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Big Data on Learning: Does Social Motivation Facilitate Skill Learning?

Registration Number: 190265841

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A project dissertation in partial fulfilment of the requirements for the Master of Science degree in Cognitive and Computational Neuroscience.

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Abstract

Several factors relating to practice methods and timing have been reported to account for individual differences in complex skill learning. Theoretical accounts that stem from small-scale studies support the case for social context as a key facilitator for learning. By analysing big data, in the form of online video game telemetry from Destiny, one study found strong evidence that playing ‘socially’, as measured by an ‘assist-to-death ratio’, led to slower performance improvements, contradicting previous findings. The aim for the present study was to modify that analysis by quantifying social play using a different metric, ‘revives per game’. This led to the hypothesis that a higher rate of revives would predict higher learning rates. Results from a preliminary analysis were consistent with those of the original study. A further inspection of the data revealed issues relating to player exclusion criteria; these were rectified, and the analysis was repeated. A multiple regression analysis found a small positive effect for revives on learning rates, when controlling for assists and initial skill level. Further exploratory analysis was conducted to investigate the relationship between social play and learning more deeply. ‘Social’ players were found to learn at a significantly faster rate than did ‘solo’ players; social players played more; a moderate negative correlation was found between the 2 measures of social play. The results broadly support previous accounts of learning in both gaming and complex skills as a whole. By integrating these results into previous research, 2 potential mechanisms through which social factors facilitate learning were proposed; one relates to socially derived information and the other relates to practice enjoyment. Qualitative evidence from Destiny players would allow for deeper insights regarding the nature of the relationship between social context and learning.

Contents

Abbreviations

KADR: Kill-Assists-to-Death-Ratio;

CR: Combat rating;

FPS: First-person Shooter;

PvP: Player-vs-Player;

PvE: Player-vs-Environment.

1. Introduction

1.1 Big Data

Big Data, traditionally characterised by the ‘3 Vs’ of large volume, high velocity and wide variety of data, has recently seen increased use in commercial settings (Chen, Chiang and Storey, 2012). Although its use often involves analysing trends and developing models of human behaviour, such as in marketing or economic forecasting, big data has not been so widely used in psychological research. One reason for this is the ‘digital divide’ (Boyd and Crawford, 2012), where access to datasets is reserved only for certain institutions. Even with access, researchers do not necessarily have the skills required to collect, sort and analyse big data (Adjerid and Kelley, 2018), as these skills are more consistent with computer science theory. However, these are not concrete barriers for psychologists. For example, access to big data without partnership with a provider can be bypassed by using a technique called web-scraping, a method of automated data collection from webpages (Landers et al., 2016). The lack of required skills can be addressed with interdisciplinary collaboration (Harlow and Oswald, 2016), which has been promoted throughout psychological research for many years (Collin, 2009). Thus, big data analytics could see increased use within psychology.

The benefits of utilising big data in psychological research beyond those of traditionally obtained data can be outlined with reference to the aforementioned ‘3 Vs’ of big data. Volume (sample size in this case), is an established issue in psychology (Cohen, 1962), where a small sample size can reduce statistical power, increase the chance of making a Type II error, and inaccurately inflate effect size estimates. When combined with related reporting biases (John, Loewenstein and Prelec, 2012), a small sample size can potentially reduce the level of reproducibility in a study, reducing the level of validity of published findings, in the form of false conclusions. Using a large dataset minimises these problems. It can increase the statistical power of a study, allows for more accurate effect size estimations, and facilitates statistical modelling. Methods of big data collection also allow for highly targeted sampling. The use of Facebook as a participant recruitment method in a substance abuse study (Ramo and Prochaska, 2012) for example, was deemed highly effective. In this case, big data has also allowed for a high level of generalisability in their results to a target population. The sample sizes alone that can be obtained with big data highlight the potential benefits of its use within psychological research.

Velocity refers to the rate of data collection and any other temporal characteristic. Under laboratory conditions, participant behaviour can be tracked precisely. In most cases, this precision can only be sustained within the temporal constraints of a laboratory study. Digital platforms, purposed for data collection, can constantly record second-by-second data on human behaviour (Chen, Chang and Storey, 2012). While experimental control may be lost, big data collection can match the precision of a laboratory study. Furthermore, recorded behaviours can be tracked at any time, without the constraints of laboratory conditions. The precision associated with laboratory studies often means that the 'natural' element of behaviour is somewhat lost. Naturalistic studies retain this natural element but often lose the control and precision of laboratory studies. Digital platforms allow for the tracking of naturalistic behaviours with the temporal and metric-related precision of a laboratory study, at the temporal scale of a longitudinal study, with the capability to capture the behaviour of millions of people at any given time point. Therefore, this method combines the benefits of several forms of experimental design at a scale far beyond that of a traditional study.

The variety of metrics within big data could also be beneficial to psychologists. Much of traditional research takes the form of a confirmatory study, where one or a few independent variables (IVs) and a single dependent variable (DV) are often identified for investigation prior to data collection. While this is in no way a major issue, it can be argued that insights into nuanced interactions between IVs that lead to the outcome DV are limited (Adjerid and Kelley, 2018). In contrast, big data collection methods allow for large-scale exploratory analysis, involving different metrics that can highlight these nuanced interactions that affect behaviour, beyond a simple IV-DV relationship.

These benefits are better understood with a relevant example. Since the release of consoles such as the Playstation 3 and Xbox 360 in 2008, player telemetry data for online video games has been universally recorded. At the time of writing, a popular first-person shooter (FPS), Call of Duty: Modern Warfare, has 2,038,061 players currently online (playercounter.com), with a set of performance measures recorded after each game (large volume); player data is being tracked constantly (high velocity); around 50 measures are recorded after each game, contributing to an individual career summary (wide variety). All similar online games provide a similar performance-tracking service. As such, video game telemetry shows great potential within research.

1.2 Investigating Skill Learning with Video Game Data

A vast and precise dataset does not necessarily have use in psychological research. Since big data is not usually collected for research purposes, identifying valid metrics is important and sometimes limits the insights that can actually be gained, due to issues of construct validity. A psychological phenomenon that could potentially be captured by game player data is skill acquisition (or learning). Skill acquisition is described as the construction and development of internal representations that result in lasting changes to the capability of an individual for a given skill (Ackerman, 1988). This is characterised by improvements with practice (Sackett, 1934). The terms learning and skill acquisition can be used interchangeably. Fitts and Posner (1967) proposed a 3-stage model of general motor learning. During the cognitive stage, an individual attempts to understand what is required of them to perform a given task. This is achieved through receiving and processing related declarative information. In gaming, this can be done by watching gameplay videos or simply by completing in-game tutorials, where task information is presented interactively. This leads to the construction of new, and the development of existing, schemata (Piaget, 1936), the ‘building blocks’ of cognitive development. These internal representations provide a framework to efficiently process subsequent pieces of information from a game. During the associative stage, a player will use declarative knowledge, gained during the cognitive stage, to develop their procedural knowledge of how best to complete tasks. In an online shooter game, a player may learn where to go within an environment to complete an objective or how to shoot in the cognitive stage but will develop deeper strategies of navigation and combat to enhance performance in the associative stage. In the autonomous stage, performance becomes largely automatic with little need for information processing. Therefore, players can direct these unused cognitive resources to considering enemy movements, allowing them to coordinate their own actions more effectively.

Skill learning research is particularly vulnerable to the drawbacks of traditional research techniques. For a given skill, a laboratory study can allow for the precise tracking of performance but information on related prior experience may be anecdotal and, as such, imprecise. A participant could technically start and develop a new skill entirely under laboratory conditions. This structured way to track learning would likely be a poor representation of any naturalistic learning. Furthermore, tracking learning through to expert level using this method would be difficult, as often hundreds of practice hours are required to gain expertise. A participant is unlikely to be willing spend this much time under laboratory conditions, thus making long-term skill acquisition difficult to study (Stafford and Dewar, 2014). If skill acquisition can be captured by video game data appropriately within the bounds of established cognitive theories, these constantly updated datasets would represent billions of hours-worth of collective practice data of intrinsically motivated ‘participants’, both long-term on an individual level and representing a large population.

The first stage in assessing the viability of video game data in skill acquisition research is to determine whether or not individual improvements over time found in the data are consistent with cognitive theories of learning. There is an established theory that learning, as a function of practice time, follows a power law (Fitts and Posner, 1967); individuals experience an initial sharp rise in performance, followed by a gradual deceleration of improvement (Snoddy, 1926). This law is thought to underpin several domains of learning and skill acquisition (Rosenbaum et al., 2001), encompassing cognitive processes such as perception, decision-making and motor control, so should theoretically apply to performance improvements in video games. Consistent with Posner's paradigm, the cognitive stage is captured by the initial sharp rise in performance, followed by a gradual deceleration in the associative and autonomous stages. This was later tested (Stafford and Dewar, 2014), using player data from the online game Axon. An average learning curve consistent with the power law was found, with variations in the slope dependant on variability in how individuals chose to practise. The fact that their study was able to produce both individual and averaged learning curves indicates that video game telemetry has some face validity in quantifying learning.

This idea that variability in the way people practise a skill affects the efficiency of their improvement (i.e. the proportion of learning achieved to the amount of time spent on practising the skill) is one key rationale for the current study. Variability, whether this is in timing or in how individuals practise, has a wealth of research within the study of learning. Schmidt (1975) originally proposed that variability in early practice is more effective in constructing schemata in motor learning than is the consistency of practice. Variability in factors such as novelty of practice, effort, successfulness and diversity of practice methods, amongst many others, have been thought to contribute to individual differences in learning (Pesce et al., 2019). As the broad aim of the present study is to contribute some insight into what the 'optimal' learning strategy is in games and complex motor skills in general, it is important to outline what current research proposes are the factors that affect learning variability in games.

Boot et al. (2016) conducted a longitudinal Verbal Protocol Analysis to investigate the cognitive processes that mediate performance in the game Space Fortress. Participants verbally expressed their thoughts and strategies over 20 hours of gameplay. One important factor that was found to mediate performance was the level of knowledge a player has about the game mechanics and nuanced rules of the game. They concluded that a lack of knowledge when a player first starts hinders their ability to process more subtle aspects of the game that affect performance, even after several hours of gameplay. Consistent with Posner's paradigm, game data here suggests that a greater level of knowledge of rules and mechanics for a new player would facilitate learning in the cognitive stage, with subsequent facilitatory effects in the associative stage. Reeves, Brown and Laurier (2009) found that this effect is present even among experts of the game Counterstrike. Expertise within higher-level players was characterised by more complete knowledge of map layout, resulting in a better understanding of how enemies may navigate. These results indicate that variability in supplementing active practice with understanding a game during early playing stages has effects throughout a game career.

In addition to analysing in-game behaviours, various studies have focussed on variability of the timing and intensity of practice in predicting variability in the performance outcome. Huang et al. (2017) assessed absolute learning against the number of matches played per week in the game Halo Reach. They found that those who played between 4 and 8 matches per week displayed the greatest improvement per game. Comparatively, this is a very low frequency practice intensity, suggesting that spacing practice out over time predicts more efficient learning than high-intensity practice. However, it was noted that this relationship is not linear; taking long breaks off playing predicts a lower level of performance when a player returns. Therefore, a balance must be found in spacing practice to fully optimise learning.

Effects of practice breaks on learning have been linked to sleep consolidation. It is generally accepted that during sleep, memories are consolidated (eg. Jenkins and Dallenbach, 1924). The same principles are thought to apply to procedural knowledge and motor skill learning (Ellenbogen et al., 2007). Stafford and Haasnoot (2016) tested this idea within the game Axon by using telemetry to determine whether or not a player has slept during a break. While they did find evidence for facilitatory effects of practice spacing on learning, they found no difference in learning efficiency between the 'sleep' and 'wake' breakers. However, Wulf and Shea (2002) claim that principles derived from simple learning do not generalise to complex motor learning and vice versa. Kuriyama, Stickgold and Walker (2004) tested sleep consolidation effects against level of motor skill complexity. They found greater effects for sleep when the skill was considered more complex. Since Axon is a simple game in terms of player output, a low level of skill complexity may account for the lack of sleep effects in the Axon study. Therefore, whether or not sleep consolidation has an effect in game learning is in dispute.

While these factors relate primarily to the individual, the recent ecological dynamics approach to skill acquisition (Araújo and Davids, 2011) places more emphasis on interactions between the individual and their environment. This is especially the case for learning in the context of a dynamic environment, such as in sport or gaming, where performance is affected by external factors. In online shooters, a player will employ their skill differently depending on the type of environment, type of game mode and the movements of their enemies. This would suggest that skill acquisition in games could be considered an emergent adaptive relationship between an individual and their environment (Davids et al., 2013), where a more complex environment provides more possible actions. Therefore, variability in factors of environment-focused behaviour, such as exploration, could also affect individual differences in game learning. Thorndike (1898) proposed that exploration within a skill learning environment is a route for action discovery within that skill; exploring different possible actions could lead to finding better actions at the risk of performing sub-optimal actions, known as the exploration-exploitation trade-off (Katehakis and Veinott, 1987). More recently, Stafford et al. (2012) found in rats and humans that greater spatial exploration in a simple motor task is associated with a higher level of final performance. In studies of video games, exploration as a predictor of learning is disputed. Stafford and Dewar (2014) found that higher initial variation in performance (i.e. more action exploration) predicts better subsequent performance in Axon. However, in a more complex game, Destiny, more exploration of novel actions did not predict higher learning rates (Stafford et al., 2017). This could indicate that exploring different options in more complex skills does not provide significant benefits to learning, or that exploration should be supplemented by other factors in order for its effects to be maximised.

1.3 'Social play' as a predictor of learning rates

Another player-environment relationship that Stafford et al. (2017) studied was the predictive effects of social play on learning. Even at the most basic level of learning how to behave in daily life, social context is thought to be important. Bandura's (1971) social learning theory proposes that the observation and imitation of others' behaviour incites learning. Furthermore, through vicarious reinforcement, individuals will learn which of the observed actions will be positively rewarded. Vygotsky (1978) placed heavy importance on the role of social interaction on cognitive development as a whole (including learning). His theory of the 'zone of proximal development' asserts that, in the case of a skill where an individual would struggle to improve alone, practice in the presence of someone with a greater skillset than the individual would facilitate learning, whether this is a teacher in a classroom or a slightly more skilled peer.

These ideas can be scaled up from simple behaviours to more complex skill acquisition. Using the example of Call of Duty: Modern Warfare, players have the option to form 'parties' of 2-4 other chosen players, with the ability to communicate through audio, a feature common in online games. A lone player starting the game may develop the way they play, in terms of gun choice, gun attachments, and ways of navigating their environment, based on trial and error (i.e. exploration). A player who develops their skill in the presence of more skilled peers can learn through vicarious reinforcement, by seeing which methods of playing are most effective, and through a more informational way, where peers can simply advise the player as to which strategies are effective. This should theoretically result in more efficient learning, especially when considering the results of the aforementioned Verbal Protocol Analysis, which indicated that increased knowledge of game mechanics would facilitate game learning.

In the context of the exploration-exploitation trade-off, information from peers could theoretically minimise the need for exploration, so a player can focus on their exploitation of suggested actions. Mason and Clauset (2013), in their analysis of Halo Reach telemetry and an additional survey, found that those who played with more people who were on their online friends list performed better individually. Their results suggest some broad relationship between playing in a social context and better performance but does not provide insight into the learning process. Assessing whether or not this translates to better learning requires some qualitative analysis of what playing with friends represents.

Nardi and Harris (2006) investigated the concept of online friends in the game World of Warcraft, concluding that social bonds within games are extensions of real-life social interaction, variability of which manifests in distinct styles of play. Through in-depth interviews, they found that social interaction within the game facilitated perceived learning. Xu et al. (2011) extended this further by suggesting that better learning is a biproduct of social bonds that are formed to enhance the enjoyment of a game. Lucardie (2014) found that increased enjoyment raises the level of engagement for individuals in higher academic learning, as shown by higher university class attendance rates in those who rated the class as enjoyable. Further, she found through interviews that more enjoyment increased the quality of engagement, in the way the interviewees felt they concentrated and improved more if they enjoyed the classes. Therefore, since there is evidence for both social interaction within games enhancing enjoyment and for enjoyment facilitating learning in general, another potential mechanism for the facilitation of learning through social interaction can be established.

Johnson et al. (2013) conducted a small-scale study of social effects on declarative learning in medical students. Primarily, they found that students who learned in a team-based setting performed better on a test than those who studied alone. 50% of the team-based students identified the ability to ask peers for help and the chance to share ideas with peers as beneficial to their learning, which supports the previously outlined accounts of learning in a social context. Furthermore, the team-based students rated the confidence in their ability higher than the individual students. Hays et al. (2013) highlighted confidence as having a huge mediating effect on performance in complex motor skills. If learning in a social context increases self-confidence in a skill, the results from the Johnson et al. study could reveal that a social context could facilitate learning through its promotion of self-confidence.

The various outlined studies and theories currently support social factors as being beneficial to skill learning. However, the evidence is inconclusive. Some studies provide anecdotal evidence (e.g. Mason and Clauset, 2013), some provide indirect evidence (e.g. Lucardie, 2014) and some relate more to academic learning, as opposed to skill learning (e.g. Johnson et al., 2013). Thus, there appears to be a gap in the current literature for strong, quantitative evidence.

1.4 Present Study

One part of the study by Stafford et al. (2017) has served to fill this gap. They investigated the effects of variability in elements of play on individual skill improvement in the game 'Destiny', which is an online role-playing game (RPG) as well as a shooter, in which players compete against each other in Player-vs-Player (PvP) matches or collaboratively in Player-vs-Environment (PvE) settings. Social play in PvP matches was one type of variability that was investigated. With access to Destiny telemetry, the researchers were able to investigate how social play affected the players' learning rates. A learning rate requires a system where the skill level of each player after each game is quantified, which the game developers, Bungie, provided with their Combat Rating (CR) system. While it is not known how a CR is calculated, it is thought that winning a PvP game raises an individual CR, with the level of individual contribution affecting the extent to which it is raised (the inverse is true for a loss). Therefore, learning has been expressed by the change in CR over time. Social play was quantified using a Kill-Assists/Deaths ratio (KADR). A player gets an assist when they contribute to the killing of an opponent without registering the final killing shot. An assist would indicate that a player has helped a teammate and when considered on a deeper level, an assist suggests that players are coordinating their play by moving together. Contrary to their hypothesis, it was found that KADR negatively predicted learning rates, which would suggest a social context is detrimental to skill acquisition in Destiny.

Thanks to the wide variety of metrics recorded by Bungie, the present study has also aimed to investigate the effects of social play on learning in Destiny by using a different representation of social play. An assist could be considered a biproduct of trying to get a kill, which can be achieved regardless of who an individual plays with. Therefore, while an assist may indicate moving in accordance with teammates, factors other than social ones may be involved in a KADR. On the other hand, a revive, where a player stands by the body of a dead teammate for a number of seconds to bring them back to life, could be more representative of social play. Performing a revive puts a player's character's life at risk, since a dead teammate usually indicates nearby enemies, during which time the reviver is incapable to shoot or to move away. This conscious decision to help a teammate at one's own expense could be considered a more valid manifestation of the social element of playing video games. In one interview from the Xu et al. (2011) study, one player expressed a conscious decision to play in a way that helps her teammates, which is more consistent with reviving a teammate, since there is no conscious decision involved in registering an assist. Therefore, calculating a 'revives per game' value for each player was considered a good measure of social play.

For these reasons, the specific aim of the present study was to investigate the effects of social play, indicated by revives, on learning rates in the game Destiny. At present, there is qualitative and somewhat indirect evidence that social motivation should lead to more efficient learning. Inferences from the quantitative evidence surrounding this are contested. As such, the value of the present study lies in its potential to give strong quantitative evidence in an area of learning research that is in dispute. The broad aim here was to contribute to the discussion on what an 'optimal' learning strategy would be and how social motivation would fit in with the other factors linked to individual learning variability.

Based on the current literature, the hypothesis for the present study is that a greater propensity for social play, as measured by revives per game, will be associated with faster skill progression. While a hypothesis is stated here, exploratory analysis will also be conducted to further investigate this relationship.

2. Materials

The software used for this project was R Studio, where the programming language R (version 4.0.2; GNU General Public Licence) was used for analysis. Player telemetry was secondary data (Stafford et al., 2017) and provided by Bungie, which included 38 metrics within each session (total 332461 sessions) for 6996 players (12633518 observations in total). Relevant metrics include CR, kills, deaths, revives, assists. The package 'tidyverse' was installed, containing functions designed to facilitate data visualisation and to promote 'tidy data'.

Code

Analysis script and data file: https://osf.io/cu493/

3. Analysis

3.1 Data Preparation

As secondary data is used, much of the ‘cleaning’ involved in data preparation has been done by Stafford et al. (2017). The data was loaded into R studio as a data frame, from which the game sessions were ordered chronologically for each unique player. Considerable time was spent on examining the 38 variables and making sure each was understood and that each variable name corresponded to what was actually being measured. The metrics that were considered potentially relevant to this analysis were extracted and new metrics, mostly cumulative and summary values for each session, were added to form a more concise data frame, for the sake of computational efficiency. This was then used to create another data frame that included summary data for each player (i.e. 1 set of metrics per player).

Within the data frame, the relevant metrics were identified as assists, initial combat rating and revives (predictor variables to learning). Revives were provided as two separate variables (given and received). A strong correlation of .89 (Figure 1) between revives given and received suggests that both are indicators of a social player, perhaps playing as part of an established party, which led to the calculation of the variable ‘Total revives per game’ (total revives given and received divided by number of games).

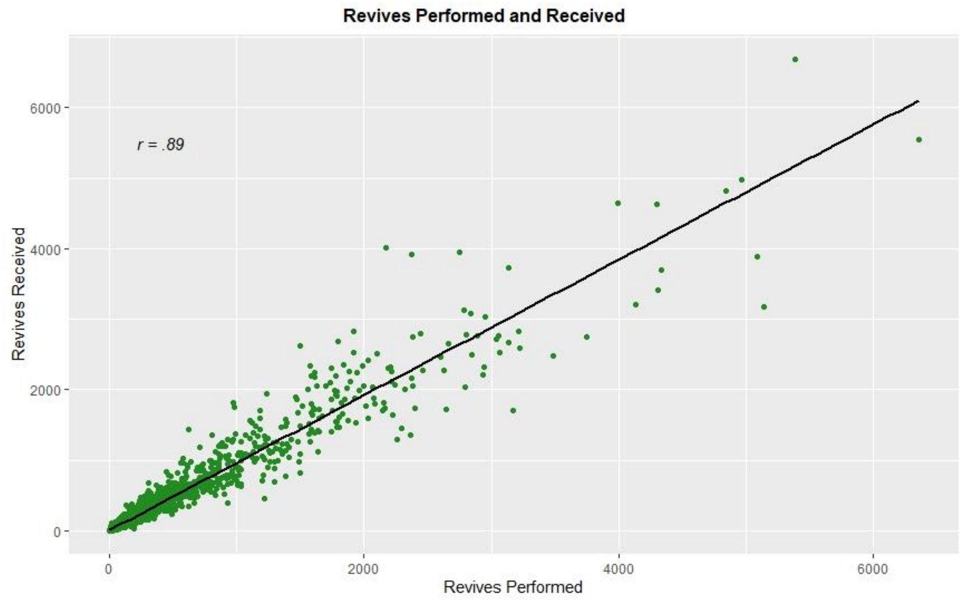

Figure 1. *A strong .89 correlation between revives performed and revives received.*

The specific outcome variable (i.e. the measure of learning) was decided during the actual analysis so will be discussed later. However, prior to analysis, some measure of combat rating difference over time was decided to represent learning. The predictor distributions were checked for normality, as normality is an assumption for many parametric tests. With large datasets, parametric tests are fairly robust against skewed distributions. However, for the sake of accuracy, heavily skewed distributions were addressed. The distribution of assists per game (Figure 2a(i)) somewhat resemble a normal distribution and was deemed sufficiently normal for further analysis. The distributions for initial scores and number of revives (Figure 2a(ii) and 2a(iii)) were heavily skewed and thus log-transformations were conducted.

While the transformed initial scores were deemed acceptably near-normal (Figure 2b(i)), the distribution of transformed revives (Figure 2b(iii)) appear platykurtic, if the zero revives subpopulation is ignored. While non-parametric analyses are often used in these cases, the dataset was continued to be prepared for parametric analysis, under the assumption that these tests were robust enough against skewed distributions, given the size of the dataset.

Z-scores were calculated for each predictor, which were used as the bases for outlier exclusion. A z-score range of -3 > x < 3 was deemed appropriate for inclusion here. Furthermore, players who had registered less than 2 hours of game time were excluded, based on the assumption that these metrics may not sufficiently measure learning. Specifically, the CRs are given at the end of each session and, since the average session in this player-base is 57 minutes, including all players would mean that learning for some players would be represented by just a single value. Given the nature of CR calculation, the difference between 0 and a single value as a measure for learning could potentially destabilise any analysis. Figure 2c shows the z-score distributions for the predictors after outlier exclusion.

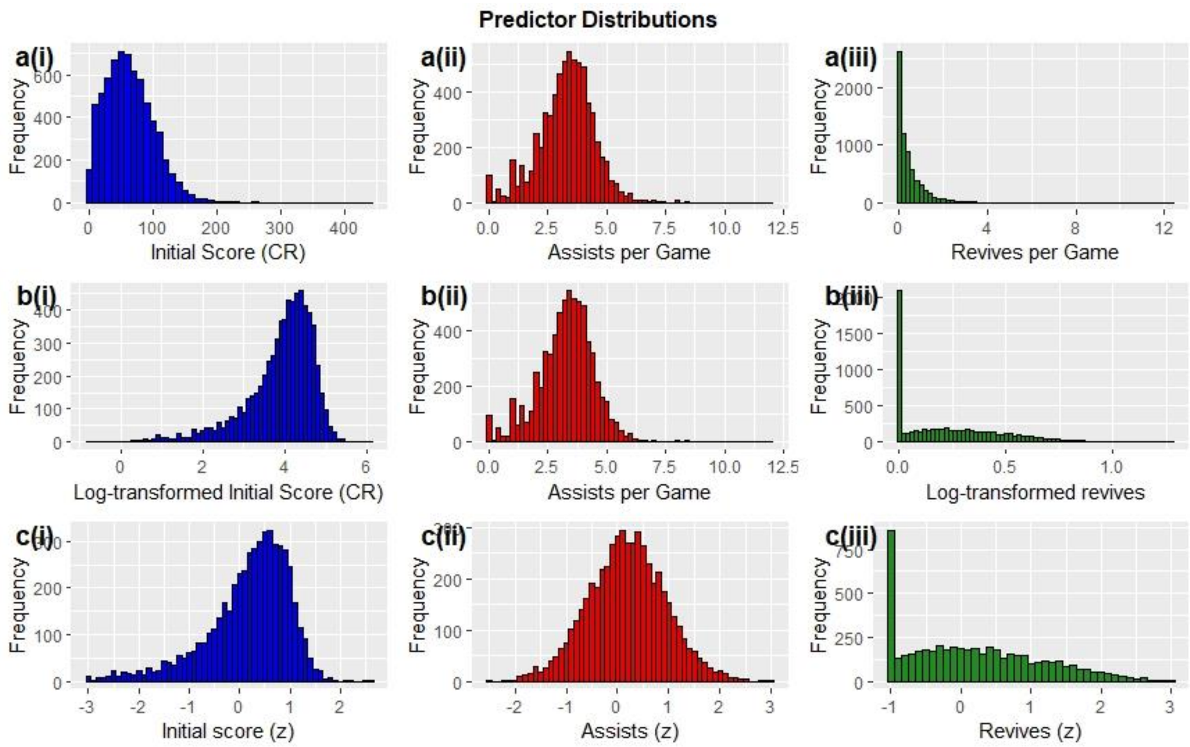

Figure 2. *Predictor Distributions.* **a** – Raw distributions of initial combat ratings, assists per game, and revives per game; **b** – natural logarithm applied to initial combat rating. Ln(revives + 1) used for revives to account for those with 0 revives; **c** – z-scores calculated for each predictor.

To account for the two distinct populations in Figure 2c(iii), the player base was divided into those with 0 revives per game and those with >0 revives per game. As the outliers, distributions, and grouping all having been addressed, the data was ready for statistical analysis, with 5207 out of the original 6996 players deemed eligible for this analysis. A further outlier exclusion was involved in the inclusion of the final 5207 players, as will be discussed in the following section. Chronologically, this omission came later than the first stages of analysis, but the conditions for omission were fed back into the data preparation stage and repeated, so the data used for all following analyses are consistent.

3.2 Preliminary Analysis

The first aim was to determine whether some broad relationship between the propensity for social play (revives) and overall individual performance (CR) exists. As shown in Figure 3a, there is a Pearson's correlation coefficient of $r = .38$ between log-transformed revives and mean combat rating. As a large number of these players have registered 0 revives (n = 828), the relationship between those who registered any number of revives and mean combat rating was calculated ($r = .34$), where a clear moderate positive correlation still remains, as seen in Figure 3b. The 'level' layered over the data represents a 2-D Kernel density estimation. When the subpopulation of players with no revives is removed (Figure 3b), the relative density of players shifts right on the revives axis.

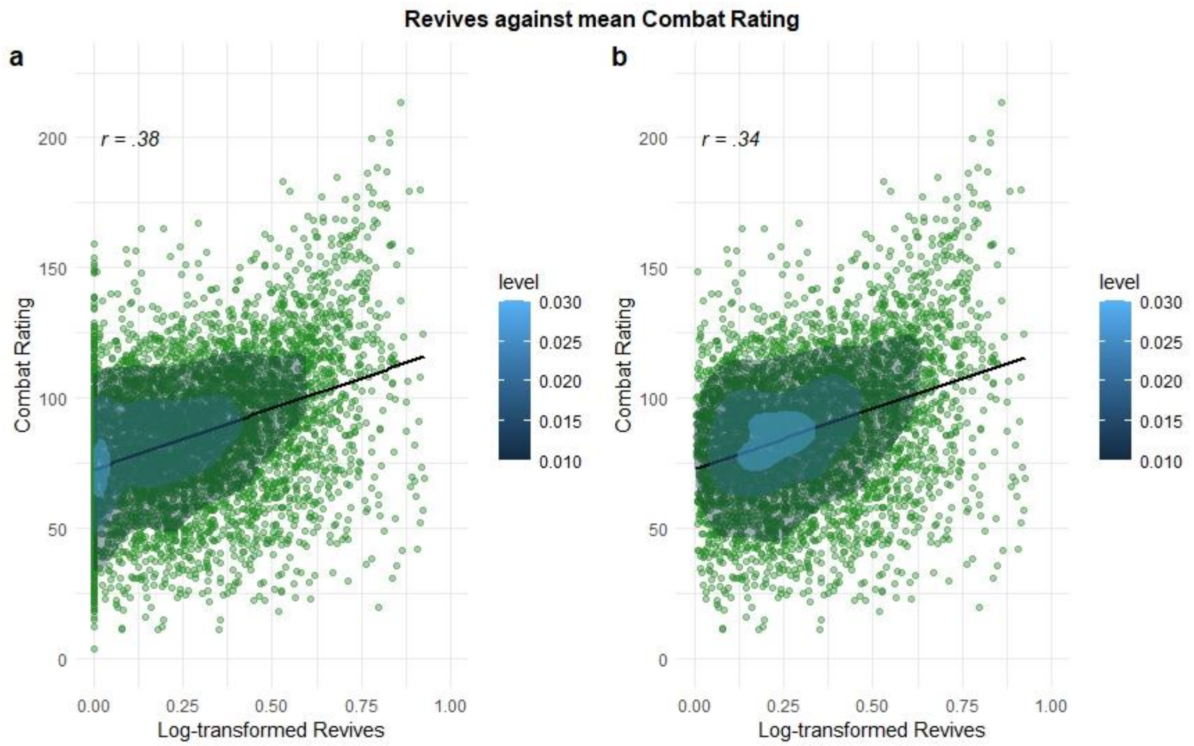

Figure 3. *Log-transformed revives plotted against mean combat rating for each player.* **a** – plotted for all players with a moderate positive correlation of r = .38; **b** – the 0 revives players were removed and a moderate positive correlation still remains for those with revives.

Learning rates were calculated by first fitting a linear regression model onto combat rating change over time (in hours) for each player. In the study by Stafford et al. (2017), combat rating change was measured against 'day number', which means that if an individual plays on a certain day, their combat rating will be expressed as an average score for that day. However, the amount of time played within a day can vary greatly; some play a few games in a day and some play for several hours. Therefore, for the present study, combat rating was chosen to be measured against time. Figure 4 shows an example of the progress of an individual player, fitted with a linear model (a 'linear learning curve' in this case). It also displays the 95% confidence interval of the linear model as a continuous variable. In 100 hours, this player has improved their combat rating by 36.71, at a rate of 0.38 combat rating score per hour, indicating that learning has been achieved through practice.

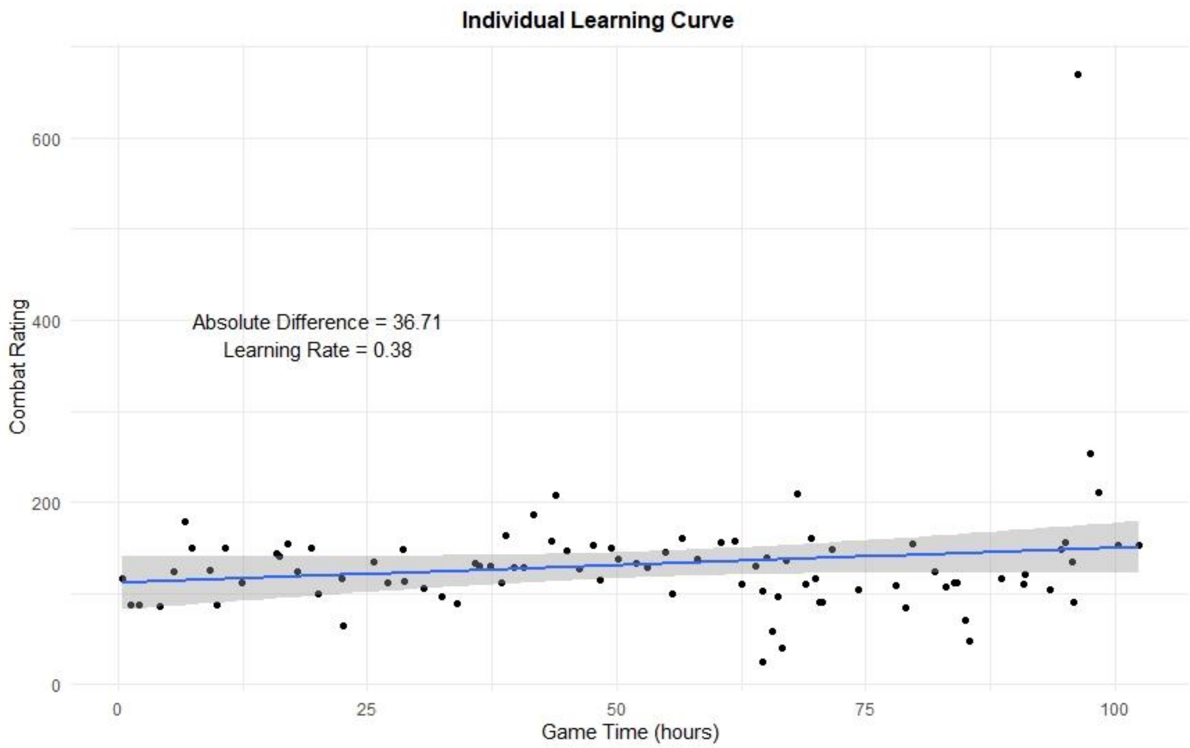

Figure 4. *The learning curve of an individual player, showing progress over time.*

Mean averages were recorded for the slope and intercept of each player, from which z-scores were calculated. In line with the previously stated range of $-3 < x < 3$, outliers were removed, resulting in the distribution seen in Figure 5. On face value, the distribution for slopes is severely leptokurtic, but again, given the size of the dataset, it was deemed acceptable to continue with analysis.

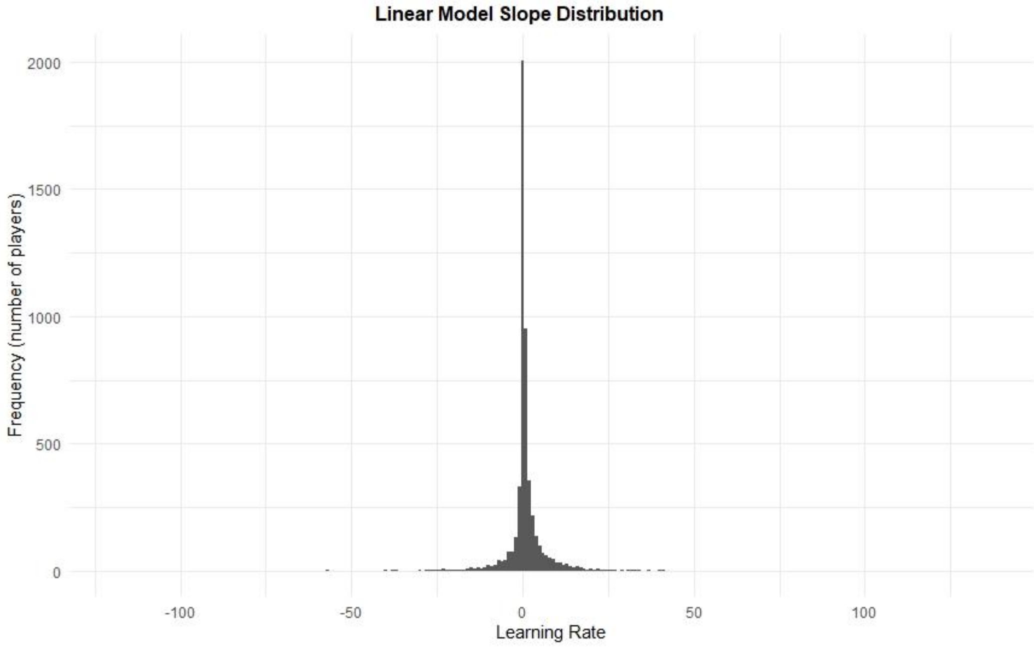

Figure 5. *Learning rate distribution.* Despite kurtosis, this distribution of learning rates was deemed acceptable for involvement in further analysis.

Figure 6 shows this average learning curve for all players (n = 5207), with an average slope of .93 and an average intercept of 74.78. Therefore, the model predicts that for every hour played, on average, a player will improve by 0.93 in their combat rating. The curve clearly does not fit the data appropriately. Especially beyond the 500-hour mark, the learning curve does not go through many, if any, data points, making this a poorly fitted curve.

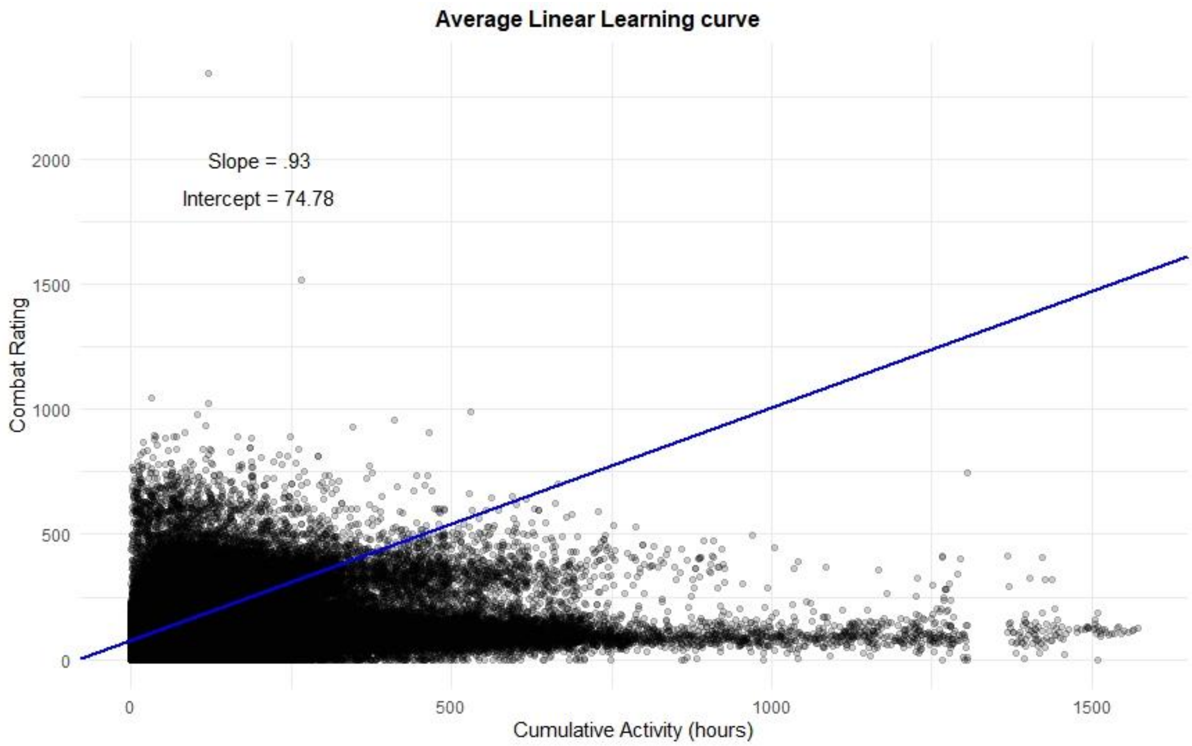

Figure 6. *Average learning curve for all players.*

Even before the 500-hour mark, it is not wholly visible from Figure 6 whether or not the curve fits the data appropriately. Figure 7 shows a more temporally restricted view of Figure 6, with CRs averaged at each 10-hour interval to better appreciate average learning. The average learning curve, as expressed by the average linear model, appears to fit appropriately only to early learning. The progression of average CRs follows the power law theory of learning, in that a sharp initial rise is followed by a gradual deceleration in improvement. One possible reason for why the linear model fits the data poorly is that a large number of players may have stopped playing relatively early. If a player does this, the individual slope value they provide that contributes to this average linear model will be high, since, consistent with the power law theory, the rate of learning they exhibit will be much higher early on. If a player continues to play beyond this initial sharp rise, the slope value they provide will be much lower, as the subsequent deceleration is taken into account.

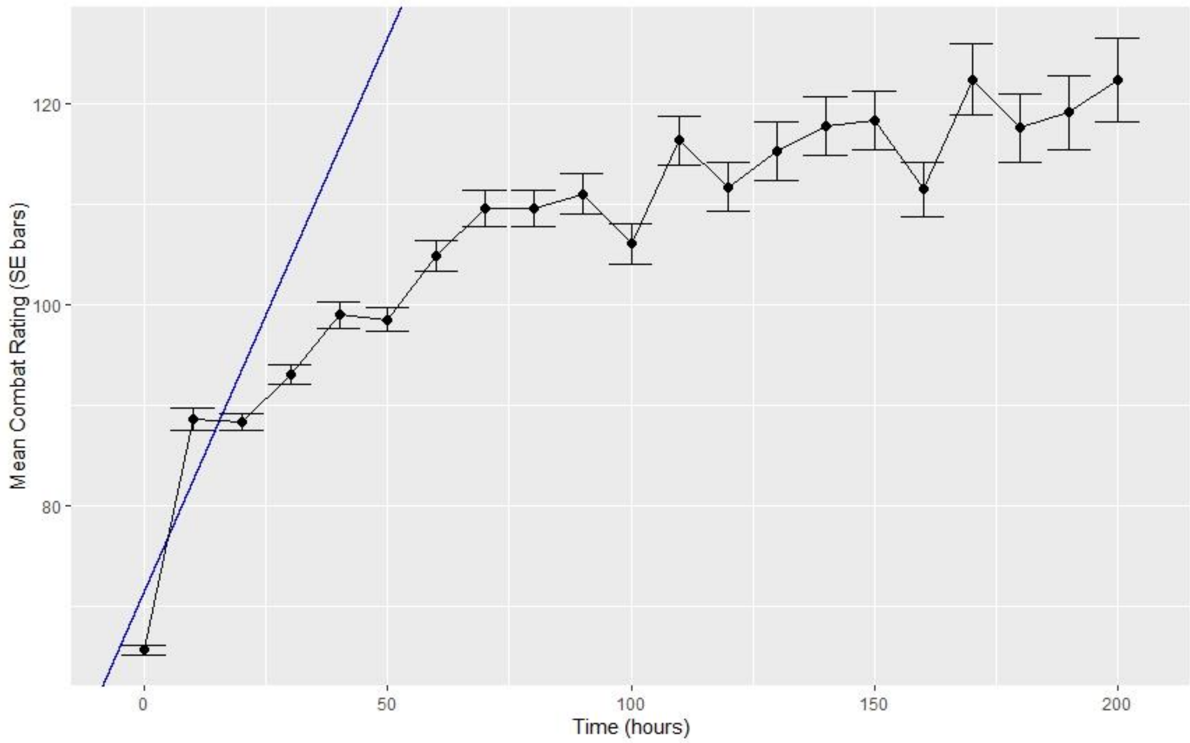

Figure 7. *Average CRs over time*

Figure 8 illustrates the drop-out rate for all players included in the analysis; 2288 players (38% of all players) drop out after the first 10 hours. As predicted, a large proportion of those who start the game have not continued enough to experience any learning rate deceleration. Those who drop out early produce high linear regression coefficients and as such, have distorted the average learning curve, so that it poorly predicts average game progression. Therefore, it was decided that the exclusion criteria should be updated.

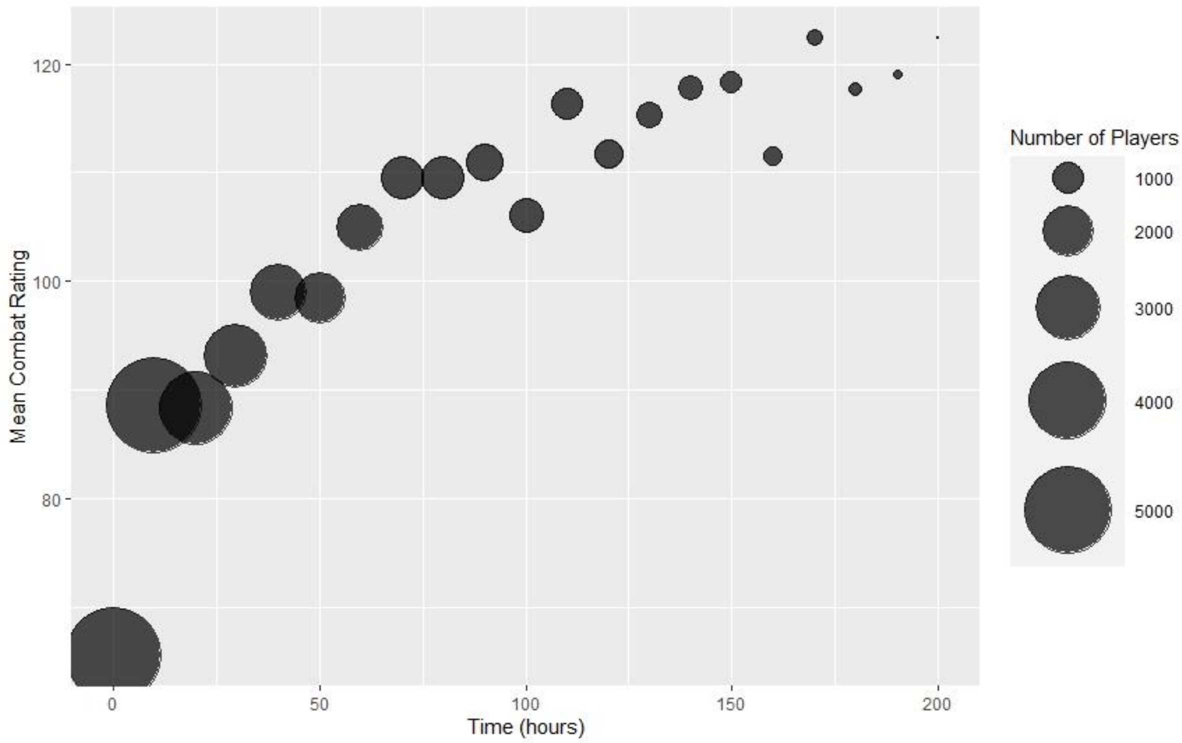

Figure 8. *Player drop-out.* The size of the bubbles indicates how many players remain after each 10-hour period

Since linear regression is being used, restricting the time-window to the first 200 hours was deemed appropriate, as this is the point at which the deceleration in learning rate appears to visually level out (Figure 8). Next, to ensure that the power law is considered, the minimum time required for inclusion was raised to 50 hours. With this new minimum, deceleration in learning rate will be appropriately captured by a new average linear model. No clear subpopulations exist in the new distributions (Figure 9) and so a regression analysis will be performed on all players (n = 1760).

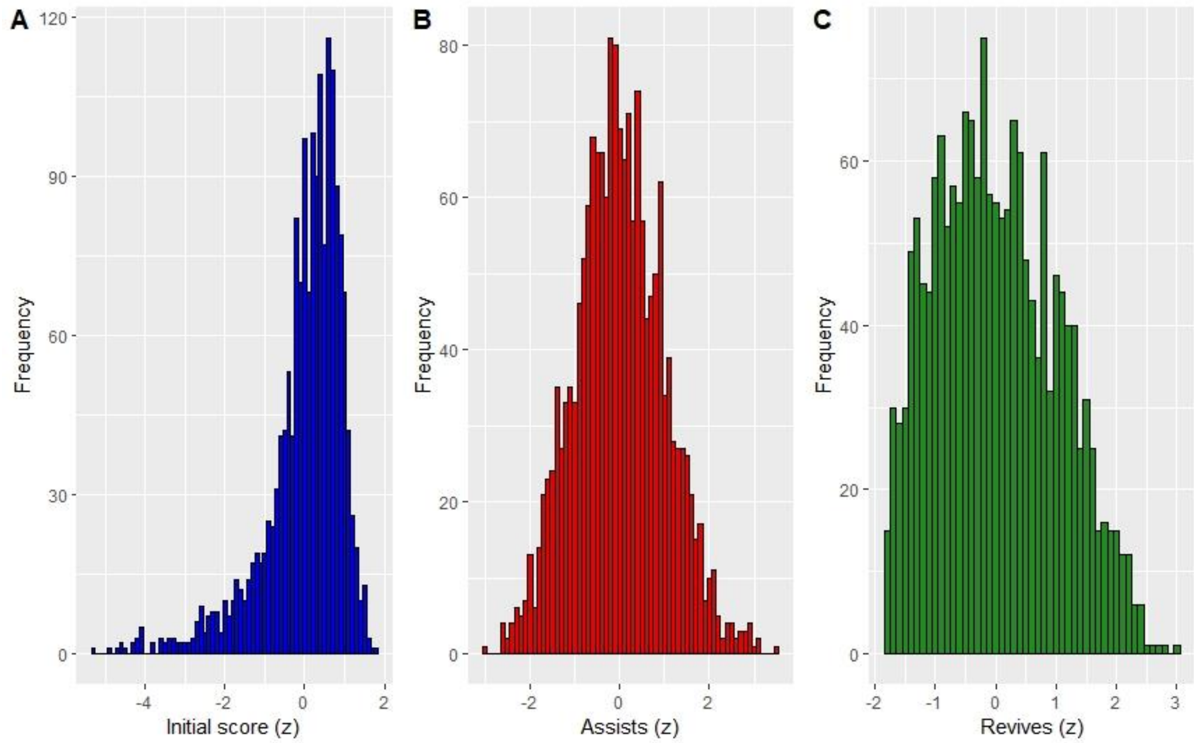

Figure 9. *New z-score distributions*. c – subpopulation no longer exists.

Linear regression was performed again under the new conditions (Figure 10). The standardised scores for revives and regression slopes have a weak positive correlation (r = .*15*), showing evidence for some relationship between the two variables.

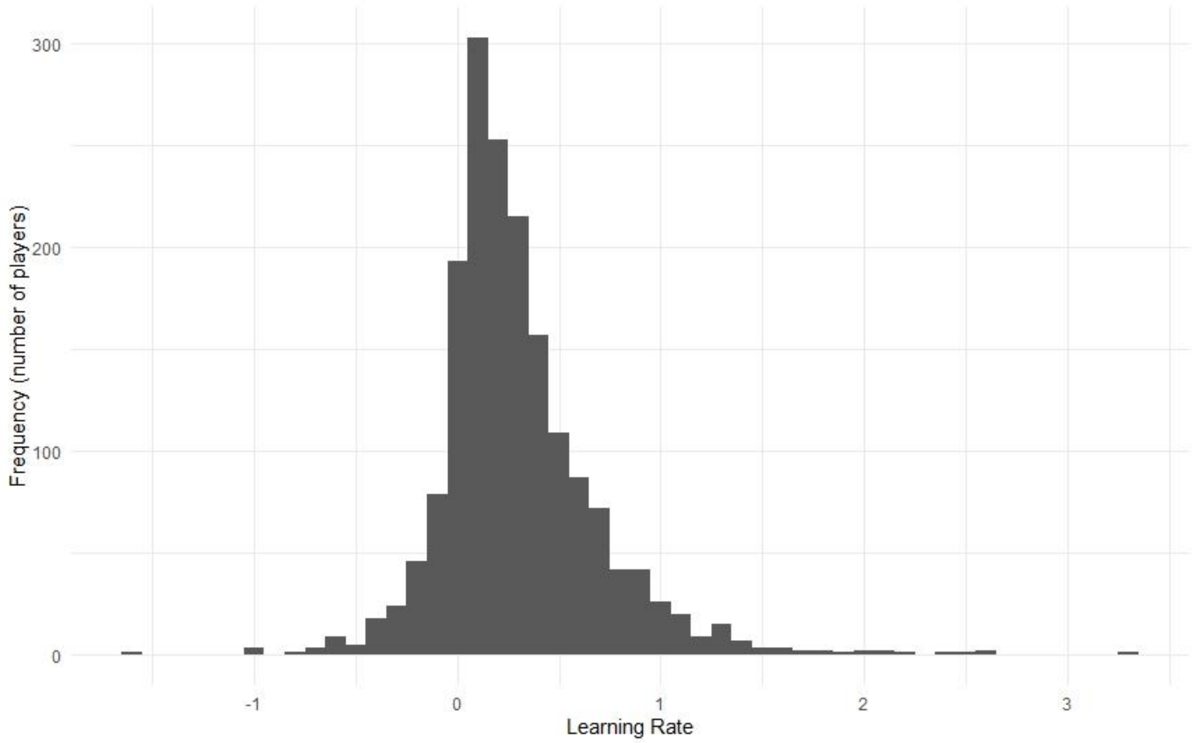

Figure 10. *New distribution of learning rates*

3.3 Main Analysis

Under the new exclusion criteria, the new average learning curve was fitted (Figure 11). When compared to Figure 7, this curve appears much more consistent with the underlying data points within the time period of the first 200 hours. The average learning curve slope for these players is 0.30, indicating that for every hour played a player will improve their CR by 0.3 on average.

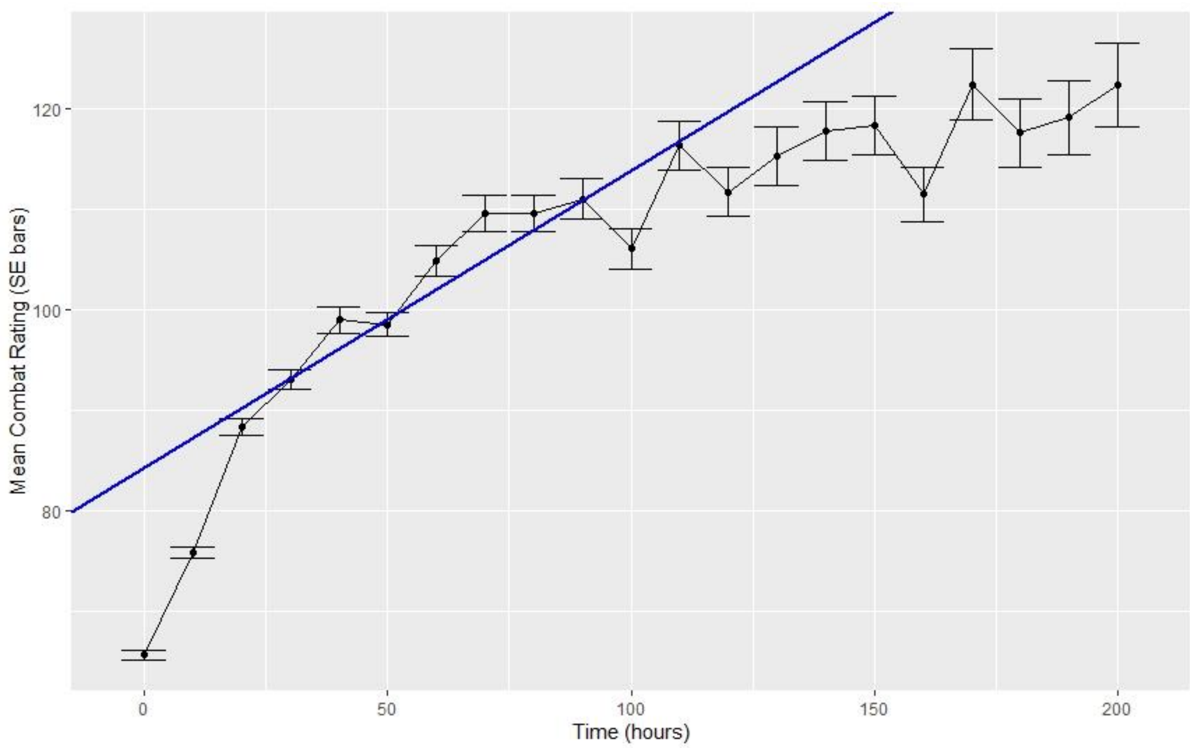

Figure 11. *New linear regression model fitted over average CR plot.*

Multivariate regression was then performed, testing the extent to which revives can predict learning rates beyond assists and initial scores (Table 1). Standardized z-scores were used for all predictor variables, in order to appreciate the beta weights, relative to the other predictors. Controlling for assists and initial score, the significant effect for revives (B = 0.0629, 95% CI = [0.044, 0.082] , p = 9.33e-7) would indicate that with each additional standardised revives score, the slope of a player's learning curve (unstandardized) will increase by 0.063 on average. The finding that assists negatively predict learning rates is consistent with that of Stafford et al. (2017). A comparison of effect sizes between these two measures of social play suggests that revives are better able to predict learning rates than are assists. With an $R^2_{Adjusted}$ of 0.068, the three predictors significantly account for 7% of the variance (*p < 2e-16*) of the learning curve slopes.

Factor	Beta-weight	t-value	p-value
Initial score	-0.0784	-8.271	2e-16
Assists	-0.0157	-1.577	0.115
Revives	0.0629	6.517	9.33e-7

R^2 = 0.06776, F(3, 1756) = 43.61, p < 2e-16

Table 1. *Regression of player social behaviours on learning rate*

3.4 Subsidiary Analyses

The player base was divided into 'social' and 'solo' groups based on their revives per game; the social group consists of players in the top quartile of the standardised revives distribution and the solo group consists of players in the bottom quartile (Figure 12). The graph clearly shows that those in the top quartile for revives learn much faster than those in the bottom; the rate of learning deceleration appears to be slower for those in the top quartile. Their performance increase rate does not fall as quickly as it does for those in the bottom quartile. Welch's T-tests were carried out in order to compare social and solo learning. The mean learning rate for the solo players was 0.26, whereas the mean learning rate for the social players was 0.41. This difference was found to be significant, $t(858) = 5.13$, $p < 0.05$, 95% CI = [0.09, 0.20], $d = 0.35$. While this is a significant difference, the effect size (Cohen's d) is small.

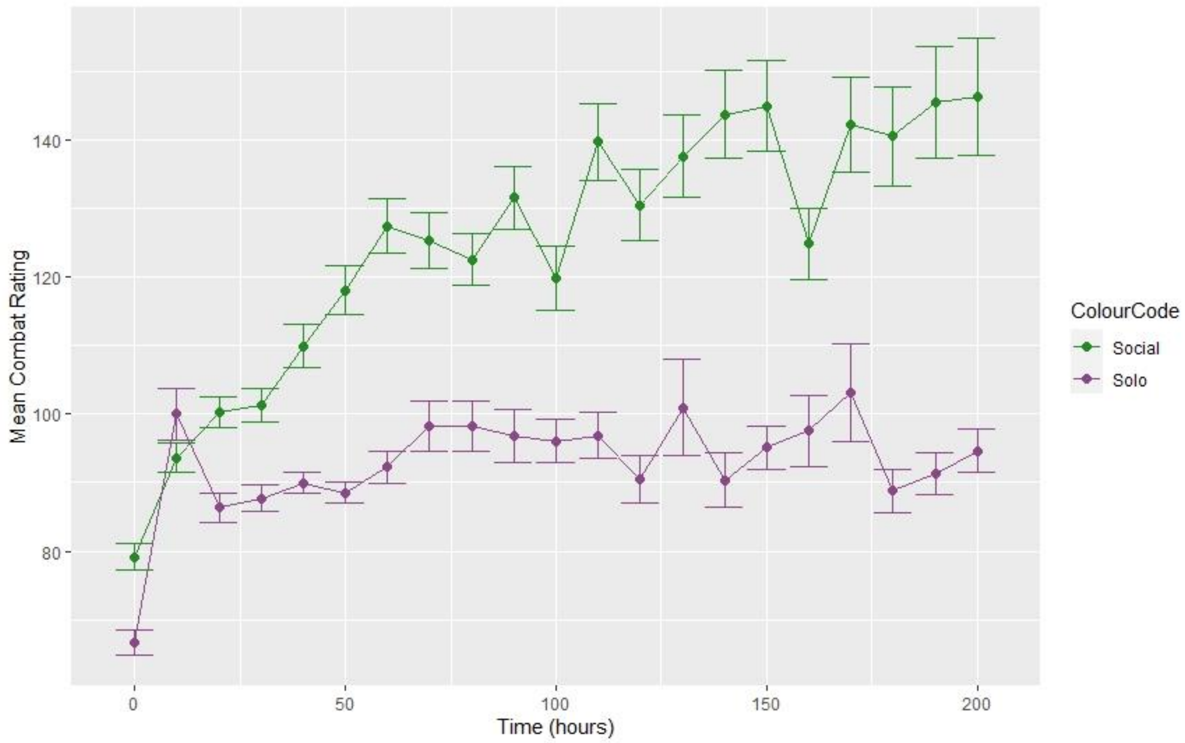

Figure 12. *Average learning curves for top and bottom quartiles for revives.*

To explore the idea that individuals who are socially motivated to learn are more engaged, in terms of the amount of time they commit to practice, Figure 13 shows the number of players who are still playing at each 10-hour interval. The social group retains a larger number of their players than the solo group. Although they start with the same number (n = 440), by the 200-hour mark, 73 solo players and 160 social players are still playing.

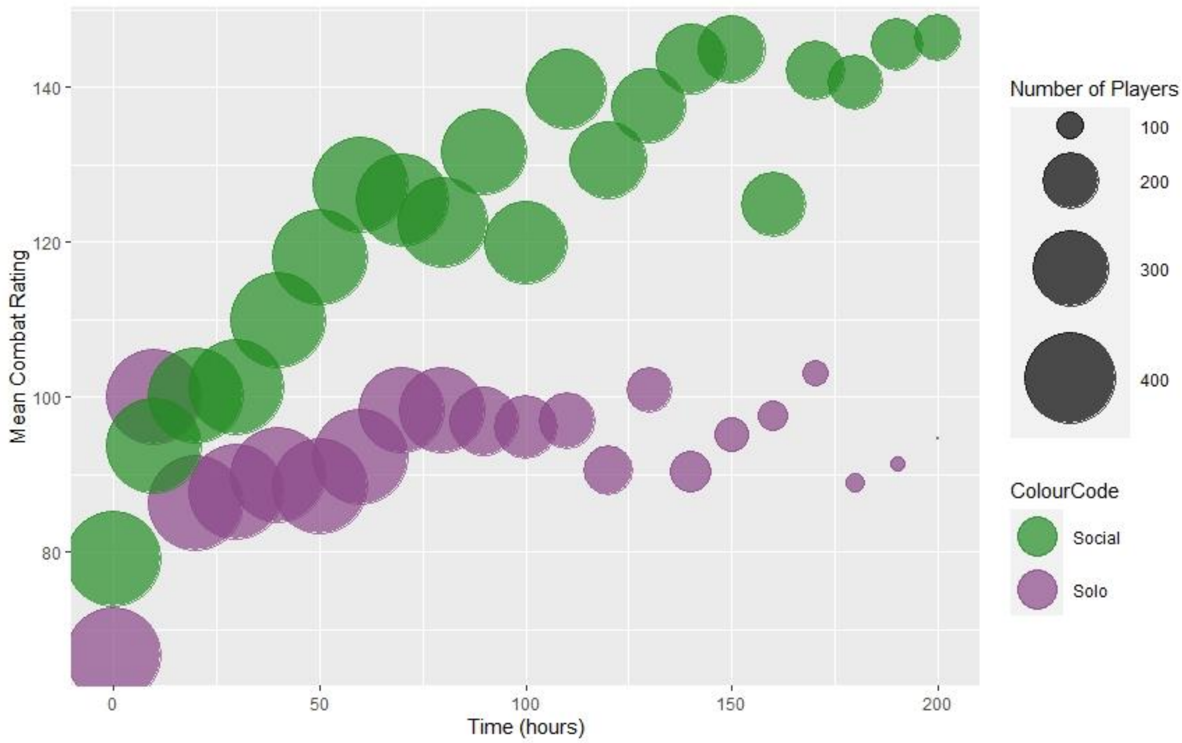

Figure 13. *Social vs solo player-retention level over time*.

In order to assess the extent to which revives and assists measure the same construct (social play), a correlation coefficient was calculated (r = -*.31*) for the respective standardised z-scores, showing a moderate negative association.

4. Discussion

4.1 Summary of Results

The aim of this analysis was to investigate the extent to which social play is a predictor of learning rates in Destiny. It was predicted that a greater propensity of social play, as measured by revives rate, would be associated with faster learning (CR progression). The multivariate regression analysis showed a small but significant positive effect of revives on learning, beyond the effects of initial score and the other representation of social play, assists. This result supports the hypothesis, in that social play has accounted for a small amount of learning rate variability.

The first subsidiary analysis (Figure 12) shows that 'social' players (i.e. those in the top quartile of the revives distribution) had a significantly higher mean learning rate than those in the bottom quartile, the 'solo' players. In addition, this analysis visually shows two distinct learning curves for the two groups. The social players experienced a much slower deceleration in their learning rate, whereas the solo players showed a sharp, early deceleration and maintained a somewhat steady score after the initial rise in performance. The second subsidiary analysis (Figure 13) shows that more social players engaged with the game for longer than the solo players; a large proportion of social players that started the game continued to play beyond the 200-hour mark, whereas a very small proportion of solo players remained at the 200-hour mark. The third subsidiary analysis shows a moderate negative correlation between revives and assists, suggesting that they do not measure the same construct.

The main result of this study shows that having a social playstyle in Destiny, as measured by a revives rate, is linked to a higher learning rate, regardless of initial skill level. This finding directly contradicts that of the original study (Stafford et al., 2017). As both studies share the aim of investigating the effects of social play on learning, this discrepancy should be evaluated fully; doing so requires its own section so will be discussed in greater detail further on. In the interest of addressing the current results in the context of previous research and wider theory, a tentative assumption, that social play has successfully been captured by the current method, will be made.

4.2 Has Learning Been Captured by the Data?

In terms of skill learning research as a whole, this study gives strong support for the use of big data in tracking skill progression over a long period of time, at a massive scale. Figure 7, a visual representation of average skill level at each 10-hour interval in the player base, clearly shows progression that is consistent with established theories of learning. After an initial sharp rise in performance, improvements begin to gradually decelerate, forming the power law curve of learning (Fitts and Posner, 1967). The average decrease in performance between the 10 and 20-hour marks can be explained by the 3-stage learning paradigm (Fitts and Posner, 1967). Simply, early performance in a skill is characterised by a high level of inconsistency. Computational accounts of the exploration-exploitation trade-off could explain this further (eg. Katehakis and Veinott, 1987). At the level of making a single decision, an individual has the opportunity to exploit a decision with known rewards, or to explore other options with a potentially better reward. In doing so, the individual will likely experience options that result in worse rewards before finding an optimal action. For a complex skill, such as in video games, there are far more degrees of freedom (i.e. explorable actions), meaning that players who choose to explore often experience many low-rewarding actions early in their career (Sledge and Príncipe, 2017). The early pattern in the average learning curve (Figure 7) could reflect this phenomenon. The average progression in Figure 7 indicates that this study has maintained the high level of face validity from the original study in using game telemetry to capture complex skill learning.

4.3 Social Effects on Learning

Consistent with Vygotsky's (1978) zone of proximal development theory of learning, the results of this study show that learning occurs faster in the presence of peers. One aspect of the theory that should be considered is the idea that learning occurs best when peers are more skilled than the learner. The current dataset provided no information as to the skill level of the teammates of each player and so limits the extent to which that theory applies here. As described in the introduction, this theory would logically apply to those who gain information on basic game mechanics and strategies from higher skilled peers. Using the conclusion from Boot et al. (2016), we know that knowledge of these strategies mediates subsequent learning, which would include any socially derived information. However, this would not account for a higher skilled social player; they would gain little from social play by this route. Nonetheless, if we assume that there is no massive disparity in skill level within a team, the survey from Johnson et al. (2013), that shows the majority of their group learners rated the sharing of information as being beneficial to their learning, even slightly higher skilled players can improve based on what they learn from competent teammates.

A more specific mechanism by which this could occur relates to the exploration-exploitation trade-off (Katehakis and Veinott, 1987). There is always some risk in exploring new actions in complex skills, that these actions may return poor rewards. In the absence of information gained from teammates, a player may continue to exploit actions that result in a known reward. While this reward may not be exceptional, it may outweigh the risk in looking for more optimal actions, which would show as a stagnation in learning. Visually, we can see this in Figure 12; the solo players appear to reach a stable level fairly early on (around 70 hours) and do not seem to progress far beyond that through to the 200-hour mark. Conversely, the social players seem to experience a steeper initial rise, perhaps accounted for by the increased amount of strategic information from teammates. This allows them to exploit better actions without the risks involved in exploration. Furthermore, beyond this initial sharp rise, they still learn at a relatively high rate, despite occasionally dropping in performance. This occasional decrease in social players' later performance could also be relevant; socially derived information is primarily linked to early stages of learning (Boot et al., 2016), so the need for exploration may become apparent for social players at some point. As learning in a social context is reported to increase confidence (Johnson et al., 2013) and with confidence a key predictor of willingness to improve (Hays et al., 2013), the social players appear to persevere with exploring new actions more than the solo players do. Figure 12 suggests that the setbacks experienced through exploration are offset by greater improvements, meaning that the social players ultimately learn faster than do the solo players. However, without any anecdotal evidence from these players, these claims, while supported by previous evidence, are somewhat speculative.

The results of this study support conclusions made by Mason and Clauset (2013). While they did not investigate learning, they did find that playing socially was linked to higher performance levels in the game Halo Reach. In their case, playing socially was represented by a high proportion of in-game teammates being on a player's friends list. This extends beyond in-game social playstyles, in that these players have decided to form social bonds online or link with people they know in real life. This could indicate some form of communication, either in-game through audio or otherwise, whereas measuring social play by revives rate gives very little indication as to whether there is any communication between players. A lack of evidence for explicit communication could be problematic for interpreting the results of the current study, as the benefits of learning socially outlined earlier assume some level of communication. However, Nardi and Harris (2006) linked in-game social playstyles in games to actual social bonds. Players rated as being social by their in-game behaviour knew exactly who their teammates were, suggesting some degree of communication. As this link is reported to be consistent across FPSs (Xu et al., 2011), the choice for this study to represent explicit social communication by an in-game metric is justified.

Another potential mechanism by which social factors may affect learning variability relates to enjoyment. As stated in the introduction, social bonds within a game are formed primarily to enhance the enjoyment of that game (Xu et al., 2011); enjoyment increases the level and quality of engagement in general learning (Lucardie, 2014). If the level of game engagement is analogous to class attendance from the Lucardie (2014) study, then enjoyment could be represented from the current dataset by the amount of registered game time. Figure 13 serves two purposes: one is that it visually shows that social players learned more efficiently than did solo players; social players also tended to register far more game time. This suggests that in addition to benefitting learning efficiency, a social context could add an incentive to play for longer, through the enjoyment it provides. As learning primarily occurs as a function of practice time (Sackett, 1934), more practice simply leads to more learning. This is especially important when considering these results with the aim of contributing to an optimal learning strategy; no matter how efficient a learning strategy may be, if there is little incentive to practice, an individual may simple stop early (as most of the solo players have done), nullifying any effective learning strategy. This idea extends to other forms of learning, such as language learning (Allen et al., 2014), where enjoyment is a key predictor in whether or not an individual reaches fluency. Although enjoyment has not explicitly been measured in this analysis, inferences from previous findings suggest that social context here, through enjoyment, could have benefited both learning efficiency and amount of practice engagement.

4.4 Comparisons with the original study and related insights

To fully appreciate the results of the present study, the methodology and results should be evaluated in the context of the original study from Stafford et al. (2017). First, as shown in Table 1, the original result that playing more socially, as measured by an assist rate, leads to slower learning, is replicated in the present study. However, the statistical significance and relative effect size from the original study here are not replicated. The differences in inclusion criteria may account for this. The minimum inclusion criterion in the original study was for an individual to have played on 25 separate days. It was chosen for the current study that a minimum of 50 hours should be played to qualify for analysis inclusion. As outlined in the data preparation section, one reason for this change in approach was that, visually, an appropriate amount of deceleration in learning was seen to occur by around the 50-hour mark. Since a single learning rate was to be used for the multivariate regression, this criterion was considered satisfactory in producing a rate that better incorporates the deceleration that occurs in a power law curve. Moreover, having a minimum criterion that relies on playing on a number of separate days could be seen as an issue. Playing on 25 separate days could mean 100 hours of gameplay for one player and 25 hours for another, depending on how much of the day is spent on Destiny. As such, the decision taken for the current study to use time was an attempt to standardise both the inclusion criteria for analysis and the output given by each player as CR change over time. However, in this dataset, a new CR is registered at the end of each session, which makes it difficult to assess the effectiveness of this standardisation. While using time could be considered a more valid way of tracking improvement over the amount of practice, it is far more convenient and easier to interpret CR changes against session number, as each player gives a new score after each session. It would therefore be interesting to see how the results of the present study would change if the original method was kept. Furthermore, changing the temporal element of the DV learning rates means that it is difficult to compare effect sizes between the two studies.

Despite this change in method, the significant negative association found by Stafford et al. (2017) between initial CR and learning rates has been replicated here. This is consistent with much of the current literature on skill learning in games (e.g. Huang et al., 2017). When considering the broad aim of this study, to contribute to what an optimal learning strategy would be, it is difficult to integrate this finding. Factors such as spacing practice and social play are relatively easy to control for a player, whereas initial performance is not. In addition, initial performance is difficult to explain with the current dataset, as we do not have any insight into the prior experiences of the players; we can speculate that initial performance variability is a culmination of a wide range of interacting factors (Stafford and Haasnoot, 2016). In particular, prior experience of online shooters should be a large contributing factor. While Destiny is the first of its series, it belongs to several well-established genres. Those who have played shooter game series' such as Call of Duty and Halo (Destiny game engine is based on Halo engine; Butcher, 2015) will likely have developed skills transferrable to Destiny. As such, any individual learning curves produced by the current dataset can be interpreted as a continuation of existing learning curves, as opposed to an entirely new skill. Similarly, initial skill in a subsequent game would be influenced by performance in Destiny. With the release of Destiny 2 (2017) and the same method of data collection by Bungie (player membership IDs stay the same for a player), one achievable way of investigating initial skill level would be to track player progression throughout both Destiny 1 and 2. Using the current dataset to make predictions about how players will perform in the sequel can be tested using actual data from Destiny 2. For the current study, however, including initial CR in the multivariate regression analysis means that it is controlled for when reporting the effects of revives and assists on learning rates. Realistically, this was the only viable way to account for data that is not available.

One potential way to explore initial skill using this dataset would be to use extend an individual learning curve backwards to see how much prior relevant practice was involved. For example, if we consider the curves to follow a power law trajectory, a player who produces a learning curve that is already relatively shallow from the 0-hour mark can be considered to be far along their learning progression for that curve. A steeper initial rise in performance would represent a player that is new to the skill. The y-axis prior to the 0-hour mark would then represent an arbitrary skill measure rather than CR. Ideally, data that accounts for this would, but collecting this data is highly unrealistic. Therefore, using the current dataset to make predictions about prior practice could be an interesting option. This type of predictive ‘back-casting’ has been used in urban planning and climate research (Dreborg, 1996), but has not yet seen any use within cognitive psychology. Thus, determining whether or not this is mathematically possible in psychology would require testing.

4.5 Revives or Assists?

The issue of construct validity in big data analytics within psychology has been outlined in the introduction to this essay. For the present study, this issue lies in the choice of metric that best represents propensity for social play. Since the main result of this study directly contradicts that of the original

(Stafford et al., 2017), this issue should be evaluated more deeply. The fact that the two metrics predict learning rates in different directions (i.e. a higher revives rate is linked with faster learning and a higher KADR is linked to slower learning) may indicate that they do not measure the same construct. The moderate negative correlation between revives and assists supports this. As there is no evidence in the current literature to support either side as a valid metric, it is entirely up to the reader to interpret the arguments presented earlier. Regardless of which side appears more valid, the other metric should not be entirely dismissed. Logically, revives do measure social play; there is no personal benefit to the individual performing a revive, whereas an assist can be considered an unwanted biproduct of a self-serving action (trying to kill an enemy). However, you cannot register an assist unless you are navigating the map with your teammates, which again, gives some logical support for assists as a valid metric of social play. One convenient explanation is that they both are valid representations of social play, but that time spent on revives is time lost for registering assists and vice versa. This accounts for the negative correlation but not for the opposite directions of learning rate prediction, so the revives-assists relationship should be explored further.

The key difference here could be skill level. The multivariate regression has controlled for initial score but does not account for any subsequent scores. Learning rates are given independent of the actual CRs to which they correspond. Therefore, skill level throughout a career has not been controlled for. Posner's learning paradigm (1967) characterises early skill performance as showing high levels of inconsistency. This could suggest that controlling for a single initial CR does not fully account for initial skill level. In fact, at the 10-hour mark (Figure 12), the solo players are better on average than are the social players, which is the only time at which the two groups come close in terms of CR, which perhaps highlights the theory-based inconsistencies in early skill performance. Using this, a logical explanation that incorporates both revives and assists as valid metrics for social play can be argued: players in a relatively bad team may be shot down more frequently, which means that there is more need and more opportunity for revives to occur. A 'bad' player would be represented by a low CR, so a higher revive rate could be linked to a low average CR. Conversely, an assist can only be registered if an enemy dies; the more an enemy dies, the better a team performs. This could link a high assist rate with a high average score. Further, players in a better team may not be shot down as frequently, limiting the need for revives to occur. If average CRs are negatively associated with learning rates in the same way that initial CRs are, this allows for revives to represent social play at a lower skill level, and for assists to represent social play for higher skilled players. Thus, the negative correlation between the two metrics can be explained without disregarding the validity of one or the other.

However, the subsidiary analyses show a higher learning rate for those with a higher rate of revives, as well as a consistently higher CR over the 200 hours (Figure 12). This indicates that two characteristics of players who have a higher revives rate are that they are better, on average, over time than those who have a lower revives rate, and that they learn faster. While these analyses do not support the idea that worse players perform and receive revives more often, the evaluation in this section does suggest that the revives-assists relationship needs to be explored further. Finding an underlying metric that correlates with both revives and assists more strongly than they do with each other could be key in determining the nature of this relationship.

4.6 General Limitations and Future Directions

A number of limitations and potential future directions have already been explored but one general observation can still be made. While Big Data analysis here has allowed for strong quantitative evidence for the role of social context in learning, many of the implications discussed rely on the generalisability of previous studies. Especially when considering that the metrics provided were not designed for the purpose of representing psychological constructs, this study could benefit from a supplementary qualitative analysis, in order to better justify both metric choices and subsequent interpretations of the results. For example, a naturalistic observation or survey (e.g. as was done by Xu et al., 2011) would help in better interpreting the results, in terms of which characteristics of social play actually benefit learning, as the current interpretations, while based on theoretical evidence, remain somewhat speculative. From such a study, linking any qualitative themes with those of other areas of skill learning could also help to generalise the results of the current study, beyond Destiny players.

4.7 Conclusion

From the findings of this analysis study, it can be concluded that social motivation has a small positive effect on learning rate. This supports much of the preceding literature surrounding the relationship, despite contradicting the results of the study on which the this one is based. The current dataset has not only allowed for confirmatory evidence to produce a size and direction of the effect, but also for exploratory analysis to gain insight into the potential mechanisms by which a social context affects learning. The analysis provides evidence for two mechanisms. One relates to the idea that socially derived information reduces the need for exploring new actions, which would increase the efficiency of early learning in particular; the second relates to enjoyment, derived from a social context, increasing both quality and amount of engagement with the game. Social context influencing confidence has also been a suggested route, but supplementary data is required to explore this. In fact, qualitative accounts from Destiny players would benefit any claim made here, in aiding both interpretations and attempts to generalise the results to other areas of skill learning. Nonetheless, the value of this study lies in the strong evidence it provides for the effects of social context on learning, in addition to solidifying links between theoretical accounts of learning. In terms of an optimal learning strategy, this study strongly supports the claim for the promotion of a social context within complex skill acquisition.

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