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MComp Individual Project Report

Can randomized fine motor exercises improve the performance of typically developed adults in a first-person shooter?

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Contents

1 Introduction

1.1 Project overview

The primary purpose of this project is to expand the knowledge base surrounding the training of expertise in esports. Esports is a generic term which covers several genres of videogames, such as Massive Online Battle Arena (MOBA), First-Person Shooter (FPS), and Real-Time Strategy (RTS) (Nagorsky & Wiemeyer, 2020). Esports are distinct from casual videogames and can be defined as the “top level of video gaming in terms of skill and professionalisation” (Cunningham et al., 2018).

This study will focus on FPS videogames and the performance metrics surrounding aiming. The FPS genre includes popular titles such as Modern Warfare and Counter Strike: Global Offensive (CS:GO). Games in the FPS genre revolve around the player shooting at other players to gain points (aka kills), or capture areas around the in-game map.

1.2 Literature

Esports is an incredibly varied area of study, with lots of opportunity for crossover with other disciplines, such as in medical applications (Chiu et al., 2021). Most contemporary esports literature focuses on the health of the players, which is relevant to esports athletes because they will often suffer injuries related to excessive play. These include wrist pain, eye strain, and back problems (DiFrancisco-Donoghue et al., 2019).

Beyond the physical health of players, mental health risks can also be attributed to problematic playing schedules. Players can fall into damaging spirals of playing more to mitigate feelings of loneliness, which in turn would then cause more intense feelings of loneliness. This is described as a “cycle of obsessive passion” (Luo et al., 2023). This is a recurring theme amongst the literature with most esports research focusing on the negative effects on player health.

There is, however, precedence for the training of cognitive skills such as dexterity using videogames. For example, games have been used to train gross motor function in patients with cerebral palsy (Arnoni et al., 2019), and Parkinson’s Disease (Gallou-Guyot et al., 2021). Few existing studies have trained participants motor skills to improve in-game performance, however, 4 main methods of intervention do exist. Those are sleep trials (Bonnar et al., 2022), nutritional supplements (Sainz et al., 2020), high intensity exercise (De Las Heras et al., 2020), and transcranial direct current stimulation (tDCS) (Toth et al., 2021).

Research into esports training is in its infancy, and a comprehensive training framework is missing for esports athletes (Nagorsky & Wiemeyer, 2020), compared with their traditional sports counterparts. This is likely because esports are still often seen as not “real” sports (Cunningham et al., 2018). This is a discussion that has surrounded many sports, such as darts (Davis, 2018), and chess (Groot, 1978). “Cognitive athletes”, as chess players were once described (Groot, 1978), are slowly being accepted into traditional sports arenas, with the acceptance of esports into the Asia Games for example (Campbell et al., 2018).

1.3 Methods

This study aims to aid the understanding of the fine motor aspect of FPS videogame performance to contribute to future work such as the creation of the aforementioned training framework. Furthermore, the gamification of fine motor training could be harnessed in medical applications to supplement traditional patient rehabilitation, in the way other games have been (Arnoni et al., 2019), (Gallou-Guyot et al., 2021).

The deliverable of this study is a piece of software used for training the fine motor movements associated with aiming. The training mechanics were designed around previous findings on the presence of motor chunks (Bera et al., 2021), (Bizzi & Ajemian, 2020), and the ability of a player to subconsciously perform Speed Accuracy Trade-off (SAT) assessments (Donovan et al., 2022).

Data was collected from the training software itself, and 3 test scenarios. Key to this study, is that the fine motor performance of each participant was assessed prior to, and after training had occurred, using the Purdue Pegboard Test (PPT). This is an important difference from existing products such as aim trainers, which attempt to train these movements, but do not test the effects on the player’s real-world motor skills.

Participants were asked to use the motor trainer for 10 minutes per day, for 5 days. Each participant was tested before and after this 5-day period, and results were analysed in terms of percentage improvement over the first test. In total 14 (7 control, 7 intervention) participants submitted usable data.

A new model of minor and major movements associated with aiming was produced during this study to aid the design of the fine motor trainer. These processes, known as the Interception and Verification stages could themselves be broken down into smaller motor chunks. The software trains chunks relevant to the FPS videogame genre to refine them in the ways described in existing literature (Bera et al., 2021), (Thompson et al., 2007).

Assessment of results was conducted via independent (group-group) and dependent (individual-individual) t-tests. The appropriateness of the t-test was first confirmed using the Jarque-Bera (JB) test for normal distribution and Levene's test for variance. Where data was deemed to not fit the criteria for the t-test, the Mann-Whitney U test was used to determine the level of significance of any improvement measured between test periods.

1.4 Results

Results from the PPT indicated that the training software did not have a significant effect on the participants' fine motor skills.

The tests used to determine normal distribution and variance are both affected by the size of the participant pool, which in this case was very small. Further testing was conducted using the Mann-Whitney U test, which is less affected by sample size, but these results often contradicted the t-test's findings indicating that further testing with more participants would be necessary to confirm either set of results.

This means that this study is unable to confirm the effects of fine motor trainers on player performance in FPS videogames. There was also not enough evidence to suggest a link between fine motor skills and in-game performance.

The Speed Accuracy Trade-off observed by Donovan et al. appeared to be contradicted by the findings of this study, which showed that when players took more time to shoot, accuracy did not necessarily increase. There are, however, more factors to the SAT than rate of fire, so these findings must be viewed in that context. Future work could focus on assessing this phenomenon in more detail as better understanding of SAT tasks such as aiming could inform the development of esports training frameworks.

Motor chunking can be observed in the training data produced by the intervention group, which supports the findings of Bera et al. Due to the substantial amount of collected data, detailed analysis was not possible.

Future work could focus on the analysis of this existing data to determine the exact nature of the motor chunks involved in aiming tasks. This could lead to a better understanding of the flaws in this version of the fine motor trainer, leading to the development of more robust motor training tools for esports researchers and potentially medical researchers to build upon.

2 Literature Review

2.1 Selection criteria

To be considered reliable, every source must meet mandatory criteria which support its credibility. Generally, research will only be considered for inclusion in this review if it was published in 2018 or later, however, exceptions may be made for works that are considered seminal. This timeframe is supported in existing literature which indicates that research in esports was sparse before greatly increasing in 2018 and beyond (Chiu et al., 2021).

It's important to note that the Covid-19 pandemic may have had an impact on this increase. The figures show a 100% increase in the number of published works in 2020 when compared with 2019 (Chiu et al., 2021), however, this is anomalous. In 2021, levels fell back to the increased number seen in 2018/2019 and have maintained that level since.

The publishing process for any work cited must have included peer review, and the authors should be of good standing in their fields. Moreover, journals will be the primary source of literature to underpin the integrity of any conclusions drawn. Other sources will include legal proceedings (Navarro v. Florida Institute of Technology, 2023), government guidance based on legislation (Department for Education, 2023), and seminal pieces such as the work of Groot in 1978, and of Woodworth in 1899.

Beyond these mandatory criteria there are several optional boundaries within which a source may fall, which speak to a work's relevance to this project.

Research is likely to be more valuable to this project if it includes video games developed with the express purpose of measuring or improving an individual's fine motor skills, however, the inclusion of interactive media is not mandatory for inclusion in this review. Moreover, research showing the effects of improved fine motor skills on any tasks, not just within first-person shooters, could provide valuable context for the design of the software used in this project.

The nature of esports, particularly the explosion in online viewing of esports (Chiu et al., 2021), means that some trends will only be demonstrable through the study of YouTube videos. Any videos referenced in this work will provide key insights related to existing training methods for esports professionals, however, no scientific weight can be assigned to them.

2.2 The state of esports research

Esports is a fast-growing sector of videogames, which has been aided in its growth by the emergence of high-quality streaming technology (Chiu et al., 2021). Recent increases in the esports market, from USD 0.49 billion in 2016 (Cunningham et al., 2018) to a projected USD 1.6 billion in 2024, have encouraged large investments from broadcasters and traditional sports teams (Chiu et al., 2021).

This has peaked researcher's interest in the topic of esports, and being such a varied field means that promising work has been published in several areas including cognitive ability (Chiu et al., 2021), therapeutics (Arnoni et al., 2019), sport management (Cunningham et al., 2018), behavioural analysis (Banyai et al., 2018), (Macey & Hamari, 2018), and mental health (Luo et al., 2023). Despite the variety of opportunities, much of the research is single disciplined, with researchers rarely collaborating across disciplines to further understanding (Chiu et al., 2021). This is likely because many areas of esports research are in their infancy (Sanz-Matesanz et al., 2023).

Participant health is extensively studied with researchers reaching conclusions on the effects of esports on hormonal changes, and sleep disturbances (Sanz-Matesanz et al., 2023), as well as physical ailments such as eye fatigue, and muscle strain (DiFrancisco-Donoghue et al., 2019). It is important to note that many studies don't differentiate between esports and recreational gaming (Banyai et al., 2019). In the context of player health, it is generally agreed that esports athletes are vulnerable to the same issues that befall players who play excessively recreationally, so the differentiation would likely make little difference to the findings of those researchers.

For example, players are at risk of physical injury related to overuse, such as wrist and hand pain (DiFrancisco-Donoghue et al., 2019), (Martin-Niedecken & Schattin, 2020), they are also at risk of problematic behaviours, including addiction and depression, which are compounded by their excessive playing time (Luo et al., 2023).

The prevailing avenue in new esports research focusses on the effects of increased videogame use on the participant's mental health, which is often negatively affected (Sallie et al., 2021), (Nilsson et al., 2022). This likely explains Frontiers in Psychology, and Computers in Human Behaviour being the most influential journals in the esports field, based on number of published articles, and number of citations respectively. (Chiu et al., 2021).

An aspect of mental health that has been studied from several angles in an esports context is motivation. Studies have found that players are shifting focus towards financial benefit through esports as a career choice (Banyai et al., 2019). The areas of esports that make the most money for esports athletes are competition winnings, streaming and sponsorships. Thus, esports athletes are extrinsically more motivated to pursue performance improvements than casual players of the same game (Banyai et al., 2019).

The motivation to become better can cause esports athletes to behave in ways that are detrimental to their health. In a study of 216 Chinese students, it was observed that feelings of loneliness would intensify the day after participation in esports (Luo et al., 2023). Moreover, feelings of loneliness were not reduced by increased playing time, while the intensity of the post-game loneliness increased. For these reasons, players could become stuck in an obsessive behaviour loop, and Luo et al., advise the use of coping mechanisms and motivation management to prevent the "cycle of obsessive passion" (Luo et al., 2023). This is supported by the findings of Banyai et al., who found that esports athletes are in greater danger of developing problematic behaviours due to their extended playing time, and the pressure applied to players' mental health during competition (Banyai et al., 2019).

These negative effects on players' mental health can be mitigated somewhat if the player has a stable sense of wellbeing and positive self-esteem (Banyai et al., 2019). In fact, it has been shown that player performance is positively correlated with self-confidence, and that players' mental toughness and capacity for emotional self-regulation are key to success in esports (Sanz-Matesanz et al., 2023).

Much of the discussion around esports also focuses on whether they can be considered real sport, with the lack of physicality often cited as a reason that they shouldn't (Chiu et al., 2021). As noted by Cunningham et al., members on the board of Sport Management Review "met the discussion with a healthy scepticism, perhaps thinking that it was a passing fad. As esport grew, however, so too did attention dedicated to the topic — by sponsors, spectators, and academics" (Cunningham et al., 2018). This is an argument that has evolved for decades. From the work of Adriaan de Groot, originally published in 1946 and translated into English in 1978, in which chess is described as a "mind sport" (Groot, 1978), to the transformation of darts from workingmen's pub game in the 1970's to international sport in the 1990's (Davis, 2018).

Indeed, the discussion on esports validity as real sport continues passionately to this day, with some relying on the courts to decide (Navarro v. Florida Institute of Technology, 2023). The Florida Institute of Technology (FIT) attempted to defend itself from a legal challenge based on America's Education Amendments of 1972, which mandate equal opportunities in sport regardless of gender (Education Amendments, 9 United States Code § 901, 1972). The FIT included esports athletes in its calculation of sporting opportunities, however the court ruled that esports cannot be considered sport for these purposes (Navarro v. Florida Institute of Technology, 2023).

On the other hand, the Olympic Council of Asia approved the inclusion of esports in the Asia Games 2022 (Campbell et al., 2018), and professional sports clubs such as Manchester City and

Paris Saint-Germain have invested in their own esports teams that compete in competitions like the Pro Evolution Soccer 2018 championship (Chiu et al., 2021). Moreover, in contrast to the US court's ruling (Navarro v. Florida Institute of Technology, 2023), 50 US colleges have esports teams, and several offer esports scholarships (DiFrancisco-Donoghue et al., 2019).

It is perhaps due to this inconsistency in the categorisation of esports that means there has been little progress in developing a health management model aimed at esports athletes, despite there being a clear need for one (Martin-Niedecken & Schattin, 2020), with many esports athletes finding themselves in the care of traditional sports departments (DiFrancisco-Donoghue et al., 2019). While there are areas of overlap between sport and esports, such as the immense cognitive load placed on competitors (Banyai et al., 2019), esports athletes rely more heavily on fine motor skills in their hands and fingers (Chiu et al., 2021) than they do on their gross motor skills, which is in contrast to traditional athletes.

2.3 Understanding player performance

Esports fall into several genres, such as, First-Person Shooter (FPS), Multiplayer Online Battle Arena (MOBA), and Real-Time Strategy (RTS). The skills required to obtain elite player status in each genre vary, and interventions aimed at improving performance should consider the game for which the athlete is training (Nagorsky & Wiemeyer, 2020).

Factors outside of individual athlete performance should also be considered as several studies have found that teamplay, communication, and tactical coordination are the most important aspects of successful gameplay (Mora-Cantallops & Sicilia, 2019). A review of such studies also noted that knowledge of the map and collective tactics based on the evolving visual cues were more important than any one player's contributions (Sanz-Matesanz et al., 2023).

Shifting focus to the individual, models of game competence have been proposed since the late 1990's with a few notable experiments supporting the model hypotheses presented over the course of the early 2000's (Nagorsky & Wiemeyer, 2020). The data collected has enabled researchers to categorise aspects of player performance into six areas of interest: sensory-motor control, cognition, emotional regulation, social factors, media literacy, and self-confidence (Nagorsky & Wiemeyer, 2020).

Sensori-motor control:
Mouse & keyboard
Eye-hand/foot coordination
Spatial perception
Flexibility, strength & endurance
Balance
Reaction & anticipation
Rhythm
Motor and sport skills

Fig. 2.1 – Many aspects of sensory-motor control affect player performance. This snapshot of a larger table shows the area of particular interest to this study, sensory-motor control, which includes fine motor control. (Nagorsky & Wiemeyer, 2020)

Fine motor skills can be further subcategorised to examine the individual stages of movement. This approach of splitting motor tasks into individual phases has been employed since the seminal work of Woodworth in 1899. Woodworth discussed the process of voluntary movements in relation to external stimuli and the consciousness of the person making those movements (Woodworth, 1899).

More recently, Thompson et al. examined the effects of target size and position on two distinct phases of target acquisition using a computer mouse. They were able to identify an initial rapid movement phase within which the user moves to the general area of the target, followed by a deceleration phase used for correction of the initial movement (Thompson et al., 2007). This is supported by contemporary studies of collaborative muscle groups which propose that complex movements may be broken down by the central nervous system into “motor building blocks”, allowing the user to subconsciously divide complex motor tasks into discrete chunks (Bizzi & Ajemian, 2020).

This process is referred to as “motor chunking”, and to become skilful an athlete requires practice so that they learn to efficiently execute the chunks related to the task they are performing. An example of motor chunking would be the use of controls in a set order, i.e., Forward – Left – Crouch – Shoot, (Bera et al., 2021). Theoretically, with significant practice, players will subconsciously optimise sensory-motor tasks by increasing the number of motor chunks, which in turn allows tasks to be performed more quickly and autonomously, allowing cognitive resources to be used more efficiently (Bera et al., 2021).

This idea is challenged by Thompson et al., who found that competitive players of StarCraft 2 saved no time by chunking tasks, nor does the number of chunks increase with the expertise of the player (Thompson et al., 2019). Thompson et al. theorise that this could be because StarCraft 2 presents a set of comparatively complex actions when compared with the simple actions completed under the usual laboratory conditions. Players could therefore require more time to develop and optimise their motor chunks (Thompson et al., 2019).

Listman et al. also highlights the complexities of applying techniques designed for motor development to esports. They point out that laboratory testing often includes simple tasks such as drawing a circle and they hypothesise that such tasks may not be appropriate for predicting the results of testing more natural movements (Listman et al., 2021).

To test their hypothesis, Listman et al. used data gathered from 7174 participants that had used the aim training software, Aim Labs. Data was collected exclusively from modes that involve “flicking” from target to target as quickly as possible. Flicking is the skill most often associated with FPS gameplay (Donovan et al., 2022), and it can be described in three distinct stages based on the work of Fitts and Posner in 1979 (Listman et al., 2021).

Firstly, there is the Cognitive Phase, which involves learning which movements to perform to complete a given task. The cognitive phase typically provides the greatest short-term improvements because the person will have never performed the task before and will quickly learn task specific strategies (Listman et al., 2021).

The second phase is the Associative Phase, in which users learn to fine tune their movements. This phase is less immediately impactful as it occurs over a long period of time, however, it is the stage where people show the greatest improvements to accuracy and time taken to acquire a target. This is the most relevant phase to improving fine motor control and is directly related to the chunking described by Bera et al. and Bizzi & Ajemian.

Eventually, users reach the Autonomous Phase, in which movements become akin to muscle memory, allowing the user to perform tasks with a much lower cognitive load (Listman et al., 2021). This supports the previously mentioned motor chunk theory, and findings of Bera et al.

As demonstrated, athletes' performance can quickly become complex on a scale comparable to that of traditional sports science (Sanz-Matesanz et al., 2023). It is generally agreed that esports athletes require the best available cognitive, physical and mental training, even if that is just to prevent injuries (Martin-Niedecken & Schattin, 2020), (Campbell et al., 2018), (Luo et al., 2023). Despite these factors, and the meteoric rise of esports described in the previous section, esports research is still scarce (Toth et al., 2023), (Sanz-Matesanz et al., 2023).

Even so, there are four main types of intervention studied in relation to the performance of esports athletes. These are:

Supplementation – Usually consisting of an intervention group, and a control group, these studies investigate the effects of stimulants such as caffeine on the performance of esports athletes (Sainz et al., 2020). Supplemental studies demonstrated that lower levels of anger were found in players supplemented with 100mg inositol and 1500mg arginine silicate (Tartar et al., 2019), and caffeine was found to reduce reaction time in acquiring a fixed target and significantly increase accuracy in first-person shooters (Sainz et al., 2020).

Physical exercise – These studies tend to prioritise the health of the player by enforcing a regimen of physical exercise. The link between that and improved game performance is seen as a win-win situation that can encourage esports athletes to prevent serious health conditions (De Las Heras et al., 2020). Physical interventions found that as little as 15 minutes of High-

Intensity Interval Training (HIIT) improved the ability of players to destroy enemies in League of Legends, with fewer attacks required per enemy (De Las Heras et al., 2020).

Transcranial Direct Current Stimulation (tDCS) – This process involves using low amperage probes on a person’s head, which deliver a constant direct current. Generally, this kind of intervention most effectively improves the performance of novice players (Toth et al., 2021).

Sleep therapies – This approach involves using education and counselling to improve the sleep of participants, with the hope that this will improve cognitive function. This type of intervention is the least successful category. A study of 56 esports athletes found that 2 weeks of sleep training, including biomonitoring and 1-1 coaching sessions, failed to make a difference to the cognitive performance of the athletes (Bonnar et al., 2022).

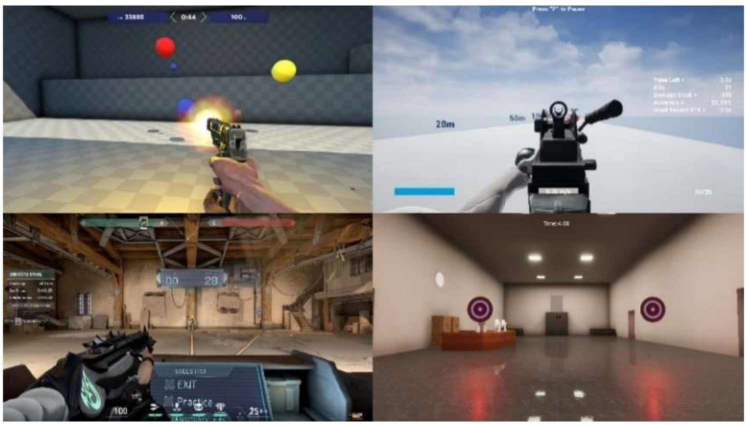
All other approaches have demonstrated minor success, with player performance increased between 1% and 8% (Sanz-Matesanz et al., 2023).

2.4 Discussion of similar products

It is clear from the literature discussed in the previous sections that success in esports is closely related to an athlete’s ability to coordinate bimanual movements in response to visual stimuli. It is also suggested that training of motor functions should closely resemble the task for which a player is training (Nagorsky & Wiemeyer, 2020).

It is therefore not surprising that several products defined as “Aim Trainers” are marketed as tools for improving player performance in FPS games. The most popular aim training software is Aim Labs which boasts a total user base of 30 million users worldwide (Roldan & Prasetyo, 2021). Many other aim trainers exist, including but not limited to Aiming.pro, AimTrainer.io, Aimtastic and Aim Hero. All these trainers involve the player moving the mouse to click on, or track (with the cursor), targets that appear at random, whether that target appears as a player model or simply as a sphere.

Fig 2.2 – (Clockwise from top left) Screenshots from Aim Labs (PC Games Archive, 2020)**, Apex Aim Trainer** (SharkFishFish, 2020)**, Aimtastic** (Pixel Pointer Studios, 2018)**, and Valorant** (Riot Games, 2020)**.**



There are also several trainers built into FPS videogames themselves, such as Counter Strike: Global Offensive (CS:GO) and Tom Clancy's Rainbow Six Siege. These trainers go beyond aim training and attempt to improve decision making, map knowledge and game sense. While these aspects of player performance are important (Nagorsky & Wiemeyer, 2020), they are not the focus of this study. These abilities fall into the cognitive area of the player performance categorisation discussed in section 2.3.

The effectiveness of aim training software is debated, however most of the debate is restricted to YouTube videos and testimonials. (theScore esports, 2021) (See also: (optimum, 2023), (eAthlete Labs, 2021)). The problem with these videos is they are of a very low scientific quality, often featuring the opinion of the creator rather than measurable effects.

Only three papers discovered in the process of writing this review mention the use of aim trainers. The first two are "*Long-term motor learning in the "Wild" with high volume video game data*" written by Listman et al., and "*Assessment of human expertise and movement kinematics in first-person shooter games*" by Donovan et al.

Neither examine the effectiveness of aim training on FPS performance but instead rely on aim training data to study motor skill acquisition, and critique methods of measuring those skills. Donovan et al. discussed motor acquisition from the viewpoint of Speed-Accuracy Trade-off (SAT) and found that traditional benchmarks such as damage dealt were poor measures of player performance (Donovan et al., 2022). They suggest that reaction time, movement speed, movement accuracy, and the precision of a variety of movements are better measures of individual performance. Both Listman et al. and Donovan et al. share many of the same authors and methodologies, and their tendency to support each other should be viewed within that context.

The third study is a conference submission titled "*Evaluating the effects of Aim Lab training on Filipino Valorant players' shooting accuracy*". Unfortunately, the authors, one of whom was previously unpublished, are not experienced in the field and their participant pool consisted of 6 people. This indicates that while they found that aim training improves player performance, the statistical validity of that result causes concern.

None of these publications discuss whether users simply got better at the aim trainer, rather than at FPS games. This is an important distinction considering the impact of the other skills featured in the player performance breakdown (Nagorsky & Wiemeyer, 2020) discussed in section 2.3.

3 Methodology

3.1 Objective overview

The objective of this research is to investigate the effect of fine motor exercises on player performance in first-person shooter (FPS) videogames. Any findings will be supported by several tests in an effort to avoid making assumptive conclusions. For example, it would be presumptuous to say that because a participant's FPS performance improved, the training software improved their fine motor skills. The research question can therefore be considered in the following terms.

"Can randomized fine motor exercises improve the performance of typically developed adults in a first-person shooter?"

- Did the training software influence the participant's fine motor skills?
- Did players only improve performance in the training software?
- Is there a correlation between fine motor skills and FPS performance?
- Did players only get better at FPS mechanics? i.e. Pointing and clicking.

3.2 Participant recruitment

Recruitment materials can be found in Appendix C.

Participants will be recruited through physical and digital advertising within the Department of Computing at Sheffield Hallam University. Simple random sampling provides a greater chance of selecting a representative sample of the population and is most suited to this project because stratified random sampling may restrict the participant pool too much. For example, if only esports athletes were selected, as was the case with the work of Roldan & Prasetyo.

Recruiting and then motivating participants can be difficult, and as such, some studies provide incentives to their participants. Macey & Hamari entered all valid participants into a prize draw for a $50 voucher, and Banyai et al., held a draw for two €200 shopping vouchers.

This study will also utilise a raffle, winner of which will receive a £250 Amazon voucher. To be eligible, participants must complete all their assigned tasks, and complete both test sessions. As the study does not rely on qualitative data, no bias is expected from participants feeling pressured to answer questions in a certain way.

Participants will conduct a demographic survey (see Appendix E) with the researcher on the first day of testing, before any testing is carried out. If the participant discloses any reason that the activities involved could be detrimental to them, they will be excluded from the study. Generally, participants will only be excluded if they suffer from serious illnesses that might be exacerbated by the exercises, such as epilepsy, or impact their results, such as arthritis. Participants will also be excluded if they are over 50 years old due to their age-related reduction in motor learning potentially affecting results (VanGilder et al., 2018).

3.3 Data collection

The demographic data collected via the pre-testing survey will be immediately anonymised using the participant's ID number. IDs are given in the order of participant recruitment, i.e. participant N signed up in Nth place. Each participant will be assigned to either the intervention or control group using an online number generator (NumberGenerator.org, 2023).

The demographic data will be analysed based on any arising needs to explain anomalous findings within the main test data. For example, if one participant shows massive improvements but they've never played a game before, it could indicate that improvement is most readily apparent at lower levels of expertise. Analysis will also be conducted on the group spread for each statistic, such as age, or computer expertise so that any biases have been identified before interpreting the results.

Qualitative data of this type should be used with caution as participants are prone to errors caused by poor memory or social desirability bias (Banyai et al., 2019), i.e. they may artificially inflate their results to appear competent within the esports community. This study will therefore not rely solely on qualitative data, however, this method has been employed in performance research focusing on metrics that are typically difficult to measure like stress (Banyai et al., 2019), motivation (Banyai et al., 2018), and variance of injury (DiFrancisco-Donoghue et al., 2019).

Studies led by both Donovan and Listman have approached the analysis of performance by collecting massive amounts of data from games like Aim Labs (Donovan et al., 2022), (Listman et al., 2021), however, converting this data into meaningful statistics is difficult as the performance metrics aren't detailed enough. The time and resources available to this project also make it unrealistic to process such vast quantities of data.

Quantitative studies often collect data in-game, and the use of commercially available games, with and without mods, is common. League of Legends (LoL) was used to study the effects of interval training on the participants' in-game efficiency by measuring the number of attacks used to destroy each target (De Las Heras et al., 2020). Furthermore, CS:GO was used to investigate the effects of adaptive difficulty on player improvements (Neri et al., 2021), and

Immersive Virtual Reality (IVR) games 20,000 Leaks, and Reflex Ridge were used to train the gross motor skills of children with the aim of assessing the effects of training on their cerebral palsy (Arnoni et al., 2019).

This study will not use commercially available software alone due to the granularity of the data required. It will, however, include data from the FPS videogame Titanfall 2 in the assessment of player performance. Data will be collected directly from the game, which has built-in measures of speed, accuracy and targets destroyed. This data will allow for the assessment of the trainer on player performance in a game that was not created for this study. This is important because mistakes in level design could affect results, and the design of a commercial release like Titanfall 2 will have undergone a much more rigorous testing process than is possible for the software made for this study.

Having been tested with Titanfall 2, the participants will undergo testing in a bespoke 3D shooting range. Key to this test's success, is that participants won't have had previous experience of the level, nor will they be able to practice the test, thereby protecting the integrity of the results from excessive game knowledge which is also an important part of FPS performance (Sanz-Matesanz et al., 2023).

To mitigate any adverse effects resulting from this, the researcher will be present during the test to give directions should the player become stuck, or not understand what to do next. The data collected from the shooting range will be written to a text file for analysis by the researcher for indicators of player performance such as accuracy, and speed of movement. Deviation from centre, time between shots, and shots fired will also be recorded so that a corroborative assessment of the Speed-Accuracy Trade-off found by Donovan et al., can be made.

To properly investigate the research question, data must be collected from an assessment of a participant's fine motor skills, outside of pointing and clicking within a virtual space. Existing motor movement studies tend to underpin findings using established tests from their area of expertise. For example, to measure the impact of motor training on body sway in children, Arnoni et al., used pre-defined protocols based around the Bertec400 force platform (Arnoni et al., 2019).

The Purdue Pegboard Test (PPT) has proved to be a useful tool for measuring the effects of rehabilitation on dexterity in patients with cervical myelopathy (Irie et al., 2020), as well as in the assessment of employees by occupational therapists (Lawson, 2019). The PPT is therefore considered suitable for use in this study to measure the effect of the fine motor training software on the participants' dexterity. Collection of data from the PPT will involve the researcher writing down results based on the protocols found in the PPT Instructions and Normative Data manual (Lafayette Instrument Company, 2015), and then transcribing them to a spreadsheet during the write up phase of this study.

The training software for this study is a separate entity to the test software and it will collect performance data of its own, which will be written to a file for analysis by the researcher. This data will be used to assess the player's improvements within the trainer, which will allow conclusions to be drawn within the context of the player's varying game performance.

3.4 Data analysis

The main method of analysis will be calculating the difference in mean improvement for each task between each test session, which will then require testing for significance. A common method of significance testing is the t-test (Listman et al., 2021), (De Las Heras et al., 2020).

There are several types of t-test, but the most suitable for this study are the independent samples test, and the dependent samples test, which assess the significance of a difference in mean values between groups, and over time respectively. Both t-tests assume that data has a broadly normal distribution.

Many methods for confirming normal distribution exist such as, the Kolmogorov-Smirnov test (Arnoni et al., 2019), and the Shapiro-Wilks test (De Las Heras et al., 2020). Each of the available tests provide a p-value which can be measured against a threshold value. In this study's case the threshold value will be 0.05, i.e. there is a 5% chance to retrieve a sample from the population that would disprove the null hypothesis (Bevans, 2023).

This study will use the Jarque-Bera (JB) test which is a goodness-of-fit test that compares the skewness and kurtosis of the sample with that of a normal distribution. The result of the JB test is defined as follows.

$$\mathbf{JB = (n/6) * (S^2 + (K^2/4))}$$

Where n is the number of measurements in the sample, S is the skewness, and K is the kurtosis. The JB test follows a Chi-Square distribution with 2 degrees of freedom, which allows a p-value to be calculated using the Excel function **CHISQ.DIST.RT(JB, 2)** (Statology, 2023). This test is affected by sample size, becoming more accurate with larger samples, however, this is true of all the available tests (Data Tab, 2023). An advantage to this test, however, is that it is calculable using built-in Excel functions which suits the researcher's statistical mathematics experience, reducing the chance of erroneous results.

The JB test asserts that a data set is normally distributed, thus, values of less than the threshold p-value would indicate that the data may not be normally distributed.

The independent t-test assumes that there is little variance amongst the data of each group, so this too must be verified. The Levene test can be used to check for this assumption's validity (Arnoni et al., 2019), (Data Tab, 2023). The test's null hypothesis assumes the variance in each group is similar. As with the JB test, a threshold p-value of 0.05 will be used, and values above this threshold would indicate that the null hypothesis is upheld.

number of cases
number of cases in the i-th group
mean value of the i-th group
overall average

$$L = \frac{(N-k)}{(k-1)} \cdot \frac{\sum_{i=1}^{k} N_i (Z_{i\cdot} - Z_{\cdot\cdot})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (Z_{ij} - Z_{i\cdot})^2}$$

number of groups
the respective value in the groups

Fig. 3.1 – The formula for performing Levene's test (Data Tab, 2023)

The t-value is then calculated as being equal to the difference in means over the standard error. Standard error is calculated as the square root of the sum of each standard deviation over the number of samples in that group. Excel provides the function STDEV.S() to aid the calculation.

Once the t-value has been established, a p-value must then be calculated. It is this p-value that must be compared with the threshold p-value of 0.05.

Mean sample 1
Mean sample 2

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Standard deviation Sample 1 and 2
Number of cases Sample 1 and 2

Fig. 3.2 – The formula for calculating independent sample t-values (Data Tab, 2023)**.**

The p-value will be calculated using the Excel formula **T.DIST.2T(t-value, DF)**, where DF is the degrees of freedom. DF is dependent on the type of t-test that was conducted. An independent t-test defines DF as **DF = $n_1 + n_2 - 2$**, where n_1 is the number of samples from the control group, and n_2 is the number of samples from the intervention group. The DF for a dependent t-test is defined as **DF = $n_1 - 1$**.

The Mann-Whitney test is considered the non-parametric equivalent of the t-test. It is more robust in dealing with outliers, however, when data meets the criteria for the t-test, the Mann-Whitney test may fail to detect a difference when one is present (Learn Statistics Easily, 2023).

It may become necessary to use this alternative test if any of the data collected does not have a normal distribution.

To perform the MW-U test, values are ranked in order from lowest (rank 1) to highest (rank n). The sums of each group's rank are then calculated to give an R value which is substituted into the following formula, where n_1 and n_2 represent the size of each participant group (Statology, 2018).

$$\mathrm{MIN}((\mathbf{n_1 n_2 + n_1(n_1+1)/2 - R_1}), (\mathbf{n_1 n_2 + n_2(n_2+1)/2 - R_2}))$$

Using a threshold p-value of 0.05 as before, the critical values can be retrieved from the Mann-Whitney U Test critical values table relating to that threshold. Exactly as with the p-values, this critical value will be less than the calculated values if the null hypothesis, that no difference is present, is maintained.

n1 \ n2	2	3	4	5	6	7
2						
3				0	1	1
4			0	1	2	3
5		0	1	2	3	5
6		1	2	3	5	6
7		1	3	5	6	8

3.5 Equipment and tools

When training using the provided software, participants will use their own equipment at home to avoid unnecessarily restricting the potential participant pool. Setting the hardware requirements as low as possible will make this easier, increasing the number of eligible participants and in turn, potentially increasing the quality of the population sample.

For this reason, there are few hardware requirements. Firstly, the built package will target Windows so only that OS can be used, and secondly a trackpad must not be used as that changes the movement profile expected from participants.

Restricting the use of trackpads does not necessarily rule out laptops which usually have comparatively weaker components. Therefore, the application should run on integrated graphics if required. This will be tested using the integrated GPU of the Ryzen 5900HS CPU installed in the researcher's laptop.

The performance constraints this imposes, coupled with the project scope, push the design towards 2D rather than 3D. This will provide a computationally less expensive application because costly features of a 3D environment such as animation, and collision will be simplified.

All tests will be carried out using an Asus ROG Zephyrus laptop containing an AMD Ryzen 9 5900HS CPU, and an Nvidia GeForce RTX3060 GPU. The laptop display is a progressive scan monitor with a maximum output of 2560x1440 at 120Hz. Participants will use the built-in keyboard, and a mouse which polls at 1000Hz and has a dots per inch (dpi) range of 100 – 25600. Participants will be allowed to find a comfortable setting within this range by using the presets that come with the mouse, so that the test equipment used for targeting is as similar to their training equipment as possible.

Practical dexterity assessment will be made using the Perdue Pegboard Test (PPT). The pegboard will be supplied by Sheffield Hallam University's technical resources department to ensure it was manufactured to the required standards set out by the guidance documents (Lafayette Instrument Company, 2015).

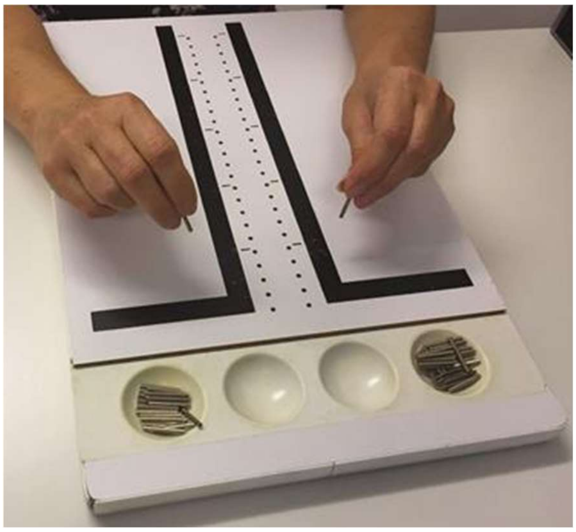


Fig. 3.4 – The Purdue Pegboard consists of two parallel columns of holes, each 1cm apart, with four collection trays at the top. (Lawson, 2019)**.**

The researcher will allow the participant to practice the tasks for a short time before beginning the test. During each PPT task the time will be recorded using the built-in stopwatch of the researcher's Android phone.

Using a game engine to develop the required software is necessary for this project as the timescales involved are relatively restrictive. Development of a custom engine would only be necessary if performance became a major concern, which is highly unlikely in this case. Game engines also provide several tools that are useful for recording detailed results. For example, cursor position, time stamps, and player position can all be easily accessed thanks to the interfaces present in engines.

Recent studies favour using existing software, sometimes modified, rather than building software from scratch, such as the modified CS:GO used by Neri et al. The most popular by far is Aim Labs which has been used in several studies of the mechanics of aiming and was developed in the Unity game engine (Donovan et al., 2022), (Listman et al., 2021).

There are several good candidate game engines. Unity, Unreal, or Godot, for example would be equally suited, however, the researcher has used Unreal Engine 5 (UE5) in professional game development, significantly reducing the time required for studying the engine, which makes UE5 the most suitable choice for a time critical project.

4 Design and Development

4.1 Variable Identification

It is common for FPS videogames to use statistics such as Kill/Death ratio, and assists (when a player injures another player, who is then killed by a teammate), to indicate whether a player has performed well (Roldan & Prasetyo, 2021). As discussed in section 2.4, these metrics have been proved ineffective in assessing individual performance because they are susceptible to outside influences. For example, the experience of the opposition will affect the perceived performance of the individual (Donovan et al., 2022).

It is therefore preferential to break down traditional metrics into performance components, i.e. how quickly a player acquires a target, or the approach the player has to the Speed Accuracy Trade-off (SAT) involved in aiming. The SAT is a phenomenon observed by Donovan et al., who noted that players using Aim Labs will trade accuracy for speed based on target size, specifically, that larger targets encourage faster aiming with lower precision (Donovan et al., 2022), (see figure 4.1).

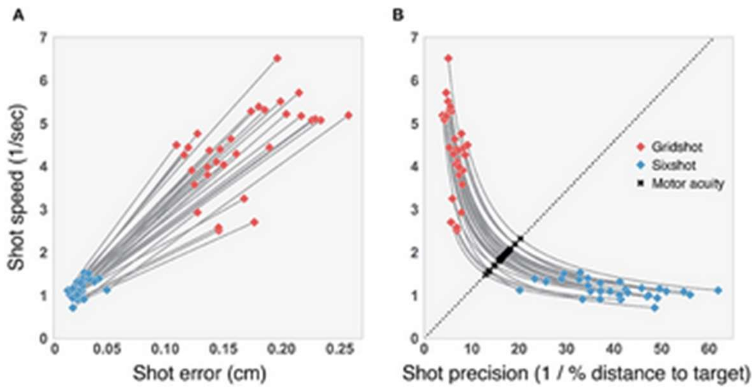


Fig. 4.1 – Data produced by Donovan et al., that demonstrates the SAT. Red targets were larger, blue targets were smaller (Donovan et al., 2022)**.**

Identifying elements of the aiming process in this way allows objective measurements of player performance to be made as distinct boundaries can be formulated, within which measurements can be taken. In this study, targeting will be thought of as occurring in four minor chunks; Identify target, Move to intercept, Adjust aim, and Fire at target. In turn, these minor chunks can be grouped into two distinct major chunks, Interception, and Verification.

During the interception phase, the player identifies their target and moves the cursor most of the way to the target's position. They then begin the verification phase by making small adjustments to their aim, if necessary, before finally firing at the target. This division is supported by the early work of Thompson et al., who used primary quantitative data to map four distinct stages of mouse movement during a pointing task, which could then be parsed into two stages of movement: the Primary Movement Phase (PMP) and the Sub-Movement

Phase (SMP). The reaction phase was determined as, from the time the target appeared to the mouse exceeding 8% of peak velocity, while the verification phase was defined as, from the last time mouse velocity dropped below 2% of the peak before the mouse button was pressed, to the button press.

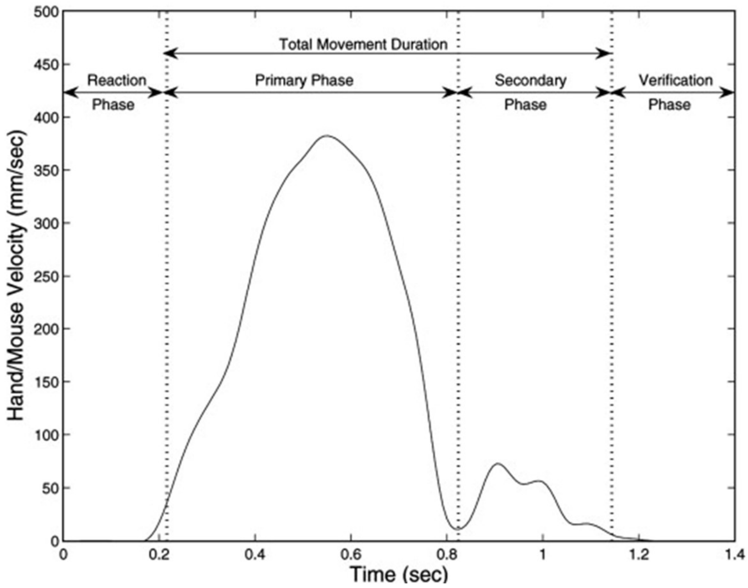


Fig. 4.2 – The four phases of mouse movement during a point and click exercise. (Thompson et al., 2007)

Interception, as defined in this research, can be thought of as equivalent to Reaction Phase (RP) + PMP. Similarly, Verification is equivalent to SMP + Verification Phase (VP).

These phases can be thought of as motor chunks, where the boundary of each phase indicates a new chunk.

As discussed in section 2.3, Bera et al., studied the effects of motor chunking on gameplay tasks using a simple game which required the participants to move from a green square to a blue square, while always passing through a red square.

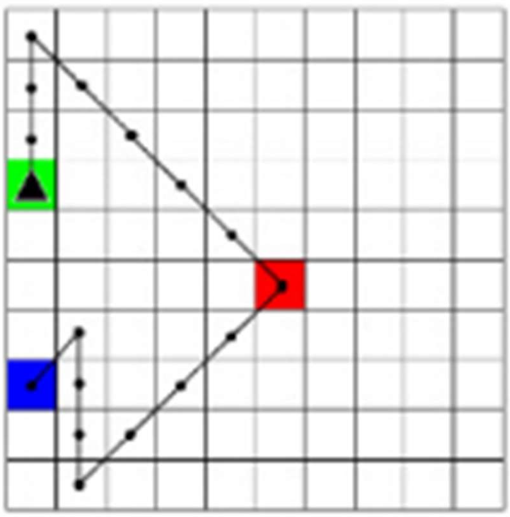


Fig. 4.3 – An example of the game board used by Bera et al. (Bera et al., 2021)

Motor chunks are often thought of as distinct movements – press key A, press key B, and so on, however, participants quickly incorporated moving through the red square into a larger chunk. Effectively, the action of moving through the red square became just another key press while the participant continued towards their goal (Bera et al., 2021).

It is therefore reasonable to assume that identifying a target, and then moving to intercept it, will become one indistinguishable process, hence, “Interception”. The same can be said for acknowledging a target’s destruction, which will be considered part of “Verification” in this study.

The player will likely subconsciously determine if the same target needs to be fired upon again without that process being its own chunk, so it is expected that several minor movements may follow each other during verification of target tracking tasks.

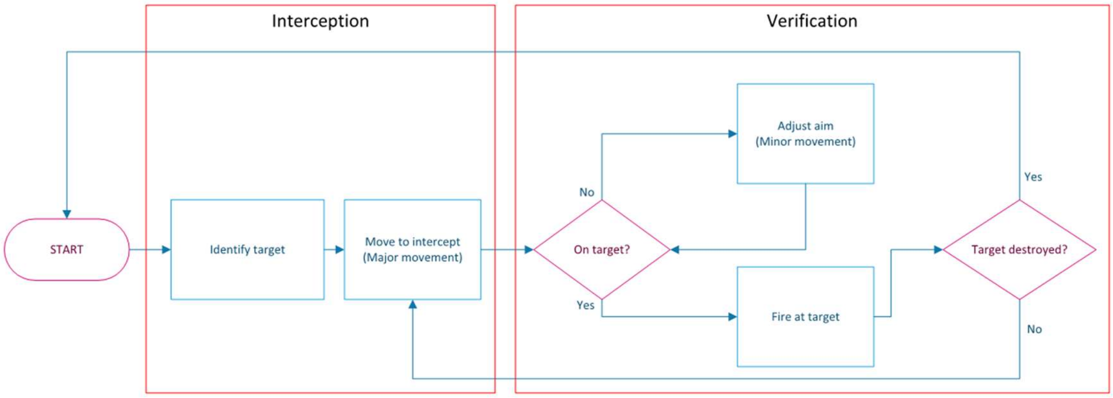


Fig. 4.4 – The separation of target destruction into minor and major motor chunks.

Having determined the structure of the motor chunks which are likely to exist, it is possible to look more closely at the variables that should be measured.

Beginning with the interception phase, the first variable will be the time it takes the participant to highlight a target. This isn't strictly the "reaction time" discussed by Donovan et al., or Thompson et al., because this study employs a multi-target design, i.e. there is no way of knowing which target the player will highlight next, and it is valid for a target to be ignored for some time. This time will therefore be measured between the end of each verification phase, i.e. previous target destruction, and the end of the following interception phase, i.e. next target intercepted.

The verification phase will start once a target is highlighted and be timed until that target is destroyed. A median target may be highlighted because it is positioned between two other targets. Thus, targets that aren't destroyed after being highlighted will not trigger a verification phase measurement but will be recorded as this may provide insight to the player's behaviour.

To gain further insight into the player's decision making, the position of the targets will be recorded, as will the key press required to destroy the target. These metrics can highlight strategies that indicate the player is gaming the training software by for example, only pressing certain keys, or only targeting larger, or nearby targets.

4.2 Mechanics

The primary requirement for the game mechanics is that they train fine motor skills, however, they should also be engaging so that participants are motivated to complete the training.

Based on the target acquisition variables described in section 4.1, and the mechanics of SAT tasks described by Donovan et al., Ozu, which is primarily a rhythm game, is a good example of a 2D game requiring fine motor expertise.

Ozu has gained popularity within the FPS videogames community, with FPS content creators reviewing Ozu as everything from an excellent way to warm up, to the best way to train a player's aim (polars, 2022), (sczer, 2020), (ApoLya, 2019). These sources are however, to be taken in the scientific context usually afforded to YouTube testimonials.

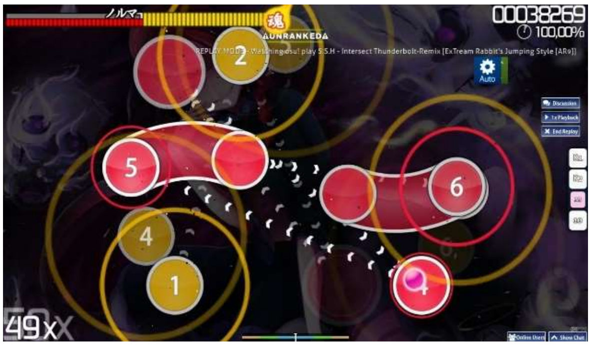


Fig. 4.5 – Ozu is a popular rhythm game with similar properties to an aim trainer (Family Gaming Database, 2023)**.**

Ozu has 22 million registered players (Ppy Powered, 2024)**, supporting its use as basis for an engaging and enjoyable game.**

It is readily apparent that precise hand-eye coordination would be beneficial in a game like Ozu, and as noted by the UK's Department for Education, "Fine motor control and precision helps with hand-eye co-ordination" (Department for Education, 2023), thus there is potential for fine motor development as player's progress through Ozu. Ozu therefore provides a promising basis on which to build fun, and engaging training mechanics.

As discussed in section 4.1, aiming in FPS videogames can be generalised to two main movements. The first, flicking, involves the player moving quickly to intercept a target with the cursor and firing. The second, tracking (also referred to as swiping (Donovan et al., 2022)), involves a more fluid movement that involves the player firing on the move. This is particularly relevant for moving targets, hence, "tracking".

In Ozu, flicking is practised on the standard targets which appear in different positions around the screen. The player is required to click on these targets in a rhythm defined by the game, however, the rhythm feature will not be present in the fine motor trainer as this will interfere with the development of fine motor processes, i.e. motor chunk memory.

Tracking is practised using Ozu's click and drag targets (see targets labelled 5 and 6 in Fig. 4.5) which the player must click on and move to a designated position. The fine motor trainer will emulate this movement by requiring the player to track moving targets.

Successfully acquiring targets using these methods was found to be a good indicator of FPS performance (Toth et al., 2021), (Toth et al., 2023). This supports their inclusion in the training software, however, Toth et al., make no suggestion that it is evidence of players having superior fine motor skills.

The participants could be better for several reasons, which is why this project includes the PPT discussed in section 3.4. The PPT will allow the researcher to determine if the player's fine motor skills were measurably improved by the software, before assessing any effects on FPS videogame performance. This potential limitation is inevitable when training motor function for a specific purpose because the training task needs to be similar to the functions we wish to improve. Referred to as "task-specific" training, it has been found to be more effective than "process-specific" training in motor skill interventions (Yu et al., 2018).

Fig. 4.6 – Examples of the key prompts.

This study proposes that aim trainers demonstrate a significant weakness regarding task-specific training as they, almost exclusively, ignore the keyboard (usually left) hand of the player. The fine motor trainer will improve upon this flaw by requiring key presses as well as clicks to destroy targets.

Using key presses ties into the motor chunking theory discussed previously. Motor chunks develop over time to have demarcations such as those proposed in section 4.1, they must therefore be practised to allow the player to execute chunks efficiently (Bera et al., 2021). For those efficient motor chunks to have a positive effect on FPS performance, the task needs to be relevant, key presses are an excellent choice in this regard as they reflect real-world actions in FPS gameplay.

4.3 User experience

Poor participant retention could endanger the usefulness of the study, so the user experience must avoid huge learning curves or boring gameplay so that players aren't discouraged from completing their assigned tasks.

For the best user experience, installation will require a software package that runs without the need for users to set it up. While all participants are expected to be familiar with using a computer, ease of installation is not just about technical competence. Participants will quickly become disengaged if they're forced to spend lots of time installing software.

The project will use Unreal Engine's (UE) packaging system, and OneDrive to ensure installation is as easy as possible. Users in the intervention group will be given instructions to download the folder "FMT_PKG" from OneDrive, which contains the game executable and the associated engine files required to run it.

Once begun, the game loop displays a menu to the user, which offers the player the option to play the game, to begin a tutorial session, or to quit.

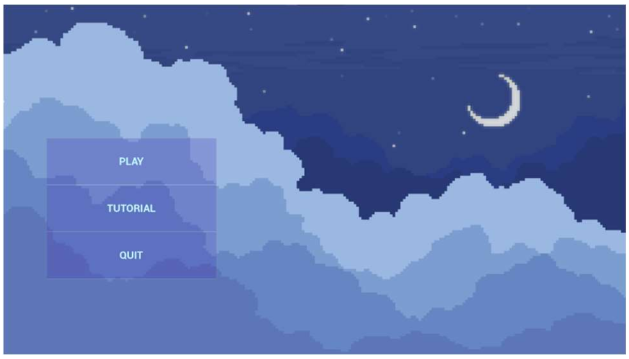


Fig. 4.7 – The main menu is the first scene presented to the player.

A tutorial is necessary because while all participants in the intervention group will be given a demonstration of the training software, they are then expected to use the software independently throughout the week, with minimal support from the researcher. With that in mind, the tutorial will be concise and use clear instructions to describe key elements of the HUD and the two target types. Effort will be made to avoid emphasising any play styles or potential strategies, because that could pollute the results.

Once the participant is confident that they know what to do, they can click “Play” to start the game. The intervention dose has been set to 10 minutes per day, for 5 days. The main factor that influenced this choice is the scale of the project, which doesn’t allow enough time for a longitudinal study. This potentially limiting factor is mitigated by research that suggests the frequency of practice is more important, with “4–5 times per week” indicated as an optimum rate (Yu et al., 2018). Moreover, improvements to sensory-motor skills in esports players were observed after participants had undertaken just 3 days of practice, for 10 minutes a day (Toth et al., 2021).

The HUD will include a countdown timer so that players don’t need to time themselves. When the countdown reaches zero, the game will display a message thanking the player for completing that day’s training. The HUD will also display a highscore and a best streak, increasing the playability of the game by providing players with additional challenge. These variables will be saved between playthroughs to give the player feedback on their progress over the week.

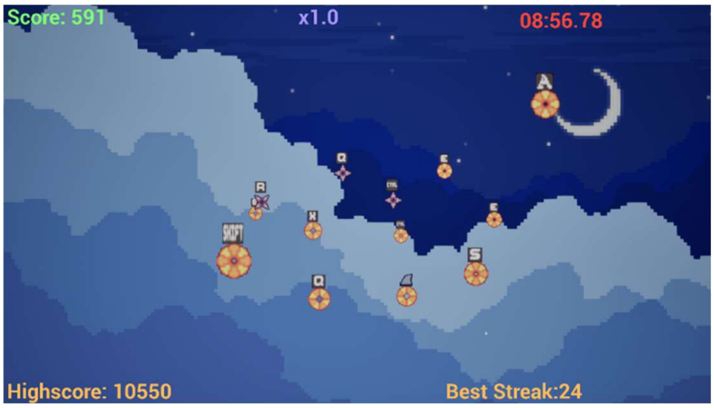
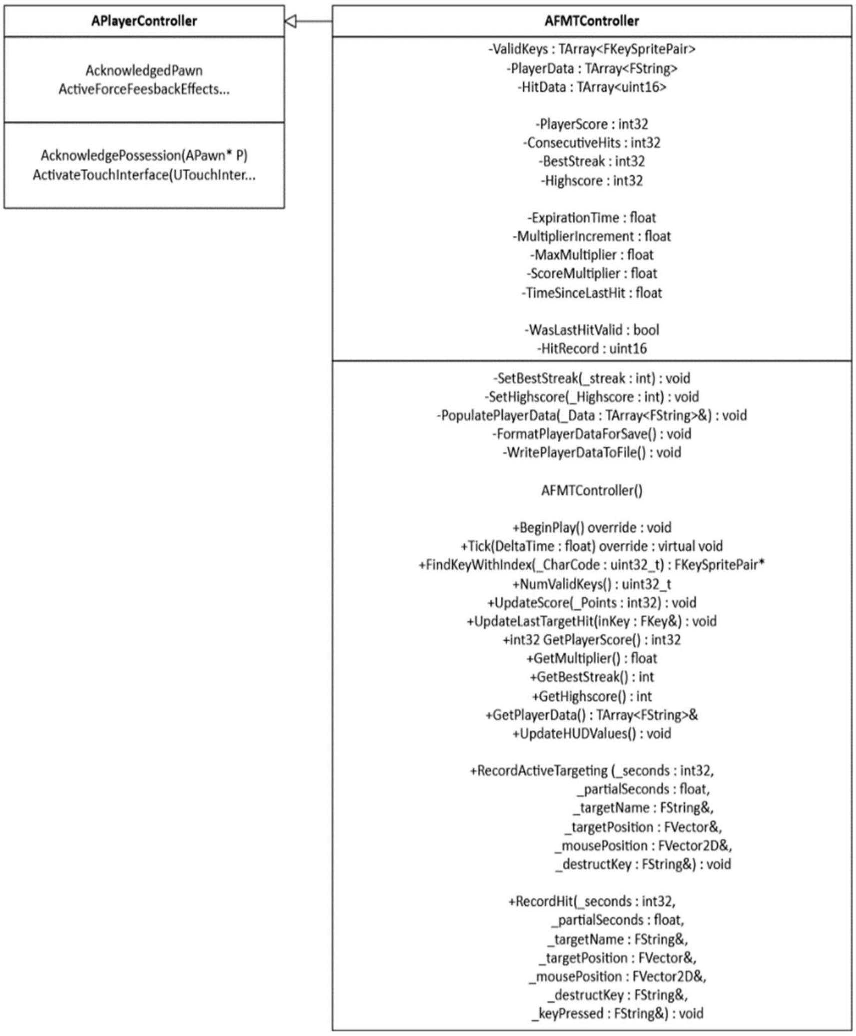


Fig. 4.9 – Letters above each target represent their destruction key. The HUD shows the score, multiplier (increased with streaks), time remaining, high score and best streak (hits without a miss).

Saving the game is triggered automatically when a session ends, and after using the software for 5 days, the participants will be given detailed instructions on sending their game data back to the researcher. This process will involve simply copying a save file into an email.

4.4 Implementation

The first important class is the custom controller class, AFMTController, which is a specialisation of the engine's APlayerController (Epic Games, 2024). Integrated with the engine game mode, and in the absence of a player pawn, the AFMTController is the link back to the UWorld object.



As well as storing player performance data, the controller stores information on the valid keys in an array.

The player controller will act as a proxy for the player in this application because there is no need for a pawn. The only representation of the player in the game is the cursor, which is controlled using the APlayerController interface. This allows it to receive calls from targets as they are hit, and record player data when required.

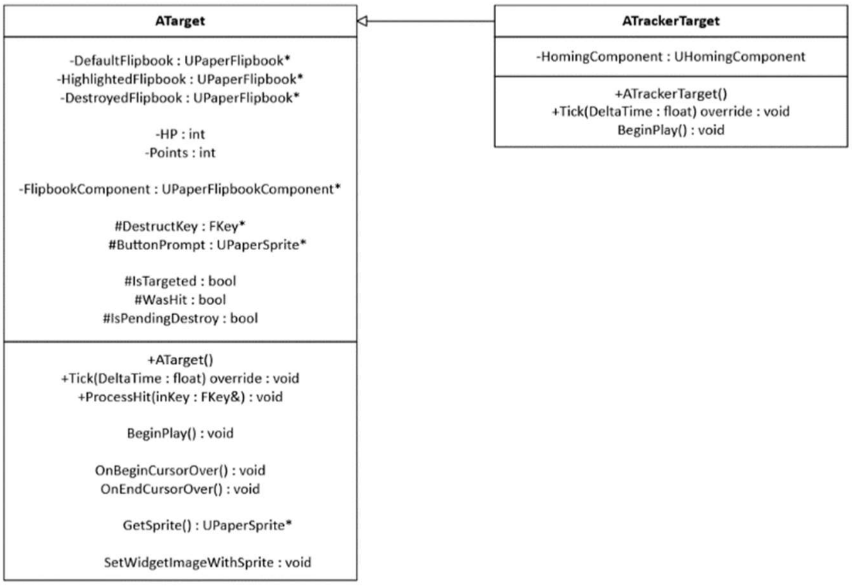


Fig. 4.11 – Class diagram showing the simple nature of the targets.

ATarget is effectively a collection of flipbooks that can process a hit based on the specifications provided to it.

During gameplay the controller listens for key press events. Those events trigger a call to APlayerController::GetHitResultUnderCursor(). The result of that hit is then cast to an ATarget, which is the base for all targets in the game. If the resulting ATarget pointer is valid, then the controller will tell the target to process the hit. The target processes the hit by checking its destruct key and health before finally informing the controller of the hit. The controller then writes to HitData and PlayerData which are in turn saved to a file at the end of the session.

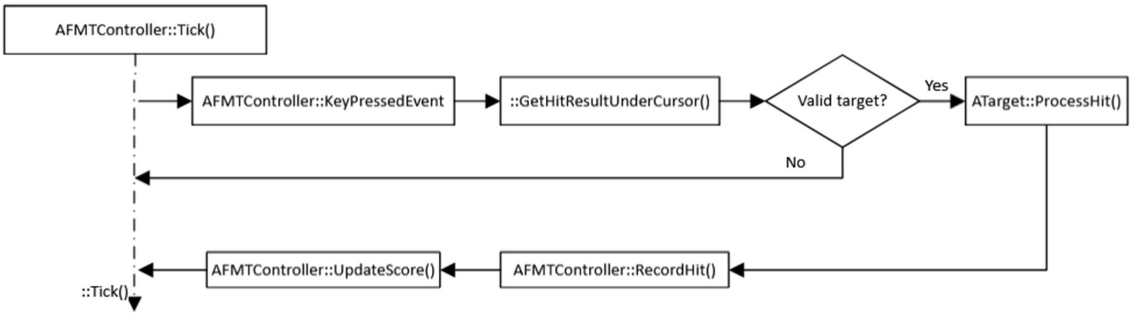


Fig. 4.12 – The controller listens for key presses, then triggers a chain of events resulting in the recording of player data.

Information about each hit is written to an array during runtime as file writes would be too computationally expensive. One file write is conducted after the session ends to prevent this performance issue.

```
void AFMTController::RecordHit
(
    const int32 _seconds,
    const float _partialSeconds,
    const FString& _targetName,
    const FVector& _targetPosition,
    const FVector2D& _mousePosition,
    const FString& _destructKey,
    const FString& _keyPressed
)
```

Fig. 4.13 – The arguments passed to AFMTController::RecordHit().

ATrackerTarget is a specialisation of ATarget with one key addition, the homing component.

UHomingComponent is a bespoke component which is responsible for the player-like movement displayed by the purple targets. Where the base targets train flicking, ATrackerTargets are designed to train more precise fine motor controls that enable the player to follow targets and control recoil in FPS videogames.

The homing component's primary job is to move towards a random position in the game world. It does this by generating a random position inside the spawn volume as a beacon, which it moves its owning actor towards at a randomly defined speed.

```
void UHomingComponent::UpdateMove(IN DeltaTime, IN Centre, IN Bounds)
        if (HasAValidOwner) then
                TimeToNextShift -= DeltaTime
                Path = BeaconLocation – CurrentLocation

                if (TimeToNextShift < 0) then
                        Speed = Random(Speed)
                        TimeToNextShift = Random(Time)

                        BeaconLocation = RandomPointInVolume(Centre, Bounds)
```

Fig. 4.14 – Pseudocode demonstrating the primary function of the homing component. Called by the owner's tick, this function runs every frame.

Spawners are the final important part of the application. Spawners use the custom ASpawner class derived from AActor. Most of a spawner's functionality is processed every frame in the tick function. Designed to be flexible, the spawner class contains several member variables that can be tweaked inside the editor. These include the type of actor to spawn, how often to spawn, how many to spawn, and the spawn volume.

The spawner also keeps track of how many targets are left by listening for callbacks triggered on target destruction. Used in conjunction with the min and max population variables, this controls the number of targets that are on the screen at once.

The spawners and the homing components use the Kismet Maths Library (Epic Games, 2024) to generate random points within a volume. The volume is defined using a vector representing the centre and a vector representing the extents of the volume.

As discussed in section 3.4, good performance is important, and the purpose of this bounding volume is to provide a cheap method of detecting if a target or homing beacon lies inside the view frustrum of the camera. The biggest performance saving derived from this approach is that the moving targets do not need to check for collisions with the border. Instead, they move toward a beacon which is known to be contained within the bounding volume.

```
void ASpawner::Tick(IN DeltaTime)
	if (NOT HasSpawnedMaxNumber) then
		if (BelowMinimumPopulation) then
			IncreaseSpawnRate
		else
			ResetSpawnRateToDefault

		if (ElapsedTime > SpawnInterval)
			GenerateRandomSpawnPointInVolume
			SpawnActorAtPoint
			IncrementSpawnCount
			IncrementActorCount

	if( HasSpawnedMaxNumber) then
		DisableSpawner
```

Fig. 4.15 – Pseudocode demonstrating the processes during each tick of a spawner.

Using random points removes predictability, which could affect player performance. Muscle memory, for example, would undermine the validity of the results and is an issue apparent in Ozu, likely because it was never designed with this use case in mind. The PPT further mitigates outside influences such as these by helping the researcher detect genuine fine motor improvements.

During gameplay, AFMTController will write player performance data to an FString array. When the session ends, *AFMTController::FormatPlayerDataForSave()* populates an FString with the data recorded by the game. FString is a UE wrapper, which was selected because it has conversion functions for most standard data types, such as integers (Epic Games, 2024). This entire character array can then be saved to a file using the engine's SaveGame class.

BP_SaveGame::SaveGameToSlot() writes the FString to a .sav file using the engine provided interface. The user cannot save manually as there is no need to record partial data sets. The EndPlay() function is used to trigger this behaviour, as it is guaranteed to be called when the controller is destroyed at the end of the session.

4.5 Acceptance testing

A breakdown of the project timeline can be found in appendix A.

During development, stable versions were tested for conformance with this design and for undefined behaviour in edge case conditions. For example, what happens when two targets overlap? And what would happen if 1000 targets were on the screen at the same time?

Fig. 4.16 – (Bottom to top) A typical development cycle implemented throughout the project. A stable build would be tested and then adjustments made based on the use of that build.

Often, implementation would be completed in UE5's blueprints before being moved to C++. This is one of the strengths of the engine, however, blueprints are less performant so only features specifically designed with a blueprint interface remain there, such as the save system. Performance was always carefully monitored, with a target of 30 fps for integrated GPUs (the limit imposed by the engine) and 60fps for all other GPUs.

After feature cutoff (approximately 2 weeks before participant testing) beta testing was conducted with a small number of volunteers selected from the same population as the participants, however, testers could not also be participants. The researcher was present to answer questions and receive feedback during the beta tests. There was no time limit on the beta test and players were encouraged to play the game for as long as they found it enjoyable.

Some minor changes were made based on feedback from testers. Firstly, an arrow symbol used to indicate "Left Shift" was removed and replaced with "SHFT". This was due to feedback that the arrow looked too much like the up arrow next to the keyboard's number pad. Secondly, all the beta testers noted that the font used for "A" and "R" meant they were sometimes indistinguishable from one another. In the final version "A" now uses a much clearer font to distinguish itself from the "R" key.

One beta tester enjoyed the challenge presented by having both a highscore and a best streak, while another immediately likened the game to Ozu. The relationship to Ozu was not information they had been given before the test, which suggests the design requirements were met somewhat.

4.6 Design alterations

The original design envisioned a reverse endless runner, in which obstacles would move from left to right on the screen and the player would move the mouse to avoid them, while also collecting items by clicking on them. It quickly became apparent that this design was not reflective enough of the tasks involved when competing in an FPS videogame. This decision was based on the idea that task-based practice is more effective than process-based practice (Yu et al., 2018), i.e. movement of the hand and fingers is not enough on its own.

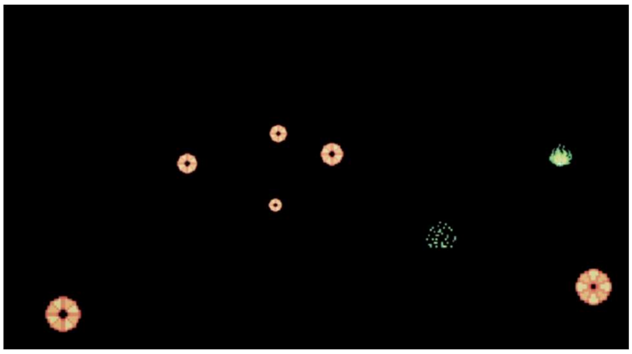


Fig. 4.17 – An early version of the fine motor trainer. Only mouse clicks were required, and no background was present due to concern for limited cognitive resources.

Once key presses were added, it became apparent that the default pawn had a fly camera, which caused the camera to move erroneously.

To solve this issue BP_StaticPawn was created. The static pawn's only purpose is to provide a default pawn to the engine, preventing it from creating a default pawn with the fly camera controls enabled.

The desire for greater involvement of the keyboard hand, led to the decision to use random quickfire presses. The first design included the use of the entire keyboard because it was thought that unusual movements would be beneficial when training fine motor movement. This, however, has been proven not to be the case and as discussed in section 4.1, the findings of Banyai et al., suggest that the development of precise motor chunks requires practice. For example, pressing the "L" key is not a motor chunk that an FPS player needs to perfect, so there's no benefit to practicing it.

This informed the design of the AFMTController which has a data member containing the valid key presses, from which, random keys can be generated. This array contains typical button assignments based on FPS control layouts, i.e. W, A, S, D, and so on. To aid development, the array is a UPROPERTY which allows the keys and their sprites to be assigned in the editor.

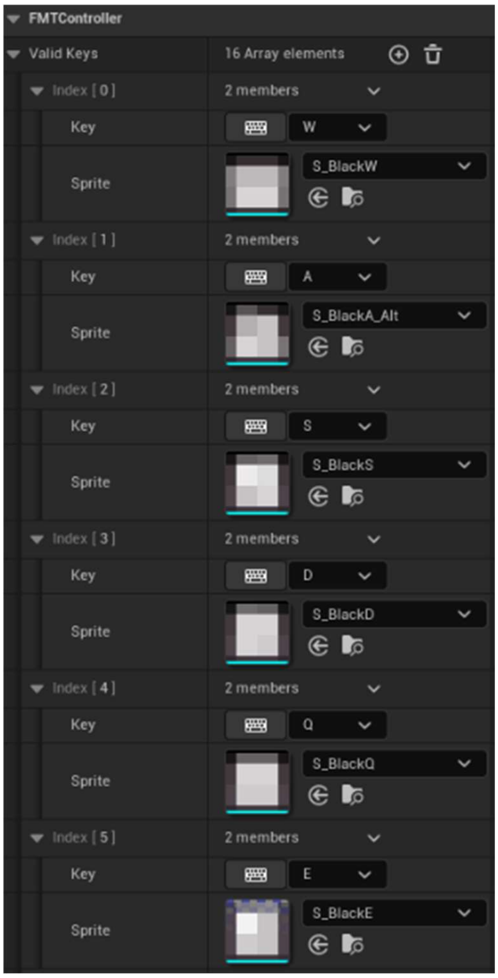


Fig. 4.18 – The editor view of the valid keys array.

To properly isolate the fine motor cognitive processes, efforts were made to minimise distractions that affect cognitive resources. For example, there was originally no HUD, and no background. This decision was reversed for the final design for a few reasons. Firstly, players are more likely to engage with a game that is attractive, secondly, the informational demands of esports are immense, and effective attentional control is an important aspect of player performance (Nagorsky & Wiemeyer, 2020). Artificially reducing the visual processing involved in training had the potential to bias results towards a favourable outcome.

For similar reasons, spawn rates were much reduced at the start of development. Play testing revealed that a competent player could soon reach a point where only one target was on the screen at a time. This led to the concept of min and max populations being implemented on the ASpawner class. These values enable the increasing and decreasing of spawn rate at runtime which in turn, allows the spawner to adapt to the player’s ability, never overwhelming a novice, nor underwhelming an expert.

The player data file was originally encrypted using memory manipulation and writing to what UE refers to as a “hex blob” (Epic Games, 2024). This middle ground between no encryption, and full AES encryption (Epic Games, 2024), which would have extended development time significantly, was attractive as it appeared relatively simple to implement. A working version was in place; however, verification of the data file was now impossible without first running the unencrypt function present in the development version of the software.

In the end, it was deemed so low risk that a user might attempt to alter their data file that encryption was likely causing more issues than it resolved. This prompted a move to the .sav file system which is built into UE5. While technically editable, the .sav is placed in a hidden AppData file, away from the training software installation location and adds a layer of variable verification present in the file header (Epic Games, 2024).

```cpp
// Convert Fstring to hexadecimal so it's not human-readable.
// Could do this for each single piece of data when it's captured but that could hurt performance.
auto GenerateHexEntry = [&](const FString& _datum)->const FString
{
	const TCHAR* CharData = _datum.GetCharArray().GetData();
	uint32 BufferSize = static_cast<uint32>(_datum.GetCharArray().GetAllocatedSize());
	uint8* Buffer = reinterpret_cast<uint8*>(TCHAR_TO_ANSI(CharData));

	return FString::FromHexBlob(Buffer, BufferSize);
};
```

Fig. 4.19 – The lambda used to write player data to a hexadecimal buffer.

5 Results and Evaluation

5.1 Pegboard results

Scores recorded during the Purdue Pegboard Test (PPT) were used to calculate an improvement percentage in terms of the first test scores for each participant as **(SecondTestScore – FirstTestScore) / FirstTestScore * 100**. These percentages were then used to calculate an average for each group, and for the entire sample.

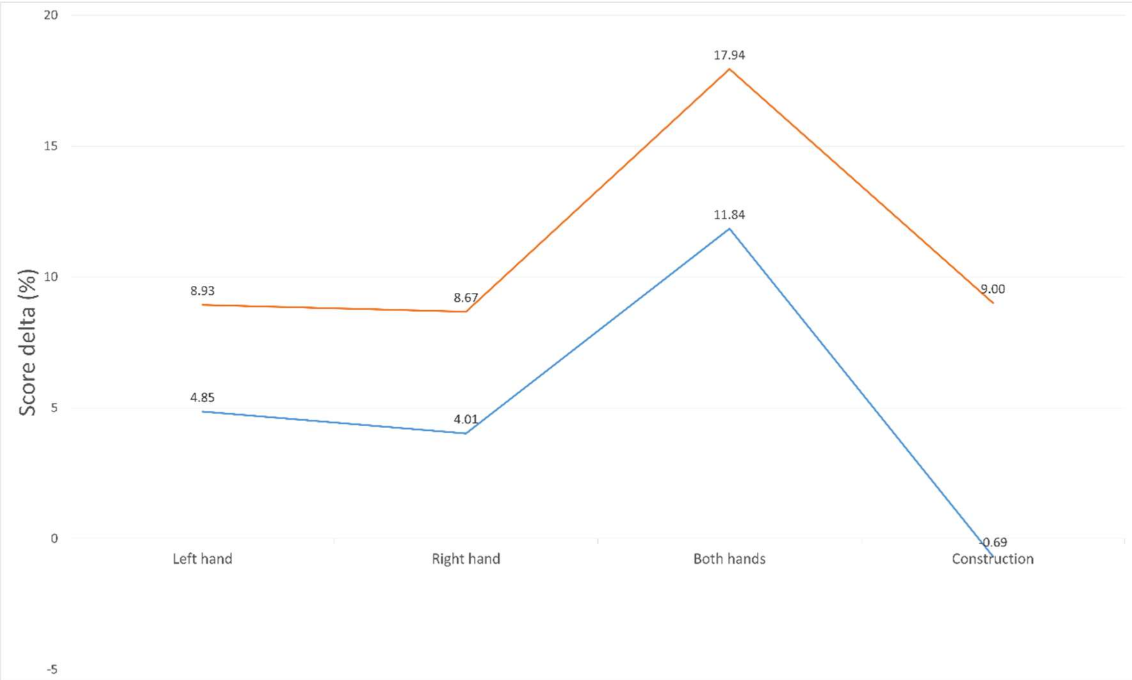


Fig. 5.1 – A chart showing the average score delta of both participant groups for each task of the PPT. Control Group is shown in blue, Intervention Group is shown in orange.

As demonstrated in Fig. 5.1, both groups improved on average for every task except for the construction task, which shows an average decline of 0.69% for the control group.

Applying Levene's test (see section 3.4) to the data sets of each PPT task produced the results shown in Fig. 5.2. These results indicate that Levene's null hypothesis stands, suggesting the data sets do have approximately equal variances.

Levene	P
0.0708756	0.05
0.56218116	0.05
0.33714524	0.05
3.37656865	0.05

Fig. 5.2 – Results of the Levene test.

The sample data was then tested for properties of normal distribution using the Jarque-Bera (JB) test (see section 3.4). After applying the JB test, the Chi-Square analysis was applied using the built in Excel formula. The results of these calculations can be seen in Fig. 5.3.

As discussed in section 3.4, all threshold p-values are set to 0.05, and values above that threshold indicate that the null hypothesis cannot be disproven with this data, i.e. the data is likely normally distributed. Coupled with the Levene test analysis, these results suggest that the data is a good candidate for independent sample t-testing.

Once calculated, the t-values provide a starting point for p-value calculation, which can either be looked up in a table of critical values or calculated. This study did the latter, using the Excel function **T.DIST.2T(t-value, DF)** (see section 3.4).

As shown in Fig. 5.3, the p-values produced for each task are higher than the 0.05 threshold. This means that the null hypothesis, that there is no significant difference between data sets, is most likely correct as the strength of evidence is not great enough to disprove it.

Left Hand		**Right Hand**	
Observations	14	Observations	14
Skew	0.0125921	Skew	-0.647443
Kurtosis	-0.147509	Kurtosis	0.2873629
Jarque-Bera	0.0130627	Jarque-Bera	1.026262
Chi Squared	0.99349	Chi Squared	0.5986184
T-value	0.8067486	T-value	0.8886528
Standard error	5.0595086	Standard error	5.2351432
P-Value	0.4355095	P-Value	0.3916551
MW Test	19	MW Test	16
Both Hands		**Construction**	
Observations	14	Observations	14
Skew	0.7575228	Skew	0.0890845
Kurtosis	-0.370408	Kurtosis	1.0972417
Jarque-Bera	1.4189963	Jarque-Bera	0.7208155
Chi Squared	0.491891	Chi Squared	0.6973919
T-value	0.7401698	T-value	1.3015532
Standard error	8.2417421	Standard error	7.4420853
P-Value	0.4734304	P-Value	0.2175022
MW Test	15	MW Test	10

Fig. 5.3 – The results of each step used to calculate the p-value via independent t-test.

This suggests that, though both groups showed improvement, and the intervention group demonstrated a greater improvement than the control group, the difference in their means is not significant. It is therefore most likely the improvements measured were random chance, as there is little evidence to suggest otherwise.

Further analysis was undertaken using a dependent sample t-test, which assesses the significance of the score delta for each participant between the first administration of the PPT and the second.

This variation of the t-test assumes a roughly normal distribution, which was found using the same JB test as the independent samples t-test. There is no assumption of similar variance as

Control	Intervent
0.9759438	0.8647347
0.8758758	0.1766557
0.3724791	0.6850816
0.7328939	0.4536996

this t-test concentrates on differences made over time, rather than between two groups. Results from the preliminary examination (see Fig. 5.4) indicated that the data set was appropriate for a dependent t-test.

Applying the dependent sample t-test found that all increases in performance in the PPT were insignificant across both groups, based on a threshold p-value of 0.05, except, the “both hands” task in the intervention group.

This result gave a p-value of 0.015 (3d.p.) and is somewhat unexpected given that the improvements in right-hand and left-hand tasks have been found to be of little significance, with p-values of 0.066 (3d.p.) and 0.098 (3d.p.) respectively. Moreover, the construction task, which also requires the use of both hands simultaneously, shows an insignificant improvement, with a p-value of 0.252 (3d.p.).

This implies that the improvement in the “both hands” task was significant for the individuals in the intervention. This is undermined somewhat by the independent t-test which demonstrated that no significant difference was present between groups, because this indicates that the improvement seen by the intervention group isn’t so great that it couldn’t have happened by chance.

It is likely that the results have been influenced by the small sample size. Both the JB test for normal distribution, and the Levene test for variance, are affected by sample size (Dataaspirant, 2023), (Gastwirth & Gel, 2010). Either one of these tests would affect the basic assumptions made during the t-tests about the data and could therefore render them unreliable.

To test this, the Mann-Whitney U test was applied to the same data. All results supported the null hypothesis, including the “both hands” task, which contrasts the t-test. This may be due to the sample size, i.e. the assumptions made surrounding the normal distribution are wrong, and therefore the dependent t-test is compromised.

5.2 First-person shooter results

Some performance metrics in the first-person shooting range were found by Chi-Square testing to not be normally distributed, so t-tests were not appropriate for every statistic. Instead, the Mann-Whitney (MW) U test was used (see section 3.4), which does not rely on the normal distribution of results.

Analysis concentrated on the time for the course to be completed, the total accuracy, the number of hits to the centre of targets, and the gap between each shot. Both time and accuracy do not follow a normal distribution, based on results of 0.011 (3d.p.) and 0.007 (3d.p.) respectively from the JB/Chi-Square test.

Using the MW-U test, the calculated values for time and accuracy were 11 and 21 respectively, while central hit percentage, recorded as the number of shots that hit central parts of the targets, returned an MW-U test value of 21.

Given the group size ($n_1 = 7$, $n_2 = 7$), the critical value in the MW-U table shown in Fig. 3.4 is 8. This indicates that the null hypothesis is maintained for these three variables, suggesting there is no significant difference between either group. This is unsurprising, given that initial analysis would suggest that the fine motor training software had no significant effect on dexterity.

Shot gap, measured as the average time in seconds between each shot fired by the player, was found to have an MW-U test value of 6. This is below the critical value of 8, which indicates there is a significant difference between the control and intervention groups. Overall, the average reduction in shot gap was 1.91% and 8.16% respectively. It's feasible that the nature of fast target acquisition and destruction in the trainer has carried over into the intervention groups approach to FPS tactics. This does not, however, indicate that any players got better at FPS games as the shot gap must work with accuracy as part of a more efficient Speed Accuracy Trade-off (SAT) (see section 4.1).

As shot gap was found to be normally distributed, and both groups were found to have a similar variance using the Levene test, an independent t-test was performed to corroborate the results of the MW-U test. The t-test disagreed with the findings of the MW-U test, producing a p-value of 0.444 (3d.p.), indicating that the null hypothesis, that there is no difference, remains intact. This contradiction between methods is likely the result of the sample size.

Comparing the changes in time between each shot and the total accuracy (see Fig. 5.5), demonstrates that participants were not necessarily more accurate when they spaced out their shots. This was unexpected as previous research analysed in the early phases of this project (see chapter 2) had suggested that when players made a conscious effort to slow down, it was usually in an attempt to be more accurate.

The Titanfall (TF) 2 test was the final, and least robust, test as there was no way to enforce restrictions on the participants' use of TF2 between tests, hence the results have been viewed as supplementary and have not undergone the same level of scrutiny as the PPT or the shooting range. The performance metrics captured indicate that the control group improved most over the course of the week. Given that there appears to have been a negligible impact on fine motor skills from the trainer, this result is unsurprising, and is likely down to chance.

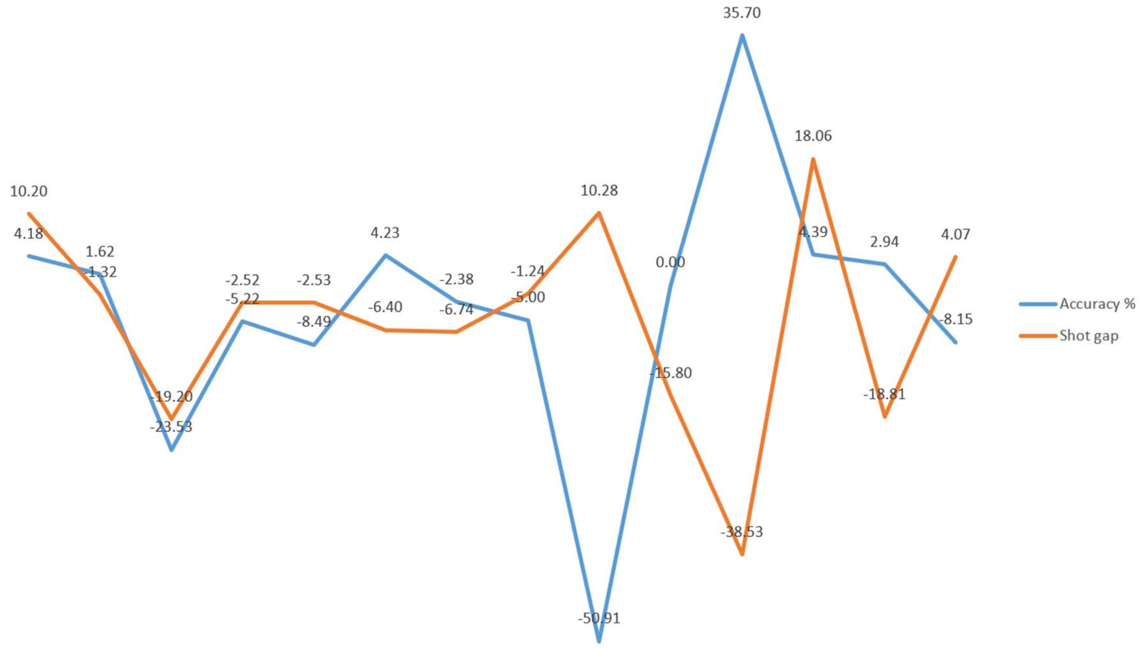


Fig. 5.5 – This graph shows percentage changes in shot gap and accuracy. It was expected that as the time between shots went up, so too would accuracy, however, there appears to be no correlation.

It should be noted that the control group's demographic information (see appendix H) reveals twice the average gameplay time each week compared to the average time reported in the intervention group. While this is not necessarily FPS time, this may have affected the data of those participants.

The huge increase in max speed percentage, measured as the percentage of time the player spends at their top speed, and in turn the increase to high-speed kills, suggests an increase in wall-running skill. This may be evidence that some participants ignored the researcher's request to avoid changing their habits regarding their time spent playing Titanfall 2.

Time	Kills	H/S kills	Ave. Speed	Max. Speed	M. Sp. %
-4.95	1.02	53.81	9.13	-0.12	61.37
0.32	3.29	28.57	-1.47	-6.58	-3.96

Fig. 5.6 – The score delta averages for Titanfall 2, control group first. Dark green indicates the most favourable result for that category.

5.3 Summary

The results show that fine motor skills were likely not improved by the fine motor trainer. Based on analysis using t-tests and the Mann-Whitney U test, it cannot be demonstrated that the measured improvements were not caused by chance. Nor can it be proved that the intervention group saw significantly more improvement than the control group in any PPT tasks.

Performance in the shooting range also varied insignificantly based on the analysis conducted, and the Titanfall 2 results suggest outside influence may have been a factor in some outlying data related to the control group's improvements. Moreover, the sample size is too small to adequately address contradictions between significance calculations applied to the same data.

The research question cannot be answered fully because the results indicate that no significant changes were made to the participants' fine motor skills. As discussed in section 3.1, there are several questions that make up the overall research goal.

No correlation between fine motor skills and FPS videogame performance can be confirmed, nor ruled out, with the current data. Participants did not show any significant changes to either motor skills or FPS performance.

As shown in Fig. 5.5., players don't appear to have got better at the pointing and clicking mechanics of FPS videogames. There are some outlying results, such as one player showing a 38% drop in pauses between shots and a corresponding 35% rise in accuracy, but generally, there is no evidence that players improved.

In the training software, players do appear to have improved quite significantly at the game itself. Every player increased their rate of target destruction, their accuracy, and highscore by hundreds of percent in some cases. This was entirely expected, as practice has long been proven a method of improvement at a variety of tasks. The aim of this research was to compare this improvement with any found in the other tests.

At best, the results of this study suggest that the improvement shown in the training software did not translate to the FPS software. This could indicate that aim trainers are not effective, however, the training software was quite mechanically different from an aim trainer, so this is not a strong argument.

5.4 Evaluation of approach

The biggest hurdle to this research has been the small participant pool. This was expected, which prompted the use of an incentive to attract participants. Somewhat surprisingly, even with the incentive, 25% of the participants had to be withdrawn due to non-compliance with their tasks.

Some studies have seen success with incentives such as a raffle entry for a $50 shopping voucher (Banyai et al., 2019), so the incentive amount (£250) is possibly not the problem. The level of involvement required from each participant may have had an affect, as participants were required to do something every day. This is similar to other studies of this type, such as Arnoni et al., who studied the effects of videogames on the gross motor function of children with crebral palsy, but the motivations of those participants are very different. The problem may therefore rest with the comparatively small gain offered to this study's particpants for the work required.

In the future it may be sensible for researchers to allow for a more flexible approach. Perhaps, instead of testing every participant on the same day, participants' testing weeks could be staggered so that they start and finish on different days. This would allow an increased capacity for participants at the same time as allowing participants the flexibility to chose a time which is suitable for them.

Furthermore, participants' prescribed training could be spread throughout an elongated timeframe so that it didn't need to be completed every day. For example, participants could be asked to train for 8 days over a fortnight.

The length of intervention may have also been a factor in the apparent ineffectiveness of the trainer. The skill acquisition stages described by Listman et al. (see section 2.3), suggest that the associative phase, in which players learn to fine tune their movements, may take longer to reach. The short time scale of this project may have only allowed participants to engage in the cognitive phase of skill development, which is where players would learn the basic movements to complete a given task. This is supported by the results, which suggest players got much better at the training software, but showed an insignificant improvement to fine motor control.

The design of the motor training software focused heavily on the minutia of player movement, perhaps to its detriment. It is possible that the other factors of FPS videogame performance outweighed such relatively small factors as motor chunks. It was thought that results would be more profound on players of lower ability as was the case with experiments run by Toth et al., however, it is possible that for fine motor skill to have any impact on the performance of a player, that player should already be in the top 1% of players.

To confirm this, future work could focus on esports professionals only, like the work of Roldan & Prasetyo, who found that aim trainers were effective tools for improving professional Valorant players' performance. Efforts were made during the recruitment stage of this study to recruit esports team members from the various teams at Sheffield Hallam University, but none applied to be participants.

The basic mechanics of the software fit the design requirements well. The design sought a trainer that mimicked the motor movements used to play FPS videogames. Specifically, the design was focused on Ozu style mechanics (see chapter 4), which it delivered. It does, however, train an unusual pattern of those movements, in that the player's motor planning patterns would be excessively influenced by the game. In natural FPS gameplay, the player would be able to plan their next movement much further in advance, which may add to the ability to subconsciously divide work into motor chunks.

Experience in the trainer would help the player plan their movements more effectively, however, as discussed in chapters 2 and 4, the trainer was designed to train only relevant motor chunks, for example, pressing "L" would not be a relevant motor chunk for the FPS genre. Perhaps this approach was too minute. It is possible that an approach considering relevant chains of movements would have a better effect. For example, reloading and then firing is a common motor chunk chain that would exist in players of FPS videogames.

The trainer did not take this into account and may therefore have wasted time forcing the player to practice a set of unlinked chunks, such as, pressing space (commonly jump) and then shift (commonly sprint), which wouldn't make sense in an FPS videogame because a character can't sprint in mid-air.

Analysis of the results should have been considered earlier in the design stages of the project. A typical player produced 7,000 lines of data during 5 days of training. This was not foreseen by the researcher, and it was too much to analyse in detail. Loading the save files to CSV helped as this facilitated the use of Excel's built-in tools, but more analytics tools should have been sought out in the design stage.

Further analysis of this data could foster an improved understanding of the processes surrounding the Speed Accuracy Trade-off discussed by Donovan et al, and motor chunking discussed by Bera et al., (see section 2.3).

It is evident in samples taken from the training data that motor chunking in the way described in section 4.1 appears to exist (see Fig. 5.11). There is evidence of a large, quick movement, followed by a slower, more precise movement before firing at a target. Given the size of the data set gathered during this study, there is ample opportunity to investigate this further. This could help to identify mistakes that were made in the design of the training software.

The trainer was also designed with the Speed Accuracy Trade-off (Donovan et al., 2022) in mind. The data collected seems to contradict the findings of Donovan et al. (see Fig. 5.5.), however future work would require a much larger sample to make a definitive contribution to knowledge regarding the SAT.

	Time	X	Y	X / second	Y / second
Major	0.302296	78	327	258.0252	1081.721
Minor	0.207604	21	22	101.1541	105.971

Fig. 5.11 – An example from the data of participant 3, which demonstrates the existence of motor chunks. They are labelled major (the large, fast initial movement) and minor (the small, precise adjustment) to correspond with the stages proposed by this research in section 4.1, and Fig. 4.4.

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Appendix A Project Specification

Sheffield Hallam University
Faculty of Arts, Computing, Engineering and Sciences (ACES)
Department of Computing

MComp Individual Project: Project Specification

Student name	Dominic McCollum	
Student contact details	**SHU Email**	Dom.Mccollum@student.shu.ac.uk
	Telephone	07757715565
Course	MComp Computer Science for Games	
Supervisor name	Mark Featherstone	
Title of project *(provisional)*	Using Unreal Engine to develop fine motor exercises to improve the user's performance in games and everyday life.	
Date	18.09.2023	

Research Question

Can randomized fine motor exercises improve the performance of typically developed adults in a first-person shooter?

Elaboration

Fine motor skills are defined as movements that involve the small muscles such as in the fingers, hands, lips, and tongue. They are supported by gross motor skills and are linked to several childhood developmental milestones (Department for Education, 2023). This project will focus on the use of the hands and fingers, the potential benefits of fine motor exercises on hand and finger movement during first-person shooter games, and any benefits seen outside of video games, measured using supplemental testing with traditional occupational therapy techniques to contextualise any conclusions drawn.

Esports are videogame competitions "conducted with an electronic system and technological immersion in an organized and structured environment" (Chiu et al., 2021). Professional esports athletes rely heavily on their fine motor skills, particularly in first-person shooter games where players are required to flick to, and track targets in fast paced environments. The cognitive load placed on players during competition is immense (Banyai et al., 2019) and as a result, much of the literature focuses on the health of the players from a therapeutic viewpoint (Chiu et al., 2021). In fact, the players themselves view exercise as a means to improve their health, rather than a method of improving their performance (Sanz-Matesanz et al., 2023).

This could stem from the inconsistency in categorising esports as sport. Courts have ruled against esports being considered sport (Navarro v. Florida Institute of Technology, 2023), whereas major sporting institutions have embraced them as sport (Campbell et al., 2018). It is a fate that many less physically active sports, such as chess (Groot, 1978) and darts (Davis, 2018), have suffered in the past, however, the situation is changing as esports become increasingly popular.

The recent increases in the esports market, from USD 0.49 billion in 2016 (Cunningham et al., 2018) to a projected USD 1.6 billion in 2024 (Chiu et al., 2021), has encouraged large investments from broadcasters and traditional sports teams, such as footballing giants Manchester City and Paris Saint-Germain who have their own esports teams that compete in the world championships of Pro Evolution Soccer (Chiu et al., 2021). Universities are also catching on, with several US institutions offering esports athlete scholarships (DiFrancisco-Donoghue et al., 2019).

This increased investment has peaked researcher's interest in the topic of esports, with promising work published from several subject areas including sport management (Cunningham et al., 2018), and behavioural analysis (Banyai et al., 2018). Player health is extensively studied with researchers reaching conclusions on the effects of esports on hormonal changes, and sleep disturbances (Sanz-Matesanz et al., 2023), as well as physical ailments such as eye fatigue, and muscle strain (DiFrancisco-Donoghue et al., 2019).

There are 4 main types of intervention studied in relation to the performance of esports athletes, although the research is scarce. They are supplementation with nutritional compounds, physical exercise, transcranial stimulation, and sleep therapies.

All except sleep studies have shown minor success, with performance increased between 1% and 8% (Sanz-Matesanz et al., 2023). Lower levels of anger were found in players supplemented with 100mg inositol and 1500mg arginine silicate (Tartar et al., 2019), and (Sainz et al., 2020) found that caffeine increases accuracy in first-person shooters. (De Las Heras et al., 2020) discovered that as little as 15 minutes of High-Intensity Interval Training (HIIT) improved the ability of players to destroy enemies in League of Legends, with fewer attacks required per enemy.

Transcranial Direct Current Stimulation (tCDS) was found to improve player performance, particularly in non-gamers (Toth et al., 2023). The least successful category of intervention is sleep therapy. (Bonnar et al., 2022) studied a group of 56 esports athletes and found that 2 weeks of sleep training, including biomonitoring and 1-1 coaching sessions, failed to make a difference to the cognitive performance of the athletes.

Research in medicine and more specifically, rehabilitation, has shown that video games can have a positive effect on developing areas of the brain which control gross and fine motor functions (Yu et al., 2018), (Gallou-Guyot et al., 2021), (Arnoni et al., 2019). It's also widely accepted that fine motor control is an important factor in esports performance (Campbell et al., 2018), (Chiu et al., 2021), (Sanz-Matesanz et al., 2023). The problem is a lack of evidence of a link between fine motor training and esports performance improvements, with some studies going as far as to suggest their results may just indicate that players are getting better at the video game scenarios used in the tests.

As demonstrated in this brief review of the contemporary literature, there are no studies that are designed to show a link between increased fine motor control and performance in games. Furthermore, several studies suggest that understanding in the field of esports training is lacking (Nagorsky & Wiemeyer, 2020), (Martin-Niedecken & Schattin, 2020), (Sanz-Matesanz et al., 2023).

Project objectives

To test for a link between improved fine motor skills and player performance, software will be developed that attempts to improve fine motor performance, and then an experiment will be undertaken that measures the participants' performance using both in-game metrics and real-world metrics to underpin the conclusions drawn.

Real-world metrics will be collected by observing participant performance in the Purdue Pegboard Test (PPT). The PPT consists of a board with 2 parallel lines of holes, which are each 10mm apart. The board has 4 pin holders at the top, furthest from the participant (Lawson, 2019). The PPT was selected because it is well established as a tool with which occupational therapy practitioners can assess dexterity (Irie et al., 2020), and for its focus on arm, hand, and finger movement, which are all related to the participants' fine motor control (Department for Education, 2023).

The project will consist of:

- Create gamified fine motor exercises in Unreal Engine which involve the use of both hands, and the fingers. i.e., Through gameplay that requires interaction via a mouse and keyboard.
- Create a brief first-person shooter (FPS) scenario that incorporates the two main actions in FPS games, flicking (target acquisition) and tracking. Metrics collected should include time to acquire a target and accuracy as a minimum.
- Recruit participants to the study. As many as possible up to a maximum of 30 to keep the testing phase manageable. Participants will need to attend some tests in person.
- Evaluate subjects based on their performance differences in FPS scenarios, then evaluate any differences in the PPT. This will either support or undermine conclusions drawn based on game performance allowing the project to provide more meaningful analysis.

Project deliverable(s)

The project deliverable will consist of 2 pieces of software, one to train fine motor skill, the other to test it in an FPS scenario. Analysis of results will also be submitted, which will answer the research question and if results are positive, suggest a good basis for the development of esports training methods in the future.

Ethics

No ethical issues are foreseen, participants are not be vulnerable, and there are no identified risks.

Action plan

Milestone 1 – Complete literature review and initial project setup.

Target completion date – 01.10.23.

Sprint 1 – 2 weeks, 18.09.2023 – 01.10.23

This sprint will focus on studying relevant literature to aid the design of the deliverable, and the setup of an Unreal Engine 5 project.

Milestone 2 – Build fine motor exercise software and source Purdue Pegboard.

Target completion date – 05.11.23.

Sprint 1 – 3 weeks, 02.10.23 – 22.10.23

By the end of this sprint, a prototype of the fine motor trainer will be ready for testing and bug triage.

The prototype should consist of a variety of randomised targets. It will be based on the 2D template provided with Unreal Engine 5 and will receive input from a keyboard and mouse.

Sprint 2 – 1 week, 23.10.23 – 29.10.23

Following the bug triage in the previous sprint, the application will undergo polishing and minor changes as required.

Sprint 3 – 1 week, 30.10.23 – 05.11.23

Create a short, first-person shooting scenario, in Unreal, for testing participants in-game performance. Approximately 1 minute of playtime is required.

Measurements should include time to target acquisition, and accuracy.

If a Perdue Pegboard has not been sourced by this point, the planned supplemental testing will be removed from the study, and any dissertation notes adjusted.

Milestone 3 – Refinement of software and participant pooling.

Target completion date – 12.11.23.

Sprint 1 – 1 week, 06.11.23 – 12.11.23

Continue to polish both prototypes to a good standard.

Recruit participants and book a space for testing.

Milestone 4 – Testing

Target completion date – 03.12.23.

Sprint 1 – 1 week, 13.11.23 – 19.11.23

Separate participants into their trial groups using a blind randomised approach.

Conduct initial tests on all participants, then distribute the fine motor trainer to the appropriate participant group.

Conduct fine motor assessments of all participants on the first and last day.

Sprint 2 – 1 week, 20.11.23 – 26.11.23

Assess results from initial testing and decide if another round of testing is required.

Recruit new participants if required.

Sprint 3 – 1 week, 27.11.23 – 03.12.23

Conduct second round of testing.

Milestone 5 – Evaluation of results

Target completion date – 31.12.23

Sprint 1 – 1 week, 04.12.23 – 10.12.23

Collate and organise results. Conduct initial analysis and begin draft.

Create presentation to demonstrate initial findings to supervisors and peers.

Sprint 2 – 1 week, 11.12.23 – 17.12.23

Continue write up and assessment of results.

Sprint 3 – 1 week, 18.12.23 – 24.12.23

Final draft of results section.

Sprint 4 – 1 week, 25.12.23 – 31.12.23

Christmas break.

Milestone 6 – Editing

Target completion date – 10.01.24

Sprint 1 – 2 weeks, 01.01.24 – 10.01.24

Final edit of dissertation, proof reading, etc.

Appendix B Ethical Considerations Form

UREC2 RESEARCH ETHICS PROFORMA FOR STUDENTS UNDERTAKING LOW RISK PROJECTS WITH HUMAN PARTICIPANTS

This form is designed to help students and their supervisors to complete an ethical scrutiny of proposed research. The University Research Ethics Policy should be consulted before completing the form. The initial questions are there to check that completion of the UREC 2 is appropriate for this study. The final responsibility for ensuring that ethical research practices are followed rests with the supervisor for student research.

Note that students and staff are responsible for making suitable arrangements to ensure compliance with the General Data Protection Act (GDPR). This involves informing participants about the legal basis for the research, including a link to the University research data privacy statement and providing details of who to complain to if participants have issues about how their data was handled or how they were treated (full details in module handbooks). In addition, the act requires data to be kept securely and the identity of participants to be anonymized. They are also responsible for following SHU guidelines about data encryption and research data management. Information on the Ethics Website

The form also enables the University and College to keep a record confirming that research conducted has been subjected to ethical scrutiny.

The form may be completed by the student and the supervisor and/or module leader (as applicable). In all cases, it should be counter-signed by the supervisor and/or module leader and kept as a record showing that ethical scrutiny has occurred. Some courses may require additional scrutiny. Students should retain a copy for inclusion in their research projects, and a copy should be uploaded to the relevant module Blackboard site.

Please note that it may be necessary to conduct a health and safety risk assessment for the proposed research. Further information can be obtained from the College Health and Safety Service.

Checklist Questions to ensure that this is the correct form.

1. Health Related Research with the NHS or Her Majesty's Prison and Probation Service (HMPPS)or with participants unable to provide informed consent

Question	Yes/No
1. Does the research involve? • Patients recruited because of their past or present use of the NHS	No
• Relatives/carers of patients recruited because of their past or present use of the NHS	No
• Access to data, organs, or other bodily material of past or present NHS patients	No
• Foetal material and IVF involving NHS patients	No
• The recently dead in NHS premises	No
• Prisoners or others within the criminal justice system recruited for health-related research*	No
• Police, court officials, prisoners, or others within the criminal justice system*	No

• Participants who are unable to provide informed consent due to their incapacity even if the project is not health related	No
2. Is this a research project as opposed to service evaluation or audit? *For NHS definitions of research etc. please see the following website* http://www.hra.nhs.uk/documents/2013/09/defining-research.pdf	No

If you have answered **YES** to questions **1 & 2** then you **MUST** seek the appropriate external approvals from the NHS, Her Majesty's Prison and Probation Service (HMPPS) under their independent Research Governance schemes. Further information is provided below. https://www.myresearchproject.org.uk

NB College Teaching Programme Research Ethics Committees (CTPRECS) provide Independent Scientific Review for NHS or HMPPS research and initial scrutiny for ethics applications as required for university sponsorship of the research. Applicants can use the IRAS proforma and submit this initially to their CTPREC.

1. Checks for Research with Human Participants

Question	**Yes/No**
1. Will any of the participants be vulnerable? *Note: Vulnerable' people include children and young people, people with learning disabilities, people who may be limited by age or sickness, people researched because of a condition they have, etc. See full definition on ethics website*	No
2. Are drugs, placebos, or other substances (e.g. food substances, vitamins) to be administered to the study participants or will the study involve invasive, intrusive or potentially harmful procedures of any kind?	No
3. Will tissue samples (including blood) be obtained from participants?	No
4. Is pain or more than mild discomfort likely to result from the study?	No
5. Will the study involve prolonged or repetitive testing?	No
6. Is there any reasonable and foreseeable risk of physical or emotional harm to any of the participants? *Note: Harm may be caused by distressing or intrusive interview questions, uncomfortable procedures involving the participant, invasion of privacy, topics relating to highly personal information, topics relating to illegal activity, or topics that are anxiety provoking, etc.*	No
7. Will anyone be taking part without giving their informed consent?	No
8. Is it covert research? *Note: 'Covert research' refers to research that is conducted without the knowledge of participants.*	No
9. Will the research output allow identification of any individual who has not given their express consent to be identified?	No

If you have answered **YES** to any of these questions you are **REQUIRED** to complete and submit a UREC 3 or UREC4). Your supervisor will advise. If you have answered **NO** to all these questions, then proceed with this form (UREC 2).

General Details

Name of student	Dominic McCollum
SHU email address	Dom.Mccollum@student.shu.ac.uk
Course or qualification (student)	MCOMP Computer Science for Games
Name of supervisor	Mark Featherstone
email address	m.featherstone@shu.ac.uk
Title of proposed research	Using Unreal Engine to develop fine motor exercises to improve the user's performance in games and everyday life.
Proposed start date	13.11.23
Proposed end date	26.11.23
Background to the study and scientific rationale for undertaking it.	The main 4 intervention methods for improving performance in video games are supplements, physical exercise, sleep therapy and transcranial stimulation. This research will investigate whether fine motor skill development has the potential to improve player performance, and thus should be considered as a new form of intervention. Fine motor control is also studied in therapeutic settings and it's possible that this research could inform the design of tools used in that sector too, although that is not the primary aim.
Aims & research question(s)	This research aims to provide an important analysis of the effects of improved fine motor skills on player performance in video games. Can randomized fine motor exercises improve the performance of typically developed adults in a first-person shooter?
Methods to be used for: 1. recruitment of participants, 2.data collection, 3. data analysis.	1. Advertising within the university via societies and Discord (with the permission of the server owner). Entry to a prize draw for an Amazon voucher will be used to encourage participation. 2. Metrics will be collected in-game and saved to a file to which the researcher has access. For in person testing, the researcher will take notes on the performance of participants in the Purdue Pegboard test. These notes will be electronically stored on a password protected laptop, to which only the researcher has access, and will contain no personal information about the participants. 3. Data from each participant's game metric files will be collated using Excel and analysis will take place using a modified Fitts Law algorithm which will quantify the ability of each participant to acquire and track targets.

Outline the nature of the data held, details of anonymisation, storage and disposal procedures as required.	Basic data will be collected from each participant, such as name, age, and email address. Only general age ranges will be used to inform conclusions drawn in the study, and participants will not be identifiable from those conclusions. Email addresses and names will only be used for contact purposes, and group assignment (control or intervention groups). They will be stored on a password protected laptop which requires 2-factor authentication and can only be accessed by the researcher. In accordance with GDPR, when the data is no longer required, usually because the study is over or the person has left, it will be deleted. Only electronic records will be kept, no participant information will be physically available. Participant data will be fully anonymized in the final dissertation.

3. Research in Organisations

Question	**Yes/No**
1. Will the research involve working with/within an organisation (e.g. school, business, charity, museum, government department, international agency, etc.)?	Yes
2. If you answered YES to question 1, do you have granted access to conduct the research? *If YES, students please show evidence to your supervisor. PI should retain safely.*	Yes
3. If you answered NO to question 2, is it because: A. you have not yet asked B. you have asked and not yet received an answer C. you have asked and been refused access. *Note: You will only be able to start the research when you have been granted access.*	N/A

4. Research with Products and Artefacts

Question	**Yes/No**
1. Will the research involve working with copyrighted documents, films, broadcasts, photographs, artworks, designs, products, programmes, databases, networks, processes, existing datasets, or secure data?	Yes

2. If you answered YES to question 1, are the materials you intend to use in the public domain? *Notes: 'In the public domain' does not mean the same thing as 'publicly accessible'.* • *Information which is 'in the public domain' is no longer protected by copyright (i.e. copyright has either expired or been waived) and can be used without permission.* • *Information which is 'publicly accessible' (e.g. TV broadcasts, websites, artworks, newspapers) is available for anyone to consult/view. It is still protected by copyright even if there is no copyright notice. In UK law, copyright protection is automatic and does not require a copyright statement, although it is always good practice to provide one. It is necessary to check the terms and conditions of use to find out exactly how the material may be reused etc.* *If you answered YES to question 1, be aware that you may need to consider other ethics codes. For example, when conducting Internet research, consult the code of the Association of Internet Researchers; for educational research, consult the Code of Ethics of the British Educational Research Association.*	Yes
3. If you answered NO to question 2, do you have explicit permission to use these materials as data? *If YES, please show evidence to your supervisor.*	Yes
4. If you answered NO to question 3, is it because: A. you have not yet asked permission B. you have asked and not yet received and answer C. you have asked and been refused access. *Note You will only be able to start the research when you have been granted permission to use the specified material.*	N/A

Adherence to SHU policy and procedures

Personal statement	
I can confirm that: • I have read the Sheffield Hallam University Research Ethics Policy and Procedures • I agree to abide by its principles.	
Student	
Name: Dominic McCollum	Date: 19.09.23
Signature:	
Supervisor or other person giving ethical sign-off	
I can confirm that completion of this form has not identified the need for ethical approval by the FREC or an NHS, Social Care, or other external REC. The research will not commence until any approvals required under Sections 3 & 4 have been received and any necessary health and safety measures are in place.	
Name: Mark Featherstone	Date:28/9/2023

Signature: Mark Featherstone
Additional Signature if required by course:

Name:	Date:
Signature:	

Please ensure the following are included with this form if applicable, tick box to indicate:

	Yes	No	N/A
Research proposal if prepared previously	☒	☐	☐
Any recruitment materials (e.g. posters, letters, etc.)	☒	☐	☐
Participant information sheet	☒	☐	☐
Participant consent form	☒	☐	☐
Details of measures to be used (e.g. questionnaires, etc.)	☒	☐	☐
Outline interview schedule / focus group schedule	☐	☐	☒
Debriefing materials	☐	☐	☒
Health and Safety Project Safety Plan for Procedures	☒	☐	☐

Appendix C Participant Information Sheet

Using Unreal Engine to develop fine motor exercises to improve the user’s performance in games and everyday life.

You are invited to take part in the research project, titled “Using Unreal Engine to develop fine motor exercises to improve the user’s performance in games and everyday life.” This research aims to discover whether fine motor exercises can improve player performance in first person shooter (FPS) video games.

This document will provide you with the information necessary to make an informed decision on taking part. Participation is **not mandatory**. If you decide to take part, you will need to provide a completed consent form. You can withdraw your consent at any time without giving a reason.

What are fine motor exercises?

Fine motor skills are defined by the Department for Education as movements requiring the hands, fingers, lips, or tongue. Fine motor exercises aim to improve the function of fine motor skills, usually by practicing them. This study will focus on the hands and fingers.

Why am I being asked to take part?

You are being asked to take part because you fit the participant selection criteria. Those criteria are listed below.

- Participants **must** be over 18 and under 50 years old.
- Participants **must** have basic computer skills.
- Participants **must** have a computer with a keyboard and mouse. (**NOT** a laptop trackpad)
- Participants **must not** have conditions that are agitated by video games, such as epilepsy.
- Participants **must not** have conditions which impede fine motor control, such as arthritis.
- Participants **must not** consider themselves to be vulnerable.

If you do not meet all the criteria, then you will not be able to take part in the research.

Do I have to take part?

Participation is **not mandatory**. If you decide to take part but later decide to withdraw, you may do so at any time without giving a reason.

What will I need to do?

You will be required to undertake 10 minutes per day of fine motor exercises using the software provided. On the first and last day of the study, you will need to come to Cantor Building at Sheffield Hallam University’s City Campus. There you will undertake an FPS scenario using a computer provided by the university, and then you will be tested using the Purdue pegboard. This will take approximately 30 minutes, and appointments will be spread throughout the day.

What do the exercises involve?

You will play 10 minutes of a video game designed to make you use the muscles in your lower arm, hands, and fingers. You will not be required to perform any movements that are unnatural or potentially harmful. Please inform the researcher if you have concerns about your ability to move your hands or fingers.

Where will this take place?

Your daily practice can take place whenever and wherever you feel comfortable, you just need access to a computer with a mouse and keyboard. A laptop trackpad is not suitable.

The testing phases on the first and last day of the study will be conducted in Cantor Building, 153 Arundel St, Sheffield City Centre, Sheffield S1 2NT. A map can be found on the back page of this document. The room number will be confirmed closer to the time.

How often do I need to take part, and for how long?

You will need to conduct 10 minutes of fine motor exercises per day, for 5 days. On day 1, and day 5, you will be required to participate in testing on site in the Cantor Building.

Are there any possible risks or disadvantages to taking part?

There are very minor risks associated with the regular use of a computer. These can include, but are not limited to, wrist injury, neck pain, and eye strain. To combat these, testing will be undertaken in an appropriate setting with an adjustable chair, a desk, and a monitor at an appropriate height for the user.

If you feel that you may suffer serious complications while using video games, such as epilepsy, then you **must** excuse yourself from the study on the grounds of being a vulnerable person.

What are the benefits of taking part?

Participating in research could have several benefits, which will vary from person to person. You may feel that this area of research is important because of its potential applications to esports performance enhancement, or because it could inform future therapeutic uses of fine motor exercises.

All participants will hopefully enjoy the process of playing video games as a form of exercise. If you indicate that you would like to be acknowledged for your contribution in the final write up, then your name will appear in the acknowledgements section of the dissertation document.

All participants that complete all their assigned practice and test sessions will be entered into a prize draw for a £250 Amazon voucher.

How will the prize draw be conducted?

All participants that are deemed eligible through their satisfactory completion of their practice sessions and testing sessions will be asked for their permission to enter their name into an online random name picker here -> https://www.randomlists.com/name-picker.

The person randomly selected will be given a £250 Amazon voucher. If necessary, for example where the winner cannot be contacted, the draw will be re-run.

When will I be able to discuss my participation?

You can contact the researcher at any time to discuss your participation. On the final day of the study, you will receive a questionnaire which will enable you to give feedback.

Will anyone be able to connect me with my results?

No. All data in the final report will be anonymised, even if you decide you wish to be named in the acknowledgements section of the report.

Who is responsible for my information?

The researcher will be responsible for storing and then deleting your information as per the General Data Protection Regulations.

Who will have access to my data?

Only the researcher. None of your personal information will be shared to any third parties.

If you consent to the use of your name in the acknowledgements section of the report, then your name may be available to those who read the report even after the study is over.

What will happen to my data when the study is over?

After the testing phases are completed, your data will be used by the researcher to draw conclusions on the effectiveness of the fine motor exercises. Your data will be deleted once it is no longer needed for this purpose. Your name may be used, with your consent, for the prize draw but will then be deleted from the researcher's participant list.

If you consent to the use of your name in the acknowledgements section of the report, then your name may be available to those who read the report even after the study is over.

How will you use what you find out?

The results will be collated into a written report which will then be submitted to the project supervisor for marking. All the information in the report will be anonymised and participants **will not** be identifiable based on their test results.

A presentation of the results and the project will take place at the end, which will follow the same rules on anonymisation as the written report.

How long is the study going to last?

The project is approximately 20 weeks long, having begun in September 2023 and projected to finish in January 2024. Your participation will last for 5 days in November or December 2023.

How can I find out about the results of the study?

The final written report will be made available to any participants that request it.

Who can I contact about the study?

Please contact the researcher, Dominic McCollum, in the first instance – dom.mccollum@student.shu.ac.uk

For queries or concerns relating to the handling of your data contact the Data Protection Officer – DPO@shu.ac.uk

For queries or concerns relating to the way the research was undertaken, or the way you were treated, please contact the Head of Research Ethics, Professor Ann Macaskill – a.macaskill@shu.ac.uk.

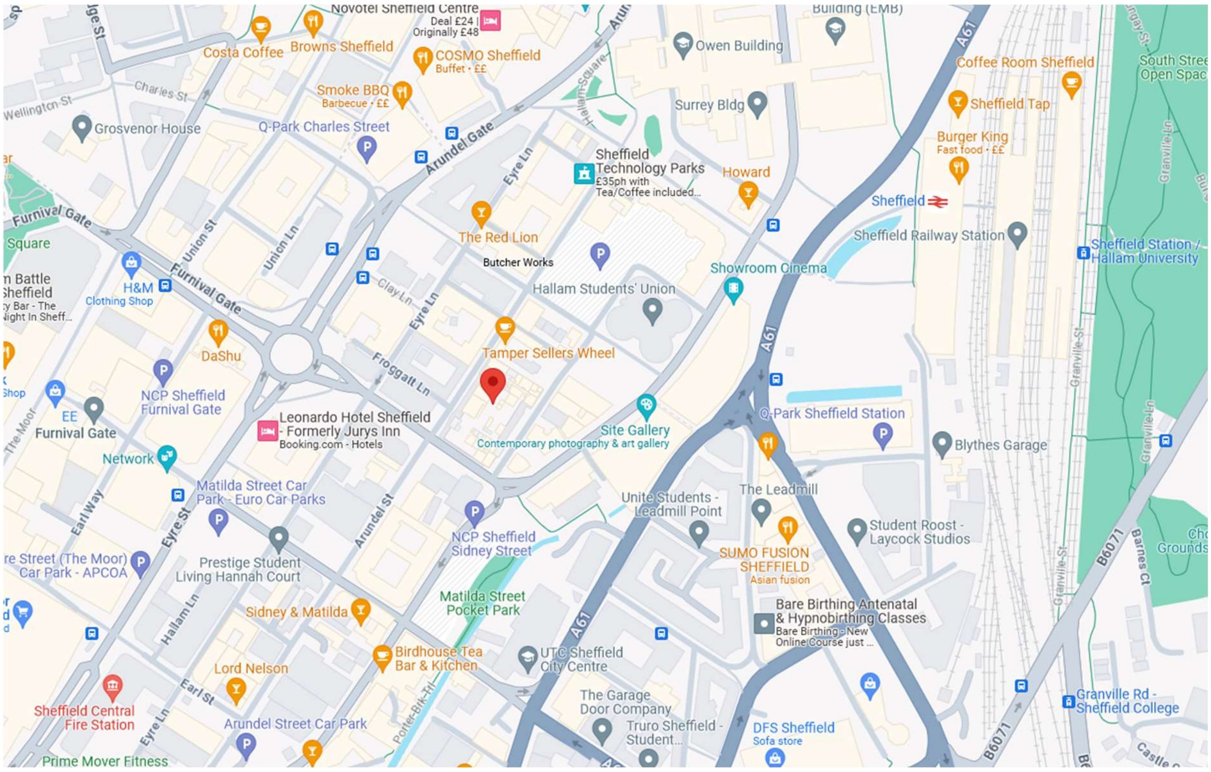
Postal address: Sheffield Hallam University, Howard Street, Sheffield, S1 1WB.

Telephone: 0114 225 5555.

The University undertakes research as part of its function for the community under its legal status. Data protection allows us to use personal data for research with appropriate safeguards in place under the legal basis of public tasks that are in the public interest.

A full statement of your rights can be found at https://www.shu.ac.uk/about-this-website/privacy-policy/privacy-notices/privacy-notice-for-research. However, all University research is reviewed to ensure that participants are treated appropriately, and their rights respected. This study was approved by UREC with ***Converis number ERxxxxxxx****. Further information is available at https://www.shu.ac.uk/research/ethics-integrity-and-practice.*

Figure 1: A map showing Cantor Building marked with a red pin.



Appendix D Recruitment Materials

Appendix E Participant Questionnaire

Participant Survey

Name:

Age:

Approximately how many hours do you spend using a computer per day?

Approximately how many of those hours are gaming?

How experienced are you with first person shooters?

- ☐ Never play.
- ☐ Play occasionally.
- ☐ Play regularly, casually.
- ☐ Play regularly, competitively.

How often do you play first person shooters competitively?

- ☐ Never.
- ☐ Twice a week.
- ☐ Four times a week.
- ☐ Everyday.

Have you ever been tested with a Purdue Pegboard before?

Were you involved in the beta test for this project?

Which hand do you favour using?

- ☐ Neither.
- ☐ Right.
- ☐ Left.

Appendix F Product Licenses

All art was purchased from either itch.io or the Unreal Engine store. In the case of itch.io, free licenses for non-commercial products were granted. The licenses for products bought from the Unreal Engine store include use in commercial releases.

Used in the fine motor trainer – the deliverable (art only):

Pixel Skies - https://digitalmoons.itch.io/pixel-skies-demo

Free Effect and Bullet 16x16 - https://bdragon1727.itch.io/free-effect-and-bullet-16x16

Used in the shooting range (some blueprint functionality already present):

Target props - https://www.unrealengine.com/marketplace/en-US/product/shooting-targets

SFX pack - https://www.unrealengine.com/marketplace/en-US/product/real-guns-sound-pack-2

Projectile pack - https://www.unrealengine.com/marketplace/en-US/product/ezprojectiles-realistic-bullet-simulation

Appendix G Test Design

G.1 Purdue pegboard

The Purdue pegboard was used in the standard way described in the practitioner's manual. A copy of that manual can be found here - https://www.limef.com/downloads/MAN-32020A-forpdf-rev0.pdf

G.2 Shooting range

A bespoke software test was built using Unreal Engine 5. Inspiration was taken from target shooting ranges found in popular FPS titles like Modern Warfare. The targets were purchased from the UE store (see Appendix F) and then extended with blueprints to register where they had been hit similarly to the targets in the training software. Time, accuracy, and central hits will be recorded so that an assessment of player performance, and of the strategies employed for the SAT task can be inferred (Donovan et al., 2022).

Fig. G.1 – Examples of ranges in the Modern Warfare franchise (Infinity Ward, 2023)

The ACharacter class provided by UE5 was specialised by the AFPSScenarioCharacter class. This class acted as the hub for the player data reporting, much like the controller had in the fine motor trainer.

Sprint and crouch inputs were added to the character class to provide a more representative FPS experience. As were obstacles, and moving targets pivoted around a spindle. The default first-person weapon provided within the FPS template in UE5 was also expanded to include sound effects and a reload action.

The players were briefed on the different types of targets and the route around the course before their first run. The HUD displayed basic information like a timer and ammo count. Care was taken when designing the level to include in-game instructions, and the researcher was present for all testing to provide prompts if necessary.

Fig. G.2 – A screenshot of the testing range.

The level was designed to mimic shooting ranges found in FPS videogames.

G.3 Titanfall 2

Design of the testing procedure changed many times during development. The original plan was to mod Titanfall 2, specifically the Pilot's Gauntlet level, so that more performance data could be assessed than what is already available in-game.

Unofficial support is available publicly to enable the modding of Titanfall 2 and the developer, Respawn Entertainment, only restrict mods that affect online multiplayer. Modders can alter VPK files with open-source tools, however the granularity required to measure things like deviation from centre of a target is not achievable in this framework.

Titanfall 2 ultimately remained included as a supplemental measure of player performance. The in-game metrics record average player speed, high-speed kills, accuracy, and the percentage of the run spent at high speed. This data is sufficiently detailed to give insight into player performance in a commercial FPS videogame.

G.4 Summary of test procedures

Participants will arrive on day 1 and receive a briefing from the researcher. They will then be asked a series of demographic questions, as well as the questions set out within the project's ethical considerations (see appendices D and B respectively).

Assuming no exclusionary criteria have come to light, testing then begins. The first test is the PPT, which will be conducted as per the standard task instructions set out in the examiner's manual provided with the PPT equipment (Lafayette Instrument Company, 2015).

Participants will then complete the 3D FPS shooting range under the direction of the researcher. Participants will have the objectives explained to them, and the researcher will provide instructions during gameplay only if the participant becomes stuck or requests clarification. Participant performance data will be saved to a text file, which the researcher will save for analysis.

Finally, participants will play a section of the popular commercial FPS videogame, Titanfall 2, which has its own built-in metrics for measuring player success. The measurements won't be as granular as the custom 3D test environment; however, the results can still inform any conclusions drawn.

On day 5, participants in the intervention group will submit their save data from the training software to the researcher in .sav format. The .sav format written by UE5 is a semi-human readable format, allowing for quick initial data verification by the researcher while also discouraging data tampering.

Appendix H Demographic Information

H.1 Demographic analysis

As discussed in section 3.4, participants were initially recruited from the Computing Department of Sheffield Hallam University. This yielded 12 participants. Participants were then recruited from Sumo Digital Academy in Sheffield, which yielded a further 8 participants.

Of those 20, 1 participant withdrew through illness, 3 participants were withdrawn because they failed to complete both test sessions, and 2 participants were withdrawn because they didn't complete the prescribed training sessions.

All participants were assigned a number, from 1 – 20, in the order that they registered with the study. A random number generator then assigned them to a group (NumberGenerator.org, 2023). Of the remaining 14 participants, 7 were in the Control Group (CG), and 7 were in the Intervention Group (IG).

Each participant completed a demographic survey before undertaking any of the initial tests. The results of this survey indicate that participants have an average age of 22.14 years, with a range of 19 – 26 years. On average, the participants spend 7.86 hours per day on a computer, ranging from 3 – 13 hours per day. Of that, an average of 2.46 hours is gaming, with a range of 0 – 8 hours.

The self-reported FPS videogame experience was spread evenly across the participant pool, with 4 reporting that their use of FPS videogames was occasional, 5 said they regularly played casually, and 5 reported that they play regularly in a competitive context. The participants that reported regular competitive play were asked to define how regularly, with 2 reporting playing competitively on fewer than 3 days a week, 2 participants reported between 3 and 4 days a week, and 1 participant reported 7 days a week.

No participants had ever conducted the PPT before, and 13 of the 14 self-reported as being right-handed.

Average age by group	
Control	Intervention
22.57142857	21.71428571

Average PC hours by group	
Control	Intervention
8.714285714	7

Average gaming hours by group	
Control	Intervention
3.428571429	1.5

Fig. H.1 – The participants were most evenly spread between CG and IG by age, with larger divides by number of hours spent on a PC, and number of hours spent gaming.