.: +61 2 9514 2478 or email: Research.Ethics@uts.edu.au], and quote the UTS HREC reference number. Any matter raised will be treated confidentially, investigated and you will be informed of the outcome.

Participant information and consent form - version, date *Page 2 of 3*

UNIVERSITY OF TECHNOLOGY SYDNEY

CONSENT FORM

Assessing the Effects of a Playstyle-Driven Evolutionary Game Content Generation System

UTS HREC APPROVAL NUMBER: ETH23-8557

I ____________________, agree to participate in the research project Assessing the Effects of a Playstyle-Driven Evolutionary Game Content Generation System (UTS HREC Number ETH23-8557) being conducted by Padraic Heaton at the University of Technology Sydney.

I have read the Participant Information Sheet, or someone has read it to me in a language that I understand.

I understand the purposes, procedures and risks of the research as described in the Participant Information Sheet.

I understand that part of the experimental session will have its audio recorded for later transcription.

I have had an opportunity to ask questions and I am satisfied with the answers I have received.

I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

I understand that I will be given a signed copy of this document to keep.

I understand that:

☐ I will have my interview responses recorded
☐ I will be made aware when recording has started

I agree that the research data gathered from this project may be published in a form that:

☐ Does not identify me in any way
☐ May be used for future research purposes

I am aware that I can contact Padraic Heaton (padraic.g.heaton@student.uts.edu.au) if I have any concerns about the research.

____ ____/____/____
Name and Signature [participant] Date

____ ____/____/____
Name and Signature [researcher or delegate] Date

Participant information and consent form - version, date *Page 3 of 3*

B.2 Participant Expression of Interest Form - Online Form

Project Bootstrapped | Expression of Interest

Thankyou for your interest! Below are some quick questions about yourself for our records.

If you have any questions regarding this form, or the wider project in general, please feel free to contact Padraic Heaton (primary researcher) at padraic.heaton@uts.edu.au

* Indicates required question

Here is the link if you would like to view the Participant Information and Consent Form prior to completing this expression of interest. On the day of your participation, prior to partaking in the experiment, you will be invited to complete this form, and will only commence the playtest once it has been completed.

To be a part of this research study, **you must meet the following criteria**. If one or more of these criteria do not apply to you, you unfortunately cannot be a part of this research study.

1. Participant Inclusion Criteria *

Check all that apply.

- [ ] I am familiar with video games and the First Person Shooter (FPS) genre
- [ ] I am fluent in English
- [ ] I have not contributed to the development of this project
- [ ] I am over the age of 18
- [ ] I am able to give consent
- [ ] I am able to travel into the UTS Ultimo Campus
- [ ] I have no pre-existing conditions related to or exacerbated by extended computer usage
- [ ] I have no medical history of epilepsy

The following questions are simply designed so that we have the necessary information to contact you and organise a time and date to perform the game playtest. **All personal information will be kept confidential and never shared without prior explicit written consent from yourself**.

2. What is your preferred full name? (first and last name) *

____

3. What is your preferred contact email address? *

____

4. How did you hear about this research study? *

B.3 Game Experience Questionnaire (GEQ) - Online Form

Game Experience Questionnaire

* Indicates required question

1. Participant ID Number *

2. When are you completing this questionnaire? *

   Mark only one oval.

   - Middle of the Playtest
   - After the Playtest

3. I felt content *

   Mark only one oval.

	1	2	3	4	5	
Not						Extremely

4. I felt skillful *

   Mark only one oval.

	1	2	3	4	5	
Not						Extremely

5. I was interested in the game's story *

   Mark only one oval.

	1	2	3	4	5	
Not						Extremely

6. I thought it was fun *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

7. I was fully occupied with the game *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

8. I felt happy *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

9. It gave me a bad mood *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

10. I thought about other things *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

11. I found it tiresome *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

12. I felt competent *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

13. I thought it was hard *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

14. It was aesthetically pleasing *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

15. I forgot everything around me *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

16. I felt good *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

17. I was good at it *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

18. I felt bored *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

19. I felt successful *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

20. I felt imaginative *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

21. I felt that I could explore things *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

22. I enjoyed it *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

23. I was fast at reaching the game's targets *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

24. I felt annoyed *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

25. I felt pressured *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

26. I felt irritable *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

27. I lost track of time *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

28. I felt challenged *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

29. I found it impressive *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

30. I was deeply concentrated in the game *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

31. I felt frustrated *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

32. It felt like a rich experience *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

33. I lost connection with the outside world *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

34. I felt time pressured *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

35. I had to put a lot of effort in *

Mark only one oval.

	1	2	3	4	5	
Not	◯	◯	◯	◯	◯	Extremely

Appendix C

Results Data

C.1 Interview Transcriptions

Participant ID: 18

[**Researcher**] Recording has begun and the Participant ID is 18

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] I guess I liked the shotgun homing with velocity boost I think it was? Because I could just sit on a high tower and just shoot for the stars and it would just find and hit something

[**Researcher**] That is good fun, and having the shotgun with more projectiles means more things...

[**Participant**] ...Yeah more things that can land.

[**Researcher**] Was there a specific weapon combination you were looking for, but could not find?

[**Participant**] Specific weapon, do you mean like a weapon type?

[**Researcher**] I mean a combination of the components that make up a weapon

[**Participant**] I don't really think about that kind of thing usually, at least to me that kind of thing seems like a roguelike kind of thing, so you kind of just pick what you can. So I just picked what was best and when I had a three weapon kit I just stuck with it.

[**Researcher**] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[**Participant**] I guess before, just because it got repetitive because obviously it's just you run around to the same spots and you shoot 10+ enemies and then you're done.

[**Researcher**] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[**Participant**] That's pretty cool actually, so it keeps track of the type of weapons you use?

[**Researcher**] Yeah it keeps track of the weapons you use...

[**Participant**] Oh that's why I got like four shotguns that one time. Does it keep track of the modifiers you pick up too?

[**Researcher**] Yeah, so it keeps track of everything about the weapon and a bunch of different metrics of how you use the weapon or don't use the weapon. And then it tries to kind of produce weapons that it thinks you might like more.

[Participant] I do like that idea, but at the same time because let's say I pick, because I feel like homing is pretty good and then anything that helps homing would probably just steamroll most enemies I feel. I feel like if that was the system, it would get a bit easy after an amount of time. After it has realised, unless you just pick random weapons and it never figures out what you like.

[Researcher] That is a downside I suppose, but it definitely has a risk of if you find the overpowered combination it would just keep giving you that. So, given a perfect implementation of this idea, how do you think this would affect other games that are founded on random loot, like Borderlands or Diablo?

[Participant] I wonder if it would change much at all, at least to me right, the roguelikes I play you can pick whatever boon or element you want and usually you can make it work because it has a bunch of different combinations. So I feel like if it keeps just giving you similar things you're just going to play one type of thing instead of experimenting.

[Researcher] Yeah, it's almost better to have the exploratory phase, trying out different tactics

[Participant] And then if some of them just don't work you can just change to something else.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] Let me think, I guess not. This is just the weapons right? Are you thinking of implementing anything else?

[Researcher] Yeah, the way this project started was essentially doing the same thing but for level generation so using your loadout to determine what type of playstyle you have. Broadly speaking the two ends would be snipers or shotguns and if you preferred a longer range playstyle it would generate a map with large long open spaces. And then, conversely, shorter closed in spaces for shotguns for ambushing enemies. That's how this started, but moved away just as it seemed too complicated and too difficult to tell that it is working. As player's don't think about how good levels are for them personally until they have played it a lot.

Participant ID: 24

[Researcher] Recording has begun and the Participant ID is 24

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] Okay, favourite weapon, gotta think about it. I really liked the knockback at the end, I was testing out a lot of different things seeing how they functioned. And I think the knockback had so much impact, more than I was expecting and I really enjoyed using it.

[Researcher] Yeah good, was it just because you could push enemies around?

[Participant] It just gave crowd control, especially in later levels the AI seemed like it was getting better, more enemies.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] Yeah, so I was looking for piercing with damage in some kind of... in an SMG or shotgun that, oh what secondary effect was I looking for, I think it was the high gravity or something like that. Because then I wanted to control exactly where to go, if I wanted it to go through a lot of enemies. But that was as the game progressed, because at the beginning I was kind of fine just playing around using different things. But then lots of enemies started spawning and I realised okay I've got to deal with all of this

[Researcher] Okay yeah definitely, so your preferences kind of changed as the game changed?

[Participant] Yeah definitely.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I preferred the game after that, I don't know why. It really made me re-think how I was playing, I don't know how it just really changed my mindset and I started thinking more... Because at the beginning I was more thinking about the weapons themselves, more than the attributes of the weapons. So I was thinking I want something mid-range, short-range, long-range and then after we did the questionnaire I realised I should priortise the attributes of the weapons so that I could get more out of them. That didn't occur to me until way too late.

[Researcher] That's okay, what do you think... Was it just having a break from the game? Or talking about it? Or?...

[Participant] I think it was just taking a break from the game, taking a second to think about something else and realising what I was finding difficult right before we started the questionnaire and realising oh hey if I change my playstyle I can do it.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] Can I ask, was it generating weapons based on the first half of gameplay?

[Researcher] Yeah, so since the tutorial it was keeping a track of which weapons you used and how you used them.

[Participant] I like it in theory, and if it was in other games I would enjoy it. But especially at the beginning when I was just picking up anything and trying it out, I wouldn't want those to be logged if that makes sense. Because I'm just testing out the different mechanics and then the game is thinking this is significant data that I'm taking in and I'll give you the same weapons back. So I think if there's like a demo period where you can just play around before it starts keeping track.

[Researcher] Yeah right so there would be kind of... Once you've finished exploring the options then it starts keeping track. Yeah that's interesting

[Participant] Yeah so maybe a little tutorial section that says hey pick up a bunch of different things, see how they feel and then now we're going to start estimating. Because I was just picking up any old weapon and seeing if it works.

[Researcher] Do you think that it would have had a different effect on the early game experience compared to the late game experience?

[Participant] I think, yeah I think it doesn't need that long a period of adjustment for someone to say that they are really enjoying this mechanic or really liking that mechanic. But I think if you had to wait until the end of the game to kind of get that experience, it might be sort of wasted. I'm trying to think of my own playstyle when I play games, and how quickly I... I don't know it takes around 20 minutes I guess until I feel pretty comfortable with something

[Researcher] In my own experience, you can pick up an item or something and you'll immediately know if you like it or not.

[Participant] Oh absolutely, I think I picked up the orbital and rebounding weapons, I picked them up and immediately was like nope not for me.

[Researcher] Yeah, I guess looking back on that second half of you playing the game, do you feel like you noticed a difference in the weapons it was giving you?

[Participant] Yeah, I did because I was looking for specific things towards the second half of the game, and I wasn't getting them. But then I kept seeing the same attributes and the same types on pretty much everything. There was variation, but I saw the same things again and again and thought oh okay I'll just stick with what I got

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] The game was really fun, I gotta say, even though it was very sandboxy. It was very... The AI was very challenging, maybe it was just my gameplay style, but I found I had to really focus on movement and switching between weapons.

Participant ID: 25

[Researcher] Recording has begun and the Participant ID is 25

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] I think it was the SMG that had double expand, so that it became enormous. And also there was a similar thing with a shotgun that had two snowball effects.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] In the second half, I was kinda just looking for a weapon that did damage. And ended up just getting two basic pistols that did damage because I got more of a hang of how many hits it took to kill things. Yeah I guess I didn't really understand the effects well enough to want to try and use them.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] It was about the same, but I felt like I more understood what was going on more later on.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] So the question is, how could that idea be translated to other...

[Researcher] Yeah so if there was a game like Borderlands or Diablo or something that is founded on grinding for loot, what would you opinion be of a game that actively tried to give you things that it thought you wanted?

[Participant] I guess it depends how I, as a player, perceive the things it's given me to be interesting options based on what it thinks I want or if it's just more of the same. I felt like I could have muddied that data the first half. Because for the first half I realised I was just picking weapons that didn't do much damage, and then the thought crossed my mind that if the game would just give me more of these weapons it's not a great thing as an inexperienced player.

[Researcher] Do you think that it would have had a different effect on the early game experience compared to the late game experience?

[Participant] Yeah I guess, unless there's another metric by which the game determines if the weapon you use is one you like or are using successfully. I don't know how you would decide that.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] Not really, I guess I wanted to experiment more or get utility out of different combinations. But almost felt that I wasn't able to do that given the time restraint

[Researcher] Yeah that's the trouble with constraining the experiment to an hour for the whole experiment, it kind of didn't have the time to experiment

[Participant] I also thought that earlier on when you were given 12 guns per box, it was sort of like making slightly arbitrary choices where I was picking things that sounded safe or things that sounded new.

Participant ID: 27

[Researcher] Recording has begun and the Participant ID is 27

[Researcher] What was your overall opinion of the game?

[Participant] It was nice, it was a good game I liked to play it

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] Definitely the one that had the platform modifier, I did not think like how that would end up happening and it was really nice to see that happen

[Researcher] Yeah that one is definitely a unique one

[Participant] Yeah I thought it was really cool

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] Yes and no, I was looking for a lot of sniper rifles with the kind of modifiers, the different ones that were rarer to find. So I didn't feel like I couldn't find them but that they were rarer to find.

[Researcher] Just out of curiosity, what were the particular modifiers?

[Participant] I was looking for the platform one which I finally ended up getting, because I wanted to be more specific with the platforms. I also wanted sticky because I wanted to see how that would be on the sniper rifle.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] Personally, because I feel like the second time I was playing I was playing better than the first time, that's probably why I would prefer the second time. If there were any actual differences in the game itself, I didn't feel any

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] Knowing that I did notice a lot of SMGs and machine guns popping up the second time, because I was playing with them the first time around. And the reason I was doing that was because I was getting used to the game, so I'm picking guns that are easier to play as opposed to those that need skill. So, I think that the system is great, but not when I'm trying to get used to the game.

[Researcher] Definitely, you needed more time to settle into your niche before it starts doing that.

[Participant] Which then explains why I didn't get the snipers that I wanted.

[Researcher] So how do think that system by itself or maybe in different games, what would be your opinion on that?

[Participant] I love it, I think all my game experiences like when I play a game, the whole reason why we go out to loot is because you're looking for that particular weapon with that particular ammo and everything so if that's going to come to me automatically I can focus more on killing people.

[Researcher] Yeah, so you can focus more on the game loop itself. So, some of the satisfaction of getting the better weapons, or the weapons that you like, comes from trying over and over again. So if there was a system that instantly gave you what you wanted, would that benefit the game? Or would that take away some of the satisfaction of trying to get it?

[Participant] I think it would take away from the game. Mainly because in the beginning I wouldn't know what weapon I would like, only because I'm playing so often and trying every different weapon, you end up choosing a weapon. Mostly you end up choosing a weapon based on heresay. But if at all you're trying to play the game because you pick up different kinds... Because I know I don't like shotguns because I've played with them so I think it would take away from the game in that sense. But it would give something to the game as well in terms of games that are not loot-based. For example, Valorant that's not loot-based and you can buy whatever, I think it's already pretty skill based but I would end up focusing more on the skill if I didn't have to buy the weapons.

[**Researcher**] Yeah so you could just focus on the playing parts of the game instead.

[**Researcher**] Are there any further comments or feedback on this session or the game prototype?

[**Participant**] I mean considering how it is right now like it seems really interesting uh but I do like when I was writing the questionnaire like I said how like would you be interested in a story like I like but that is not a storyline like yeah so like I am interested but I put a lower score on that because I'm interested, like, in having a storyline at least. Yes. But I don't have one. Yeah. So I couldn't give it, like, a highest score. Yeah, that's very understandable. So that, and in terms of playing the game, like, it was interesting, like, I also feel like I'm more like a survivor player. Like, I want to know that I can protect myself. So I couldn't see where I'm being shot from. Yeah, true. So I don't know which side I should be focusing on, who's coming from where. And when I... I think it's also because of the modifiers. When I shoot the things, the robots, like, the smoke is so much, I can't see whether they died or not. So I'm like, should I not fire on them like am I spacing my ammo yeah definitely yeah there is a bit of feedback that needs to be worked into the game I'm like I'm sure like it's like I don't know if I need to say it and probably show it's already visible please do any for any other feedback what else like did I find uh I think like having like a mini health bar over all of them would really be helpful because I need to know. Like, the bigger ones, if they have more health than the smaller ones. And also a bit of feedback that you know you've hit them.

[**Researcher**] Well thankyou, that is all I have for you.

Participant ID: 31

[**Researcher**] Recording has begun and the Participant ID is 31

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] Definitely the homing because it just... the damage output was alright, especially as it was the machine gun, it was literally the one I had at the end which was two machine guns both of them had three homing attachments on them which meant that all I needed to do was jump around. And I was able to dodge the bullets very easily, I didn't have a challenge with that, so as a result I kept spamming bullets that they couldn't avoid so it didn't even matter the type of weapon, like the weapon type or the damage type. Although it was magnetic and no-weapon, shutting down their weapons, that didn't matter to me, the fact that I was killing them did.

[**Researcher**] Was there a specific weapon combination you were looking for, but could not find?

[**Participant**] Well I wouldn't have minded if it was, how do I put it this might sound a bit harsh but it... not really... Because I just picked up what I saw in the moment. I wasn't trying to get something in the long run, like oh maybe if I waited out this long I could get this and this and that but no I didn't feel like that at all because it was more or less the short term that I really cared about.

[**Researcher**] So there wasn't a specific thing you were looking for that you couldn't find?

[**Participant**] No not really

[**Researcher**] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[**Participant**] I would actually say before the mid point, because it was at least giving me more variety so I kind of had the option to try and use stuff. But after the mid point it just gave me a majority of homing weapons, so that means it was almost encouraging me to be scummy. But yeah if I wanted to pick a new weapon I would still be the same scummy homing spammer that I would be. But I will say though, I forgot to answer this for the last question I guess, I should've clarified I was looking for any weapon without platform. Platform is probably the worst upgrade for me. Because, especially with the shotgun, it just makes platforms in front of me that really serve no purpose cause I can jump so high. But in regards to this current question, definitely before the mid point.

[**Researcher**] Are there any further comments or feedback on this session or the game prototype?

[**Participant**] No that's about it really.

Participant ID: 34

[**Researcher**] Recording has begun and the Participant ID is 34

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] The SMG. I can't exactly remember what was on it but I liked it because it made me feel like I was doing something cool, like it just felt cool. I didn't have to have super accurate shots.

[**Researcher**] Was there a specific weapon combination you were looking for, but could not find?

[**Participant**] No I don't think so, no.

[**Researcher**] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[**Participant**] Probably before, only because it was new and I was still exploring and getting to know stuff.

[**Researcher**] Yeah the exploration, especially with how many different types of things there are, that's a big part of it.

[**Researcher**] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[**Participant**] I think that's cool, I think that's a good element. Yeah, because I was finding how many weapons it was spitting out a bit overwhelming, so maybe when it narrows down to things that you tend to pick up it would be less overwhelming.

[**Researcher**] And how do you think a system like this would affect other similar games? You mentioned Genshin, if that game had this system in it, what do you think the effect would be?

[**Participant**] I think it would make it like almost less strategic in a way, like taking out the element of strategically choosing weapons that fit your playstyle or fit your character or whatever it is. Like I think it would lessen that element of strategy.

[**Researcher**] Do you think that it would have had a different effect on the early game experience compared to the late game experience?

[**Participant**] I think it would be difficult because you have played so many hours and you've gotten to know every single weapon really well. It would be difficult if some of those choices might be taken away at the end, if you got used to a lot of different weapons or you've gotten sick of the weapons you have been using and wanted to try a new one.

[**Researcher**] Are there any further comments or feedback on this session or the game prototype?

[**Participant**] I loved the music! I thought it was cool, once it is more fleshed out with game design and once the story is there because I felt towards the end of the test it was a bit repetitive. So maybe with some more elements or new maps ... Something to motivate you to certain goals.

Participant ID: 35

[**Researcher**] Recording has begun and the Participant ID is 35

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] The triple sniper was quite fun, quickly switching between the three weapons and shooting them let me do a lot of damage very quickly.

[**Researcher**] That was a very interesting strategy I don't think I had thought of that before.

[**Researcher**] Was there a specific weapon combination you were looking for, but could not find?

[**Participant**] I was hoping to find more homing shotguns again because they also did a lot of damage, but unlike the sniper they were a bit more interesting as a lot of bullets came out of them. Which is a lot of fun.

[**Researcher**] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[**Participant**] The one before seemed to have better variety, but I am not sure if that was just luck or something you've programmed in.

[**Researcher**] That's the mystery...

[**Researcher**] Are there any further comments or feedback on this session or the game prototype?

[**Participant**] No I can't think of any.

Participant ID: 36

[**Researcher**] Recording has begun and the Participant ID is 36

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] Yeah so for me personally, the most memorable weapon would be the SMG like weapon type with the frighten or ghost effect basically. I thought that was a very cool mechanic and I liked the fact that sort of fear or intimidate mechanic could be put on a weapon like the SMG. You know, high fire rate you could spread it to a lot of enemies quite quickly, so I found that to be the most memorable

[**Researcher**] Was there a specific weapon combination you were looking for, but could not find?

[**Participant**] I don't think so at any point, I felt like whenever, especially earlier when I didn't have an idea of what weapons were in the game. When I initially hit those boxes, I had quite a vast choice very quickly so it was a lot of the main categories I sort of saw. Yeah there was nothing else I was looking for throughout.

[**Researcher**] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[**Participant**] I struggle to pick one I prefer over the other, maybe simply the fact that the initial one everything was a lot newer and it was an experience I wasn't as familiar with. So I would say that had more of like a shock factor for me, it was more exciting so to say. As for the weapons and differences, I'm not really sure. Because the second time around I was more familiar with the weapons, in what I was expecting so I sort of stuck with ones that I had pre-established ideas of that I wanted to use. So I'd say the first one I was a bit more experimental with what I was picking up so that one for me was more personally exciting.

[**Researcher**] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] Yeah definitely, I think that's an awesome system, personally I have played some games like you mentioned Destiny and Borderlands and I do find that there is a point where you lean towards a certain weapon or archetype but of course the game doesn't really know that to any extent. So when you are hunting down loot for example, when it is randomised, you'll get drops or you'll do a raid or a big boss encounter only for it to drop a weapon class that you don't use or something that doesn't fit your playstyle or build. So I can find that there is a bit of frustration there, almost like there is a bit of randomised grind. But if the game was to be aware of my build, or archetype or preference, I think that would be super helpful.

[Researcher] Do you think that it would have had a different effect on the early game experience compared to the late game experience?

[Participant] I think innately it takes a period of time for the player to initially explore what options are out there before they gravitate towards a build, at least for myself. I'd like to experience what the game has to offer and then pick an archetype, whereas maybe if I was forced into it too early for example maybe I wouldn't experience something that later on I may have enjoyed. But definitely at some point if the game was to recognise my playstyle or preference, but in the longer term maybe after 20 or 15 hours.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] No I was very impressed, I actually found it really engaging. I usually in games with that graphic style I don't gravitate towards usually, but I was very surprised in a positive light as to how engaged I was. I found the gameplay quite engaging, I am a sucker for assessing all my options before going ahead so every time there was the boxes that gave you a bunch of guns to choose from I was really taking my time with it trying to read through all the modifiers and then any that I wasn't too sure on and were clarified to me I could make an educated choice going into the next round.

Participant ID: 47

[Researcher] Recording has begun and the Participant ID is 47

[Researcher] What was your overall opinion of the prototype?

[Participant] I thought it was cool like the whole research you're doing on dynamically changing the gameplay, I think it was during the second gameplay where it starts to kick in right? So I noticed in my first gameplay I was like using a double platform weapon and later all my weapons had double platform. So I thought it was pretty funny how like if you decide to stick to one playstyle it would eventually stay like that. But yeah I liked how it matched your certain playstyle.

[Researcher] Yeah awesome, it was great that you picked up on that also.

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] I kind of like the anti-gravity playstyle, I like how it can kinda go straight... Ah another thing I found platforms pretty funny. So I saw double platform and thought it was pretty funny using it, even though it wasn't very useful I just thought it would be funny to use. The bouncy one too, I kinda had a preference for that too because it was easier to hit enemies more often. And sticky, I don't think I found much use for sticky other than just like shooting at the floor and hope that enemies would walk into it.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] Probably a bouncy shock machine gun. I found shock pretty useful, it just keeps them in place and I was generally trying to look for that exact combination but there wasn't really anything. For sniper rifles, I wanted more anti-grav sniper rifles but I could only find like one or two. Other than that, anything seems to work with shotguns. And I also wanted to try shock on orbital and just run into enemies but I could not find orbit on shock.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I feel like after the [questionnaire] there was a heavy skewing on a specific type. So I feel that there might be some room for more variety still but I did like how some of the options were kept there.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, would it be better to have more randomness? Or maybe an option to turn the system on or off if you didn't want it?

[Participant] I'm not too sure how to answer that because in some cases it's very useful for people that only have one specific type of playstyle. But then for me I just like joking around a lot and it eventually just creeps up on me.

[Researcher] Yeah, and always with a new game there's always a period where you want to explore all the options and kind of having a system that is trying to give you one specific thing might not be beneficial.

[Participant] Yeah so in games like Borderlands you know often I try to find something with a good magazine count and I'm not too worried about damage but often times the modifiers are not correct. So randomness might be good still in that case, and then later eventually once you have found something good... Maybe if there is some sort of way to determine if a player actually really likes something.

[Researcher] Yeah so maybe a system where the game can identify if the player is just looking for one thing or if they are trying to explore different things?

[Participant] Probably something that as the game time increases, newer weapons you pick up have a higher priority than weapons you pick up earlier.

[Researcher] Yeah that's an interesting point. I guess that kind of answers my next question which is how do you think a system like this would affect similar games like Borderlands or maybe other loot driven games that aren't shooters.

[Participant] I would say it's kind of fun to try to exploit the whole mechanic. So you can force yourself to use one type of weapon and you will always have that one. In multiplayer you could have one person force themselves into one role and another can change to another type.

[Researcher] So it would be different if the players knew it was a part of the game, compared to if it was just under the radar.

[Participant] I think if it was under the radar, players might find it kind of strange. So they might be forced to use a specific weapon and the game would think they really like that weapon. So again maybe as game time increases the newer weapons they pick up have more priority than older weapons. As it would take a while for them to find a weapon they really like.

[Researcher] Definitely, and before that you need the variety otherwise you might not find something you like.

[Participant] So maybe it would be good if that was implemented and wasn't told to the player?

[Researcher] It is an interesting point that if the player does know it is in the game, they can intentionally skew it in the direction they want to go in.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] Was there like a specific modifier... Were they completely random like unbiased random modifiers?

[Researcher] Every part of the weapons were preference based, in the second half - in the first half it was completely random.

[Participant] Okay so I reckon maybe the first half does not have to be fully random, maybe you can try to find out which modifier is suitable for newer players and which are better for later and skew it that way. So anti-grav might be more useful for newer players for example.

[Researcher] Yeah I intentionally put the anti-grav ones in the tutorial because I thought that would make a lot more sense, but yeah that is an interesting idea.

[Participant] Yeah so maybe you could have a bunch of user tests and see the preference on the first attempt and cross that and remake the prototype with a bias towards certain modifiers.

[Researcher] Yeah you could almost automate the concept of slowly drip-feeding players new mechanics... That's an interesting idea.

Participant ID: 49

[Researcher] Recording has begun and the Participant ID is 49

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] Hmm, most memorable weapon? I think probably the first one that comes to mind is that sniper rifle I got the first time around because I stuck with it for so long. Just because... I think there was another similar one later, it was just doing a lot of damage for picking the enemies off. But there were definitely more memorable ones in terms of the effects they had and stuff, but I wasn't really... I think the platform ones as well I hadn't really seen before. But there's not one that sticks out more than that first one just because I used it a lot.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] Not really, I was just kind of exploring the different weapons that were there. Trying to see the different effects. Maybe if I played for a long time maybe I would start thinking oh what if there was something that did this, this and this.

[Researcher] So, over a longer period of time...

[Participant] Yeah, I think if I played a game with that sort of mechanic for hours, then I would start to pick up different things.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I think after it felt a bit more challenging or it felt more like... I think in the first one at least, at least in the first half of the first half was sort of very easy I think. Very small packs of enemies, sometimes had to shoot them more I think but generally it was a bit dull. But then towards the end of the first half it picked up a bit and then in the second half I felt like, other than the first round where there were literally just two or three or four enemies, I feel like I had to look around a bit more and I was being surrounded a bit more, and more could be picked up.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] I didn't realise that was what was happening okay... I'm going to be honest I wasn't paying that much attention to that okay cool. I think, see with a game like Borderlands it's tricky because sometimes the variety is the fun bit right? Like you find a gun that's a legendary but it's not quite the sort of thing that you'd usually use and you give it a go and realise that you really like it or it's like you might really prefer... I only played the sniper character in Borderlands, but you might only prefer sniper rifles with a lot of ammo. So it might only drop weapons that have a lot of ammo but if it drops one that's really really powerful but doesn't have a lot of ammo, that would make you have to make an interesting choice of do I keep the six bullet gun that I have? Or change to a two bullet gun that does way more damage? But I think, the principle is good but I am just a bit skeptical if that is what makes that sort of game fun necessarily.

[**Researcher**] Do you think that a game with this system would work better if it was implemented in the early game or in the late game? So if it kind of switched halfway through, or if it was used from the beginning?

[**Participant**] My head is going to I think if you, at the beginning had that system in place then I feel there's a risk of getting sort of pigeonholed into a particular type of weapon that randomly showed up the most at the start of the game. Or even if it's random for the first decent chunk, maybe of that random selection you could find a dozen different weapons and of that dozen you prefer this particular type but if you were given a hundred different weapons you could prefer this type. So, I think maybe it could be not necessarily switched halfway through but if it's like a part of the generation system rather than the whole. And, I know it's going to be random anyway but if it was kind of light and maybe built up over the game then maybe.

[**Researcher**] So still promoting the exploration and variety...

[**Participant**] Yeah, allowing for variety and like I say, not getting pigeonholed into one type of weapon.

[**Researcher**] And then slowly cutting out the grind...

[**Participant**] Yeah, so as you play it sort of refines it. And maybe then, if you get it really spot on, then you could go here is the really hard quest where you will find this perfect weapon that you have been working towards the whole game.

[**Researcher**] Are there any further comments or feedback on this session or the game prototype?

[**Participant**] I think that with the whole weapon generation system, one kind of strange thing I noticed is just how every weapon has this very like all the projectiles are very physical. I know that the modifiers react and relate to that but yeah it was very strange. It felt almost as if you were shooting a bullet that then ran along the ground and hit the enemy, I'm not saying that everything has to be hitscan necessarily but in the sense that it was already a bit of a weird mechanic to get my head around. And the weapon variety was so wide, which is good but there were so many different types of weapons that I think it was really hard to make a mental mortar for how everything was working together. It was kind of just like there's a gun that does some things. That's probably the main thing that stuck out to me. Oh and just one thing I wanted to say, the first weapon I picked up at the start was like a magnetic shotgun and that totally confused me and it was also orbital so I shot these things and the spread was really wide and then one of them hit the enemy and then it started going around me - it was really confusing. But yeah that's all.

Participant ID: 56

[**Researcher**] Recording has begun and the Participant ID is 56

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] My favourite weapon was... Like the bullet types? Or just the weapon in general?

[**Researcher**] Just the whole weapon combination...

[**Participant**] Ah definitely the shotgun, yeah the shotgun. Why did I like it? I think I just found the amount of projectiles that came out and just the way it didn't really feel like a short range weapon necessarily, like the bullets just kept kind of going and seemed good at dealing with every situation.

[**Researcher**] Yeah I guess with the shotguns, if the power of the weapon is the modifiers on the projectiles, it just has more of them.

[**Participant**] Yeah some of the modifiers just worked really well for it.

[Researcher] Definitely, were there any modifiers that stood out to you?

[Participant] The modifiers, I really liked the snowball one I don't know if it did much other than just get bigger but I just found them really satisfying.

[Researcher] Yeah so those ones got bigger and did more damage as they got bigger.

[Participant] Yeah I just found them really satisfying.

[Researcher] Some of the combinations you can get, between expand and snowball can cover the whole map with a single projectile.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] I don't think so, I think I got a pretty good range of different ones. I tried to keep mixing it up but I found that I really liked the shotguns so I still tried to use different weapons but I feel I got a pretty good taste of the different modifiers.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I think I preferred the second one, I think found the variety and moving around in a different ways felt a bit more dynamic and trying to find the enemies using different cover and everything.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] I didn't notice too much that I was only seeing guns that were meant to be tailored for what my preference was, I did try to keep using a different range of modifiers to try and test what everything did. So, maybe I didn't give it enough over that time... Because I spent a lot of time opening those caches of guns and reading what each thing was. But I was kind of quickly able to go of pistol, I don't want that, sniper I don't want that, oh machine gun that's good.

[Researcher] So, knowing that system was a part of the game, what's your opinion on that being the way weapons were being generated?

[Participant] Yeah I think it would work well, especially if I had more time I would have kind of narrowed down a bit more rather than trying different options.

[Researcher] So you wouldn't have to leave the exploratory stage until you know what you like.

[Participant] Yeah like the range, when there's up to three modifiers, trying to find the three that I really like as well.

[Researcher] Given a perfect implementation of this idea of generating weapons you prefer, how do you think it would affect other random loot driven games? Like Borderlands or Diablo, Destiny, that type of game?

[Participant] I suppose Borderlands is the best example for me, especially Borderlands 2, I suppose if everything started off completely random but over time and by the end of the game you were only really getting the gear you like... I suppose the pros would be that you'll always get a gun that you like but it does kind of take away from the experience of getting a legendary that might not be the one you're after. But then when you do finally find the one that you want it does create a sense of 'finally I've got it'.

[Researcher] So there's value in the journey towards getting it.

[Participant] Yeah, I can definitely see more merit in especially a game more like this where it might not be kind of bosses necessarily but over time, whether it's 10, 20, 30 minutes the guns get better with more modifiers but it also starts to show you not only guns that you like but more around that... But more the varieties in the bullet type and the modifiers, because I found that with the guns I found I was more able to resonate with specific gun types and then the bullets types and modifiers made it a bit more fun to be testing out those in particular.

[**Researcher**] So I guess tell me if you agree with this or not. The system would be better in a game that's not founded on the gameplay loop of random loot, but still has the variety of a huge amount of weapons. But the gameplay loop isn't about grinding for the right weapon.

[**Participant**] So getting the guns would be a means to completing the main objective?

[**Researcher**] Yeah exactly

[**Participant**] I think that would work pretty well. If it is more about maybe it's like you're trying to escape something, there are enemies coming and you do get those loot caches as well and the reload chest. If it does kind of tailor towards what you prefer it would add to the gameplay, because you know as the levels are getting harder and there are environmental changes but you know that you will be getting a gun that I do like. Even though there will be some that I don't, I know that there's something that I will. I can definitely see how that would benefit.

[**Researcher**] Are there any further comments or feedback on this session or the game prototype?

[**Participant**] I found it really fun just trying the different guns and the modifiers and types in particular as the main thing I was kind of looking for between the rounds or the enemies. Yeah, I thought it was good, the movement felt really good like jumping around and everything. And the guns, I felt like they did what they were meant to, I didn't feel like they did something unexpected.

Participant ID: 72

[**Researcher**] Recording has begun and the Participant ID is 72

[**Researcher**] What's your overall opinion of the prototype?

[**Participant**] Yeah it's very cool, I like the idea of having a lot of customization on the weapon it's like Borderlands or something.

[**Researcher**] Yeah definitely, Borderlands was a big inspiration.

[**Participant**] What was it like over hundreds of thousands of unique weapons?

[**Researcher**] Yeah because of all the different combinations there were over a billion of different combinations. But yeah that's great to hear!

[**Researcher**] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[**Participant**] The sniper, because it's quite handy to use especially with the modifiers.

[**Researcher**] Yeah definitely, so the sniper with which particular modifiers did you like?

[**Participant**] I wanted to try out more but I keep on getting ice.

[**Researcher**] So what made you pick some weapons over others? Were there specific parts you were looking for? Or was it a combination that you were looking for?

[**Participant**] I was a looking for a combination, I tried to avoid the SMG because it runs out quite fast. Sniper rifle reloads quite fast but I did enjoy using the shotgun, especially because of how the bullets work because the just slide on the floor. So for the sniper I would try to probably look for any modifiers that isn't haunt.

[**Researcher**] Was there a specific weapon combination you were looking for, but could not find?

[**Participant**] More shotguns could be good like snowball shotgun with shock or ice. I'm not sure if fire has any impact by itself...

[**Researcher**] Yeah, I mean that's a personal preference type thing.

[**Researcher**] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[**Participant**] I prefer the one before that, because the one after kept giving me ice snipers.

[Researcher] Was it just because it kept seeming to give you the same thing over and over? That's what made you not like it?

[Participant] Yeah.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] It could be annoying, you'd probably need to wait to tell the user that it does have this kind of thing.

[Researcher] Yeah right okay, so you wouldn't want it to be overly pushing the player in a direction that they don't want to go in?

[Participant] Yeah

[Researcher] So, do you think that if the system... Because the system learns from your decisions and what weapons you pick up, do you think it would have a different effect if the system only activated at the late game? Once you've had a chance to play around with weapons?

[Participant] I think it would be fine at any point in the game, I think it's something that you would want to be able to toggle.

[Researcher] Yeah interesting, so maybe if there was an option to turn it on or off or maybe a special encounter that gave you preference based weapons that would be better? Just the ability to have it or not?

[Participant] Yeah

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] To be honest, I actually enjoyed both sections of the game. I just like the previous because there was slightly more freedom. Because personalised can be a bit frustrating.

[Researcher] Definitely, there is a fine line between personalised and then just pigeonholing you into one specific thing

Participant ID: 82

[Researcher] Recording has begun and the Participant ID is 82

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] I think the most fun I had was with the sniper rifle with the magnetic thing and volatile too, and I think it was also anti-gravity

[Researcher] Yeah, it does make it a bit easier to control

[Participant] It was also because when you shoot at the enemies they just go flying. It was awesome.

[Researcher] Yeah of course, that is a big part of it.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] Yeah maybe, I wanted to look for an orbital weapon that expanded either through a machine gun or SMG and would either also be snowball. But maybe just expansion and orbital. Another one would probably be a more stable platform anti-grav sort of gun.

[Researcher] Yeah definitely, often explosive is a good pair for platform because that makes it explode when it hits a wall, but another time maybe.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I think I preferred it after the first one, mainly because in the first one I was really trying to get used to the game and its statuses and elements and everything.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] For this game, I think it worked pretty well because there were actually a lot of weapons that I didn't enjoy not appearing in the second version. But I think I also enjoyed the random aspect because it made me explore more options and find more combos to have fun with. But yeah I think the second one where the AI made weapons based on my preferences seems more controlled and fun. I think actually yeah I would prefer the first one where it is more random.

[Researcher] Yeah right, so how do you think this sort of system would affect other similar games?

[Participant] I think it would definitely make it a lot more... In a way it feels a lot more controlled and fun for a short time. Because it would appeal to your sort of playstyle, but then in those types of games you want to explore a lot more. So their aspect of having purely random weapons generated or found in random areas is a lot more appealing.

[Researcher] And the gameplay loops of those games also often revolves around getting random loot as well.

[Participant] I think it's also about how there are also different scenarios where you use different playstyles as well.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] Not much, I think it was just very enjoyable with just all the random weapons. I feel like I would like a bit more variety, I liked how a lot of the weapons used pushing and pulling mechanics but I feel like there could be a bit more. I think there were only two or three element types but I feel like they were less useful.

Participant ID: 87

[Researcher] Recording has begun and the Participant ID is 87

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] I forget the weapon type, but the modifiers were snowball and I think it was the frictionless modifier - it was a shotgun - which let me bounce it off of walls with the spiderman tactic of glitching into the wall and letting the enemies pile up on top of me. In the end I saw the orbital modifier, which I think would have been very fun if I had found it with a high projectile count weapon - so I was trying to find different combinations of the weapon fire rates, because really that's what matters in the end you either want low fire rate or high fire rate. So for the orbital modifier you would want a high fire rate for a nice little shield around you, and then for the low fire rate you would want lots of condensed damage with anti-gravity to have that ray shot basically. So yeah I was very engrossed in trying to strategise and find what weapon combination would work best.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] For me, it's more about that I found the modifiers that I wanted and I was like "oh it's not on the kind of weapon I wanted" so yeah in a way I was going more for... I usually enjoy sniper rifles in most games but here since the gravity was so high, it was difficult to use. So I was more focusing on low fire rate shotguns or high fire rate SMGs with lots of projectiles.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I don't think it made much of a difference, it made me keep in mind what type of things to look out for. For example, whether or not if I was focusing on it or how much I was enjoying it - which I was but it made me more aware of it for the second round.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] Yeah that makes a lot of sense, in the second round I was getting a lot of sniper rifles as by default I picked a lot of sniper rifles up, which I'm sure made it think I wanted sniper rifles. But by the mid-to-late-point I was like oh I don't really like the sniper rifles, I want to go for the shotguns and that's why there were no more shotguns and had to switch back to sniper rifles. It is good in terms of if I find a niche I like... It would be nice if it was... was it focusing on weapon types? Or effect types as well?

[Researcher] It was focusing on everything, all parts of the weapons.

[Participant] That makes sense, I was using the sniper rifles pretty frequently which makes sense why I was seeing those later. It is useful but you do kind of like put yourself into a niche that you can't get out of easily. If there is some sort of place or menu where I can select which type of weapon I want... And then have it automatically generate that weapon although random loot would nudge you in that direction, it would help to break up those little cycles.

[Researcher] Yeah right, so how do you think this sort of system would affect other similar games?

[Participant] So I think it would all depend on the build that you are going for, you know explosive damage or elemental damage or whatever. If there was a way to get... You know if you were very committed to getting explosive it is nice to have more access to explosive loot but if you swap builds your preference for those items should change as well. So maybe if the game recognises that, for example, this build is 68% explosive damage and 32% elemental, whenever you change builds it could update what you get accordingly.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] Not really much I can say about the game prototype aside from some minor bug fixes and quality of life stuff. But I do like the fact that it does change the output of the loot based on what your preferences are. And if there would be a way to manually change your preferences later in the game that would be very very useful.

Participant ID: 88

[Researcher] Recording has begun and the Participant ID is 88

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] There was a shotgun or an SMG that was making platforms and it got me stuck which was new. But no probably the homing feature and the spiraling was really fun.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] No, I could find every weapon.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] Before for sure. Afterwards I felt it became a bit repetitive, I felt that was getting a little samey and I was just trying different weapon types and experimenting with them.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] I don't think that would be a good idea. Personally, I think the whole point of having all those different types is to explore all those different types. Basically I don't think that you want to curate a certain amount of META builds to people, you want them to experiment. I think I wouldn't want to go for the META build, I would rather go for different playstyles.

[Researcher] Yeah, it is always nice to experiment with different things. Building on that as well, do you think it would be better if this system was implemented in the late game? Or would that still be a detriment?

[Participant] The best example I can think of is the Division by Tom Clancy, they tend to make you lean towards a DPS build with high damage with specific weapons. And it got boring after a while as it became all the same thing. There was no building different ways with strategy.

[Researcher] That is true, it wouldn't be as exciting to get loot if you knew what you were expecting.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] The game is nice, I liked the music. Yeah not too bad.

Participant ID: 96

[Researcher] Recording has begun and the Participant ID is 96

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] The platform SMG with the, I think it was the magnet sniper was great. It was awesome, it was fun.

[Researcher] That's great! Did you feel like you could use the platforms properly?

[Participant] Yeah, I didn't use them to their best ability for sure.

[Researcher] They are kind of hard to manage.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] The platform one I was looking for for a while, but eventually I did find it.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I don't know, fairly similar. Maybe more engrossed in the second one. I felt like I was concentrating a bit more in the second one. I was pushing pretty hard to get further and further into the second one.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] I think it worked pretty well, I did notice that it kept giving me sniper rifles and then I wanted to change it so it took a little bit of time to get a different weapon. But the variety was great.

[Researcher] Do you think at any point it pigeon-holed you too much?

[Participant] It hit a point where it was a little bit obscene amounts of sniper rifles coming out. But that's probably my fault for keeping on picking them but once I started changing weapons it seemed to change with me.

[Researcher] Yeah right, so how do you think this sort of system would affect other similar games?

[Participant] I think it would be good in some... I'm thinking about Borderlands primarily and I feel like it wouldn't it lose some bits of the 'hunt for a legendary' if the game was just constantly giving you things that you wanted.

[Researcher] Yeah definitely, because the idea would be to side-step the grind but if the grind is what makes it rewarding then it would also side-step that

[Participant] But it would be fun, if you got to the point where you would be getting those weapons then it would be fun in the game.

[Researcher] Do you think that it would have had a different effect on the early game experience compared to the late game experience?

[Participant] It wouldn't make it worse, I can't see it making it any worse. It might be better because if it is inactive at the start then you can explore until you know what you like. And once you do it can give you what you want.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] It was fun! Really good, had a good time.

Participant ID: 97

[Researcher] Recording has begun and the Participant ID is 97

[Researcher] What was your overall opinion of the game?

[Participant] I think this game is a competitive game where you use different guns to shoot enemies and during this game I think I must also find different stages located in different places to go to the next step.

[Researcher] Awesome, so how did you enjoy the game? Did you like it or not like it?

[Participant] Yeah I liked it because I have never played this kind of game before. I had to find that blue hole to jump into to go to the other places to go to the next step.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I think I preferred the game after that.

[Researcher] Yeah okay, any particular reason why? Or just that you knew the game more?

[Participant] I think just the feeling of the game really.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] So like weapon recommendations?

[Researcher] Yeah like that.

[Participant] I never thought that the weapons that were given to me were weapons that I liked. Because during the whole game period I had no idea what kind of weapons to use, or what their features were. I just used them to shoot freely.

[Researcher] That is an absolutely fine strategy because all the weapons are effective, there are no bad weapons. So do you have any comments on a system like this in any other similar games?

[Participant] I never thought about this question before because this is the first time I knew that this system gave users the weapons that they like. So I think it may be good for some professional users who play video games because they can make more educated decisions. But for other users like me I am not very interested in video games so I didn't know what the purposes of the weapons are and did not make big decisions on the choices.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] I think this game is very interesting, and the most interesting thing was the blue hole you had to jump in. Because during the first and second stages I used that hole to go through but in the final stage I used it to jump.

Participant ID: 98

[Researcher] Recording has begun and the Participant ID is 98

[Researcher] What was your favourite, or most memorable, weapon combination? And what made it so enjoyable?

[Participant] There were a lot, but the most memorable... I think, there was one shotgun that had homing and explosive. So whenever I would aim it at an enemy they would die immediately of course, but you would watch their corpse just slide because of the explosive - and I found it very funny.

[Researcher] I guess yeah because that would eliminate the downside of the shotgun, which is that it is inaccurate

[Participant] Yes it would, I basically made a super weapon.

[Researcher] Was there a specific weapon combination you were looking for, but could not find?

[Participant] I don't think so, I think I saw most combinations and got a pretty good idea of what I did and didn't like. So I was happy.

[Researcher] Did you prefer the prototype before or after the mid-playtest questionnaire? What do you think made you prefer one over the other?

[Participant] I think I did prefer it before the questionnaire, specifically because - I don't know if it was longer but the second part did feel shorter. And the first part I was very engaged with it. There are only a certain amount of attributes and they do begin to become repetitive but at the start it was very engaging.

[Researcher] Prior to the mid-playtest questionnaire, the game generated weapons completely randomly. After this break, the game actively tried to give you weapons it thought you preferred. Given a perfect implementation of this idea, how do you think it would affect other random loot driven games?

[Participant] Honestly that might have been why it felt like it was becoming more repetitive. Because part of this is obviously I became more attuned to what I was finding interesting, but the game starts giving me the same things over and over again it's going to become stale. However, sometimes I was getting things that were completely different to what I expected and that did lead to different gameplay styles. I think it is an interesting point, I guess if there was more to the game you could work with it. It being the only thing about the game would be part of the whole and that getting aligned with the player's interests could be very useful. But in this specific example it could end up hurting the experience.

[Researcher] Yeah okay, so how do you think it could affect other games like Borderlands, Diablo or Destiny or any other game that's centered around random loot. Specifically comparing the late or end-game loot.

[Participant] I suppose it would make it easier because you're getting things more often that you are seeking out. And there are issues with those games where it can become very boring when you're looking for specific things and not finding them because it is just random. But yeah I still can't shake the issue that pure random does allow for experimentation, and taking that away could be a problem. But specifically for the very end when you really know what you're looking for it would be good.

[Researcher] Are there any further comments or feedback on this session or the game prototype?

[Participant] I think the issues on this game are because you're focusing on the random system instead of the levels or the visuals so I don't think that's relevant. I think some weapon types were objectively worse than others. For example, the pistol, I felt there was no reason to use it. Now obviously certain attributes on certain weapons were particularly powerful, for instance we saw homing on the shotgun immediately removed the only downside. So there are some natural preferences with weapons - I don't know if that is an issue necessarily. So maybe if you were tweaking the system you could make those types of combinations rarer to make finding them a bit more special.