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Analyzing player networks in Destiny

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ABSTRACT

Destiny is a hybrid online shooter sharing features with Massively Multi-Player Online Games and first-person shooters and is the to date the most expensive digital game produced. It has attracted millions of players to compete or collaborate within a persistent online environment. In multiplayer online games, the interaction between the players and the social community that forms in persistent games forms a crucial element in retaining and entertaining players. Social networks in games have thus been a focus of research, but the relationships between player behavior, performance, engagement and the networks forming as a result of interactions, are not well understood. In this paper, a large-scale study of social networks in hybrid online games/shooters is presented. In a network of over 3 million players, the connections formed via direct competitive play are explored and analyzed to answer five main research question focusing on the patterns of players who play with the same people and those who play with random groups, and how differences in this behavior influence performance and engagement metrics. Results show that players with stronger social relationships have a higher performance based on win/loss ratio and kill/death ratio, as well as a tendency to play more and longer.

1. Introduction

The social networks in persistent online games play a fundamental role in the user experience and retention of players, and building and maintaining communities in games form an important aspect of the design and maintenance of persistent games.

The networks forming between players in online games can be difficult to investigate without the right tracking of player interactions and behavior, and furthermore are relatively volatile in terms of constant change as the community in a game evolves. This means that insights gained from investigating these networks are usually short-lived in the commercial sense. However, in recent years it has become possible to explore the networks forming between players in online games, thanks to new tracking technologies and business models that have enabled the collection of big data-scale telemetry datasets about player behavior in games. This further augments the investigation of player networks by providing contextual data about the in-game behavior of the players in the networks, for example. In parallel with this development, the domain of game analytics has grown up to target the problem of dealing with behavioral, performance and process data from game development and game research, seeking to inform both game development and behavioral research [1,2]. The interest in using large-scale behavioral telemetry data to investigate player behavior is increasingly used to target design, business, and research issues in digital games. Nowadays, game analytics form a core element in the toolbox of game developers.

From a research perspective, social networks in online games form the basis for investigating the nature of human interaction and also provide a basis for behavioral experimentation. The networks between players in multi-player or massively multi-player games thus play a fundamental role, and several researchers have investigated such networks in a variety of different games from Real-Time Strategy (RTS) games to Massively Multiplayer Online Games (MMOGs) [3,4], for example to analyze group formation processes [5] or to investigate the robustness of multi-player games against player departure [6], as well as for outright churn prediction [7].

In this paper, the focus lies on a previously largely unexplored type of player network in online games: *Competitive Networks*; which form

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via competitive, team-based play. Specifically, these are the networks that form among players in team-based play, and are extending across either the friendly or the competitive team. Combined with behavioral telemetry about player activity, such networks permit the investigation of correlations between network behavior and player behavior and performance. Similar networks can be established in Multiplayer Online Battle Arenas (MOBAs) [6,8] and instanced battlegrounds in some MMOGs [9]. In this paper, different forms of competitive networks are described and their potential for player network analysis in the context of multi-player persistent online games is discussed. The basis for the investigation is the hybrid online shooter game *Destiny*. However, the behavioral features utilized in this investigation are generic to team-based online shooter games such as *CounterStrike* and *Call of Duty* and thus could also be potentially relevant to a number of major esports titles [10–12].

Destiny is a hybrid game title because it merges design elements from several different genres, including first-person shooters (FPS), MMOGs, MOBAs, and role-playing games (RPGs). While traditional multi-player online games are based on RPG or RTS elements, *Bungie*, the developer of *Destiny*, introduced a different kind of shared, persistent world game that incorporates RPG, MMOG, and MOBA elements into a FPS genre, and thus enables a wide variety of gameplay options, which is evident in the many game modes across Player-versus-Environment (PvE) and Player-versus-Player (PvP) in *Destiny*, with the latter gameplay mode being the focus of the current paper. Of direct relevance to player network analysis are the restricted communication options in the game, which do not permit open communication between players, unlike in mainstream MOBAs, MMOGs and FPS. Notably, *Destiny* lacks friend lists and text-based chat channels. Moreover, voice communication between members of a group is only possible for specific fireteams (consisting of 3 players) and is an opt-in feature which has only recently been enabled for random groups.

2. Research questions and contribution

2.1. Research questions

As the analysis of social structures in games becomes increasingly important, we want to investigate the player's interactions within *Destiny* through graph-based methods and analyze the impact of these interactions on elements such as performance and engagement. We focus on answering the following main research questions: (1) Do player relationships/interactions relate to the win/loss ratio in multi-player PvP matches? (2) Do player relationships/interactions relate to combat performance (measured by kill/death ratio)? (3) Do player relationships/interactions relate to combat performance (measured by time/match ratio)? (4) Do player relationships/interactions relate to engagement (measured by the number of matches played and total playtime)? (5) Does clan membership correlate with the performance and engagement of *Destiny* players?

2.2. Contribution

In this paper, social player networks are constructed based on data from almost 3.5 million players of the online hybrid shooter game *Destiny* and the relationship between the social tendencies of players correlated with their performance in the game. The networks are based on records from the Player-vs-Player component of *Destiny*, the *Crucible*, which acts as the hub for all competitive aspects in the game. In the *Crucible*, players compete across a variety of game modes in team-based competitive play. Players can choose to play with random groups or with friends. The networks utilized here are built directly from records of whom players choose to play with and against.

The networks are combined with performance telemetry data from *Destiny*. This makes it possible to use player networks in order to explore the impact of playing with random people or repeatedly with the same groups on the performance and engagement of the players. In five main analyses, we explore the correlation between the tendencies of the players to play with the same vs. random people and selected the following Performance and Engagement metrics: (a) win/loss ratios; (b) kill/death ratios; (c) the impact of player-run guilds/clans; (d) total time and number of matches played; and (e) time per match played.

The results show that players with stronger social relationships in *Destiny*, i.e. players with a tendency to play with the same people, and being a clan member, have a higher performance based on win/loss ratio and kill/death ratio, irrespective of the number of PvP matches played. Additionally, players with strong social relationships have a tendency to play more PvP matches than those with weaker social relationships. They also played for a longer time in total, but needed less time per match.

While *Destiny* is a hybrid online shooter game, the emphasis here lies on the PvP aspects of the game as these are most directly comparable to non-hybrid (non-MMO) online team-based shooters such as the major commercial titles *CounterStrike*, *Medal of Honor* and *Battlefield*. This facilitates the potential transferability of the presented methodology, and possibly also results. To the best knowledge of the authors, this is the first time that such competitive networks have been constructed in hybrid online shooter games or regular online shooter games.

3. Related work

The work presented here rests in two separate but related domains under the umbrella of games research: Behavioral Analytics (BA) and social network analysis (SNA) in games. Behavioral Analytics is a specific application of game analytics [1,13,14], and is focused on the analysis of player behavior, usually in real-life situations outside the lab environment and generally using behavioral telemetry as the source of detailed behavioral data about the users. In the context of games research, SNA is focused on the interaction between players and the associations forming between them during and around the playing activity [15,6,16,17].

3.1. Behavioral Analytics (BA)

With respect to BA, the use of telemetry to analyze various aspects of player behavior has been the subject of increasing attention in recent years, covering a variety of topics across design, development, monetization, prediction, behavioral research, psychology and user experience optimization [1,13,18], and using methods ranging from simple descriptive statistics to machine learning [2]. The central focus of the work in the domain is to describe, analyze, and explain player behavior. Given that the success of games is directly dependent on the players and the experience they gain from playing the game in question, the majority of the work in game analytics focuses on the users [1,13].

Examples include the use of behavioral data to analyze and visualize specific in-game segments in games [8] or to investigate specific processes such as player progression [18,19].

3.2. Social gaming

While behavioral analytics is most often focused on the analysis of the player, the players' behavior and their interaction with the game, the environment, and in-game elements; data relevant to interactions with other users is often left unattended. Especially in online games, the interaction with other players is a key element. One very early observation of the different interaction forms was presented by Bartle [20] in MUDs (Multiuser Dungeons). He presented a first taxonomy describing the interaction of players with other players within a game. In terms of social playing, he described on the one hand "Killers", who enjoy "imposing themselves upon others" and are engaged by beating or distressing other players. On the other hand, he observed

"Socialisers", players who enjoy conversing and interacting with fellow players. Collaboration and competition are often identified as social elements in multiplayer games and described as important elements for player performance, engagement, and motivation [21]. Several studies have discussed concepts and implications of different types of co-players or the effects of competition vs. collaboration. Peng and Hsieh [21] discussed the impact of the type of relationships (pre-existing relationships (friends) vs non-preexisting friendships) on player motivation and goal commitment. The authors were able to show that playing with friends resulted in a stronger goal commitment in collaborative settings, while they did not find differences in competitive settings. While most prior research on SNA in video games focuses on MMOGs, an interesting example of a study analyzing a online first person shooter through SNA tools is conducted by Mason and Clauset[22]. They found similar results in their contribution. They investigated the impact of friendship on collaborative and competitive performance in the multiplayer online shooter *Halo: Reach* and were able to show an improved individual and team performance influenced by friendships [22].

Social structures within video games often enable us to research human interactions in a non-controlled environment and give us the option to access a vast amount of interaction data. This often allows us to examine different social concepts and structures and to investigate further those social concepts which are often hard to observe in real life. Shen, Monge, and Williams [23] propose a structural approach focusing on bridging and bonding social capital and tested this approach in the large-scale MMO *EverQuest II*. Social capital describes the advantages, values, and access to resources based on the structural position and the relationships in a social network [24,25]. The authors were able to show that brokerage (the extent to which a player is tied to unconnected individuals in the network) had a significant impact on tasks performance. Also, closure (the extent to which a player is embedded in a densely connected group) was empirically shown to have an impact on trust towards other players [23]. In a more recent study, Benefield, Shen, and Leavitt investigated the connection between group social capital and team (guild) effectiveness in the MMOG *Dragon Nest*. Their results suggest that groups are more effective when there are moderate connections between members across different networks [26]. Several of the discussed works investigate social structures with *social network analysis* (SNA). In the next section, we investigate SNA as a tool to analyze user behavior and player interactions in more detail.

3.2.1. Social network analysis (SNA)

In parallel with the development of behavioral analytics, the analysis of social connections and structures has become commonplace with the introduction of various kinds of social media. In particular, work on large-scale user platforms such as *Facebook* or *Twitter* and their potential for recommendation and prediction of user behavior has drawn the attention to the power of SNA techniques to analyze such graphs [27–29,19].

Social network analysis (SNA) provides a powerful tool to analyze and understand social structures and relationships between individuals [30]. The individuals or actors are represented as nodes in a graph-based structure. This representation allows the investigation of interactions and dynamics between the actors using mathematical methods from network and graph theory. It can be used to study relationships, groups in networks, and the importance of individuals for understanding social behavior and context [31], but also the influence of social relationships on different features such as engagement, performance, behavior, or retention rate in social systems (e.g. social media networks, learning platforms, or exchange platforms). Looking at the resulting social graph, questions such as "*Which individuals in this network are connected?*", "*Who are important/relevant individuals for the graph?*", *"Can we identify pattern or groups?"*, *"Can we recommend new connections?"*, *"How well are individuals connected to other individuals in this graph and how could these connections be improved?"*, *"What is the best path to transfer information through the network?"* can be asked [32].

3.2.2. Social network analysis in online games

The use of SNA to investigate social interactions and connections among people has attracted interest in many different domains, including digital games. Initially, such work focused on Social Network Games (SNGs) i.e. games played via an existing social network [33–36]. In recent years, research has also described and analyzed networks in online/networked games with multiple players, as well as other forms of social game environments. A primary challenge here has been the identification of meaningful connections between players to generate networks [17,5,16]. Nevertheless, SNA has also been shown as a valuable tool to be used to segment player populations into subgroups such as guilds or playing groups based on their centrality [37].

In online/networked digital games in general (i.e. games not embedded in social network platforms), social networks are employed to analyze player interaction dynamics in a social context. Social networks are of interest because research has indicated the influence of direct and indirect interactions and collaboration with other players on players' in-game behavior and its effect on the user experience, and learning, in these games [38,15,39–41]. Furthermore, social connections and interactions in games appear to be important motivational drivers for the game-playing activity itself [42,43,33,34].

The motivation to play in online games incorporates many other components, such as socializing, building relationships, or playing as a team, but also many competitive components such as achievements, or even the demonstration of power or status [43,35]. However, the form, extent, and nature of these social interactions can clearly differ. As a tool for representing and analyzing rich social connections and interactions, social network graphs have been employed, e.g. [17,5,16].

Social networks forming through or around games have been mentioned in numerous studies across ethnography and social science, and in some situations these have also been described using qualitative data. However, substantially less attention has been given to the quantitative analysis of social networks in games, notably at a large scale. Furthermore, such large-scale work has been focused on Massively Multi-Player Online Games (MMOGs) and shared online virtual environments such as *Second Life*. This means that there is a gap in the current state-of-the-art in terms of how social networks operate for games in general, and notably for games outside the MMOG and virtual world genres, including esports games, major commercial titles such as *Destiny*, casual game titles and mobile games. The rapid evolution of game forms and formats is possibly an important factor in explaining these gaps in the current knowledge, meaning that it can be hard for academic research to keep up with development in the industry.

Most SNA research in general is based on explicit relationships such as "friendship" connections in social media [44,45]. In games, the majority of current social network research similarly uses social interactions based on direct connections such as friendship information and guild information or indirect connections such as map data. Recent work in quantitative SNA includes Ducheneaut et al. [15] who investigated social structures and connections in *World of Warcraft* based on longitudinal data and found that even though players are often in the same area with other players, joint activities are not prevalent and direct interactions are less important even though the social presence of the others appears to be essential and engaging for the players' social online experience. Stafford et al. [17] analyzed networks in *Second Life* based on shared group information and explored the relation to different social networking websites. The authors used link definition of groups between avatars to generate the network. Williams et al. [37] use social network analysis to identify and analyze subgroups such as guilds in *World of Warcraft*.

Another way to investigate social interactions and the significance of presence and interactions of players is the analysis of guilds and the player tendencies towards player-run guilds [5]. Ducheneaut et al. [15] described the impact of guilds on the player pattern as significant. Players are not only engaged to play more often but also to play longer and to support the informal playing group process. The authors investigated the guilds by building social networks based on online-time or location-based information. In [46] the authors also extend on this work by showing the power of social network analysis to analyze the behavior of groups and to optimize their structures to increase growth and survival.

There have been very few studies examining social networks in games outside MMOGs/virtual worlds. Exceptions include Iosup et al. [6], who examined networks in the Multi-Player Online Battle Arena (MOBA) games *DOTA 2* and the Real-Time Strategy (RTS) game *StarCraft* with the focus on modeling the social structure, socially-aware matchmaking, and network robustness against player departure.

Additionally, Jia et al. [16] compare social relationships in four multi-player online games and discuss how these compare to online social networks such as Facebook.

The authors introduce a model to analyze such relationships, describing five types of interactions, which can be used to generate graphs for online multi-player match-based games: Players (a) in the same match, (b) on the same side of the match, (c) on the opposite side of the match, (d) who won together in a match, and (e) who lost together in a match. The authors focus on evaluating network measures, whereas the focus here is on relating network information with behavioral performance metrics. The connections formed between players in multi-player matches can be both explicit and implicit. They are explicit when players form the relationships on their own initiative, e.g. joining a clan or playing in a group with real-life friends, and implicit when formed passively, e.g. via skill-matching in *Destiny's* skill-ranking and subsequent skill-matching process.

As discussed already in an earlier section, Shen, Monge and Williams construct social networks in the MMOG *EverQuest II* through sever logs. They use the networks to investigate online bridging and bonding social capital in the game [23]. In a later study, Benefield, Shen, and Leavitt [26] use social networks in the MMOG *Dragon Nest* to investigate team effectiveness in groups (guilds). They found that teams are more successful when being bigger, more experiences, and relate it to a moderate level of the social captial structure *closure*.

In summary, prior work on SNAs in digital games has covered a variety of genres, including MMOGs such as *World of Warcraft*, MOBAs such as *DOTA 2* and Real-Time Strategy (RTS) games such as *StarCraft*. In contrast, *Destiny* does not fit the previously described genres. It is described as a first "shared world shooter", a massively multi-player online game, which focuses on first-person shooter elements and lacks many traditional role-playing features.

While most previous studies on analyzing social structures in online game communities focus on identifying the network and the interactions, the focus here is on connecting network analysis and network metrics with the performance of the players in *Destiny*. Furthermore, in contrast to prior work, in this paper we are able to analyze the social influence of different types of interaction on performance in a hybrid game genre.

4. Destiny - gameplay

Destiny is a hybrid online game that combines elements from a number of game formats, notably those of FPS, RPGs, MMOGs and MOBAs (see Fig. 1). As mentioned above, *Destiny* forms an unusual case in that it shares design elements across these different kinds of games, without being completely similar to any previous title. For example, similar to MMOGs, the game has a persistent world, in-game currencies, public events, etc. Similar to RPGs, character development is a primary underlying mechanic, and the game features crafting and collection of items (weapons, armor, clothing, insignia, vehicles). Similar to FPSs, the vast majority of the gameplay deals with the elimination of enemies which can be computer-controlled agent entities or other players. Finally, similar to MOBAs, team-based multi-player combat within restricted environments are a substantial part of the games which support PvP (accessible via the *Crucible*, a hub for PvP-type content). All content under the *Crucible* takes place in new instances (separate and closed instances of the game world).

The game was developed by Bungie and published by Activision in September 2014. The game is only available on major gaming consoles and requires always-online access. Three major expansion packs have been released since launch: *The Dark Below*, *House of Wolves* and *The Taken King*. The latter made considerable changes to the core gameplay. Following, Bungie introduced new events which were only available for a limited timespan.

In the game, single- and multi-player activities are featured in a distribution similar to MMOGs, although the core mechanics are more comparable to an FPS such as the series of *Counter-Strike* and *Medal of Honor*. However, the persistent world sets *Destiny* apart from these titles, and both, player-versus-environment (PvE) and player-versus-player (PvP) gameplay, are included. Similar to MMOGs, *Destiny* provides incentives for players to explore the different zones of the virtual environment via quests and missions provided by Non-Player Characters, generally from an area referred to as *Tower* which also features vendors where in-game items can be bought and sold. The combat system and damage system in *Destiny* is highly complex and includes a variety of damage types, weapon types, resistances, upgrade possibilities, customizations, etc. Every player character belongs to a class (Titan, Warlock, Hunter) which provide different core abilities. Each class has three subclasses. Players increase in character level by earning experience points gained through completing missions, killing enemies, etc. The current level cap is 40 and has been increased since the initial release through expansions. Social or group activities in *Destiny* are based on teams of three players completing missions. Team-based PvP matches in the *Crucible* involve up to two fireteams per side. There are a number of PvP modes, from traditional deathmatches to take-and-hold scenarios. Co-operative PvE content exists in the form of strikes and raids, which is instanced (similar to PvP content) and involves one or two fireteams. Raids include more content than strikes.

Destiny does not feature the same kind of social and communicative options as seen in MMOGs, given that communication between players is restricted. This is particularly the case due to the lack of text-based chat channels in the game, which means that a core component of the typical MMOG experience is missing from *Destiny*. The lack of text-based chat may relate to the game being focused on consoles. Voice communication was initially only possible between members of pre-formed "fireteams", i.e. between players who specifically accept being a member of these teams and thus this typically relates to people who know each other outside the game, including clan members. Only recently, the option of voice communication between players who are randomly assigned to teams via automated matchmaking has been enabled. However, the voice-chat feature remains optional and players have to consent to participate in communication. These differences mean that social networks examined in MMOGs (e.g. by Kawale and Srivastava [7]) such as friend lists do not directly apply to *Destiny* and that other approaches have to be adopted to define social networks in the game.

5. Dataset and pre-processing

5.1. Dataset

The data was generated from *Destiny* telemetry: To begin with, a random sample of 10,000 *Destiny* players who had played the game for at least two hours was provided by Bungie, the developers of the game. The two-hour limit was set to avoid having people in the sample who had installed the game but never played beyond the first few steps of the tutorial. Using these players as the source (what we called active players), a variety of in-game activities were extracted for these players as well as for the players that had been in contact with the original sample via PvP gameplay. The data were extracted from Bungie's

Fig. 1. *Destiny* gameplay example. (c) Bungie, Inc, Destiny, the Destiny logo, Bungie and the Bungie logo are registered trademarks of Bungie, Inc. All rights reserved.

telemetry servers for *Destiny* using an API provided by the company. Specifically, in-game activities in *Destiny* are based on either player-versus-player (PvP) or player-versus-environment (PvE) gameplay. The PvP mode, accessed via the *Crucible*, covers a variety of different match-based activities played across three-versus-three to six-versus-six team-based matches.

The initial 10,000 player sample participated in 930,720 Crucible matches, covering their entire play histories from September 2014 to January 2016. This dataset forms the basis for the current analysis. Each match record covers information about the teams, the players, their classes, their weapon load-outs, and information about different scoring mechanisms as well as performance data such as Kill/Death (K/D) ratios and distances associated with kills for each player on both sides of a match. Also included in the dataset are 318,007 clan names (clans are player-formed communities). In order to build the players' networks, matches were processed, which in total included 3,450,622 *unique* player identifiers. From this sample of players, we have the complete history of the matches played in relation to the initial 10,000 players. The basic statistics about the used dataset are shown in Table 1.

Table 1
Statistics of the Destiny dataset.

Players	3,450,622
Matches	930,720
Clans	318,007
Classes	3

5.2. Pre-processing and feature definition

The first step in processing the data was identifying the important values in every single PvP game. Each entry contains match details such as the game mode, participating teams, and more detailed information about each player, including different scoring mechanics and weapon usage.

There are three general categories of behavioral features (or metrics) in the *Destiny* data: Performance, Engagement, and Social features.

Performance metrics provide data on the skill and playstyle of the players. Features include, for example, details about which weapons the player has used, when, where and with how much success. Key performance features in shooter-type games include kill-death ratios. Given the skill-matching in *Destiny* (at the time of writing based on Microsofts TrueSkill system), this kill-death ratio is a proxy measure of how well the player in question performs in combat with peers. In the retrieved dataset, there are roughly 30 *Destiny*-specific performance metrics (such as K/D, Combat Rating, Revives Performed or Received, Orb Dropped or Gathered, Longest Killing Spree, W/L Ratio, Kills and Grimoire Score, to name a few) which are being tracked for each player in each PvP match, in addition to further information such as whether a match was won or lost, total points scored etc.

Engagement features focus on the amount of time the player has spent playing *Destiny*, the duration of play sessions and the amount of time spent playing in the different modes of the game (PvP or PvE).

Social features provide information about the interactions between players. In the current case, the social feature we refer to is the "gamertag" of people on the same team or the opposing team of the player in PvP matches.

After identifying interesting and important values, we generated a list of game modes and matched them to the actual *Crucible* game modes. The next step was to eliminate free-for-all games and other special modes that do not necessarily fit into a team-based model. While a free-for-all game mode can also serve as the basis for social network definition, this game mode is not common in comparable game titles and was therefore not included here in order to facilitate the potential applicability of the method and results to other online shooter games such as *CounterStrike*. The resulting property lists were then divided into classes in order to extract information on a per-class basis.

We represent the player relationships as a social network, where nodes represent players and edges represent the link between two players who have interacted in a match. Details on the network will be also discussed and introduced in the following sections. Fig. 2 shows how the network size changes by applying a threshold. The chosen threshold is defined by the minimal number of games a player has to play to be relevant in further data processing. This is further shown in Table 2, which displays the remaining player network data when the thresholds are applied. This table describes how many nodes are remaining in the dataset after deleting this threshold (minimum number of shared games).

5.3. Player preferences

Out of a total of 3,450,622 players in the dataset, 38.64% play in the class Hunter, 29.20% are Titans and 32.15% are Warlocks. Fig. 3 shows the varying preferences of users for these three classes. Fig. 4 shows the level distribution of the players, including the reference to the different Down-Loadable Content packs (DLCs) (expansion packs). The split in the level distribution between DLC2 and DLC3 is caused by a leveling system overhaul which allowed jumping from level 34 to level 40 in less than a day, as well by restricting the access to many new activities to

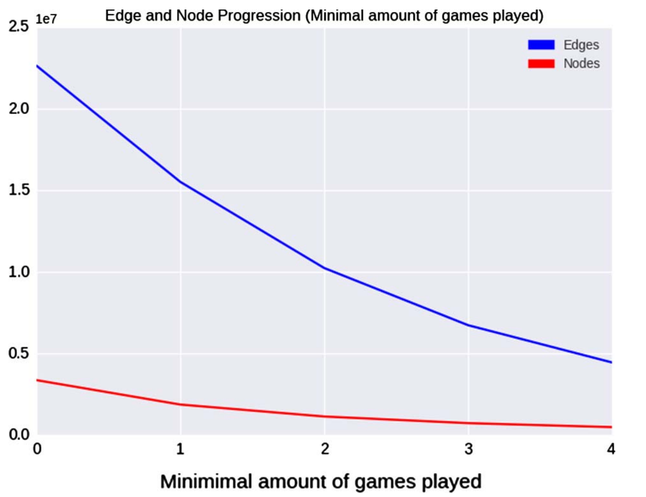


Fig. 2. Deletion of nodes – after removing players who have not played at least four games, many connections are removed. This is also illustrated by Table 2

Table 2
Overview of the threshold behaviour - Values in brackets show the change in relation to the previous threshold.

Min Games	Nodes remaining % (Rel)	Edges remaining % (Rel)
1	55.46 (55.46)	68.53 (68.53)
2	33.68 (60.72)	45.21 (65.97)
3	21.58 (64.09)	29.73 (65.74)
4	14.35 (66.47)	19.64 (66.08)

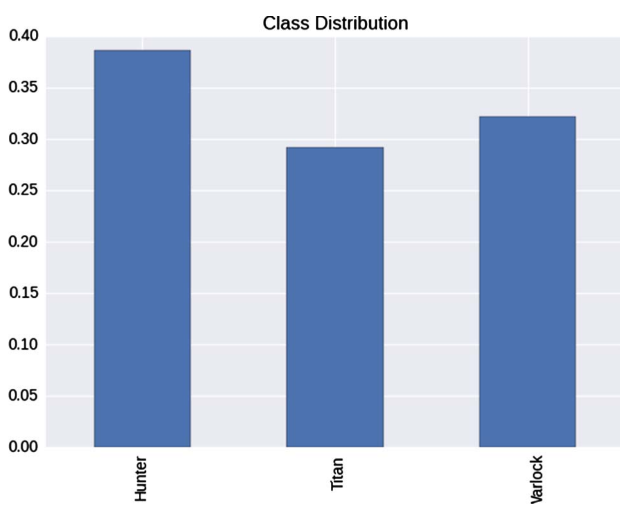


Fig. 3. Class distribution of players' "first choice" character.

level 40 characters only.

6. Player networks

The central question addressed here is whether match data from *Destiny* can be used to inform about how players are connected and if variations in these connections impact the performance of players. Based on the match data described, we study different player networks. We represent the player relationships based on undirected graphs: nodes (v) represent players, edges (e) represent the link between two players who have interacted in a match. Based on different interaction types, we generate three different networks.

For the network generation, we can build different networks (player interaction networks) based on match interaction information. Players might be connected with other players in different ways. Based on the match data, we were able to create three networks on how players interact with each other. For such interactions, we distinguish between players who are connected with each other by playing in the same team (T) or because they were playing as opponents (O) in a match. The last interaction network consists of Matchmates (M), players who were playing in the same match (on either side). Based on this match information, we have built three interaction graphs to demonstrate the different relationships. Table 3 summarizes the networks and the relationship information.

These networks can be created as weighted graphs with different metrics for weights, such as the number of times the players interacted with each other, the number of won/lost matches, or similar interaction numbers. Table 4 shows how many matches were played by players in the dataset. 97.93% of the players in the dataset have played less than 11 games. Table 5 illustrates how many matches are played with the same players on either the player's own team or the opposition team. For players with only a few matches, there is a small tendency to repeatedly play with the same people in the opposite team. However, for players who have played 6 or more matches, the tendency is strongly reversed; showing that these players are more likely to play again with the same players in a team than in the opponents team.

7. Network structure

In this section, we examine the relation between the social network structure and the players' behavior together with gameplay or playing success. To answer questions that cross social networks and player performance (for example those posited in Section 8 below), we first need to investigate the social network structure of different player groups, focusing on network size, density, and interconnectivity.

Analyzing the network characteristics of the three created player networks sheds light on different aspects of player interactions. In this section, we present and discuss the common social network measures. Table 6 gives an overview of the different social network measures for the three different graphs. For the following analysis, a threshold of 3 (a minimum of three games played together) was applied.

Degree distribution The *degree* (k) of a player in the graph refers to the number of links to other players. Table 7 shows that 79.19% of players in teams have a degree between six and twenty. Less than 20% of players have played games with teammates who had significant differences to this distribution pattern.

Average degree (k_avg) The *average degree* (k_avg) describes the average of all players' degrees in the graph. As shown in Table 6, the average degree is much lower in "same team" graph T compared to the other graphs. As all the data in the table was generated from the same number of games played, two main influences have been identified. In the 6-versus-6 player format, players always have more enemies than teammates, which naturally leads to a higher average degree. This is probably reinforced by the notion that players tend to play more often with the same players, but this cannot be shown from the available data.

Diameter (D) Looking at all the shortest paths between two nodes, the *diameter (D)* of a network is the longest path of this list and is used to describe the linear size of the network.

Clustering Coefficient (C) The clustering coefficient (C) of a player describes the connectivity of its neighbor. The clustering coefficient (the network average clustering coefficient, C_avg) for an entire network is the average C for all the players.

$$C(v) = \frac{E(v)}{k_v(k_v-1)}$$

Edge Weight Distribution Based on the number of interactions (number of matches played together), a weighting can be applied to the single links. The edge weight distribution relates to how many times players have interacted with the same players. Fig. 5 illustrates the

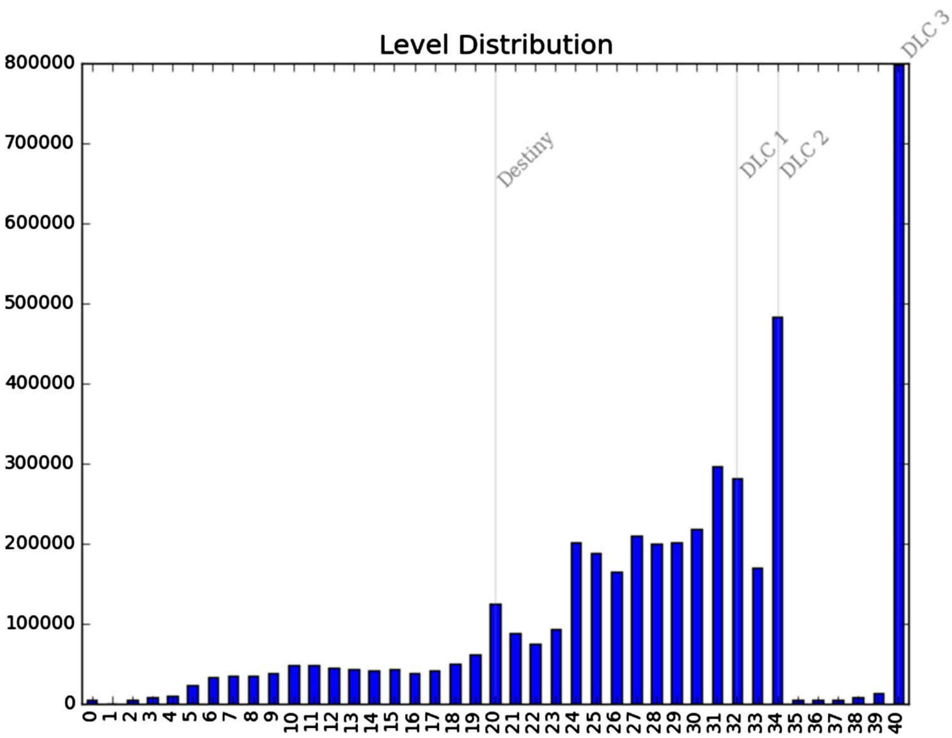


Fig. 4. Level distribution of players including a reference to the Down-Loadable Content packs (DLC).

Table 3
Network relationships.

M	Players in the same match (Matchmates: M)
T	Players playing together in the same team (Teammates: T)
O	Players playing against each other as opponents (Opponents: O)

Table 4
Number of matches played by players.

Games	Players
1–10	3,293,187
11–20	54,836
21–50	8758
51–100	2660
101–200	1674
201–300	610
301–500	469
501–1000	333
1000 +	109

Table 5
Number of matches played together between different players.

Games	Same Team	Opposite Team
1–5	22,582,015	27,491,957
6–10	32,816	2561
11–20	12,851	201
21–50	7025	20
51–100	2140	1
101–200	873	0
201–300	207	0
301 +	135	0

comparison of edge weight distributions between players playing on the same team and players as opponents in matches. Players who play in same teams play more often with the same players than they do with players on opposing sides.

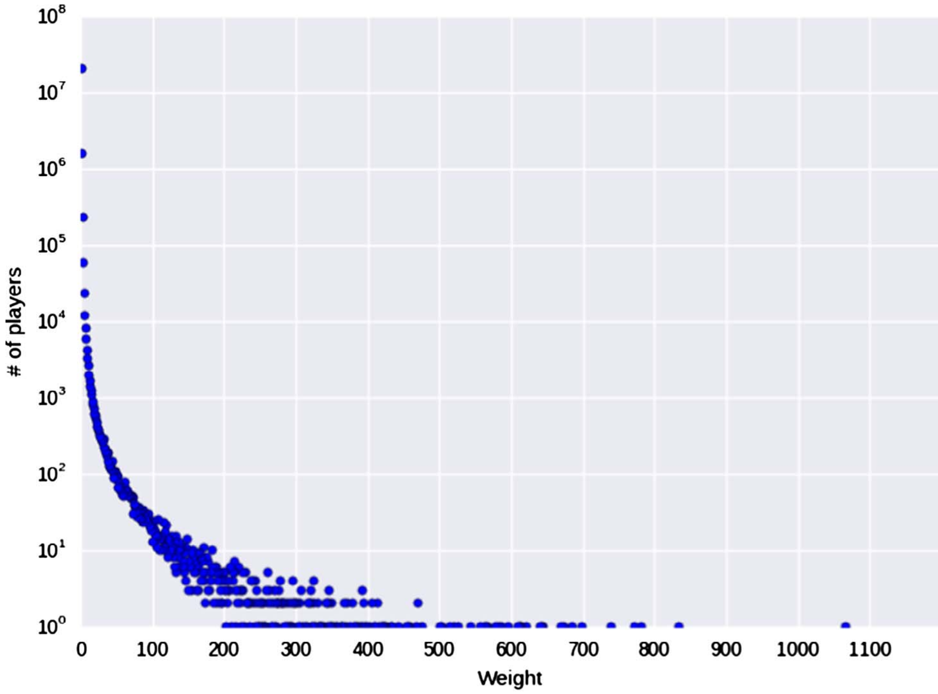
Table 6
Methodological comparison of the three networks (Threshold minimum games played – 3).

	Same Team (T)	Opposite Team (O)	Same Match (M)
Nodes	725,704	725,704	725,704
Nodes in LCC	725,599	725,693	725,703
Avg. Degree (k_avg)	18.55	23.93	38.72
Links	6,729,257	8,682,726	14,048,455
Links in LCC	6,729,190	8,682,726	14,048,455
Diameter (D)	13	11	9
Avg. Clustering Coefficient (C_avg)	0.024	0.0082	0.026

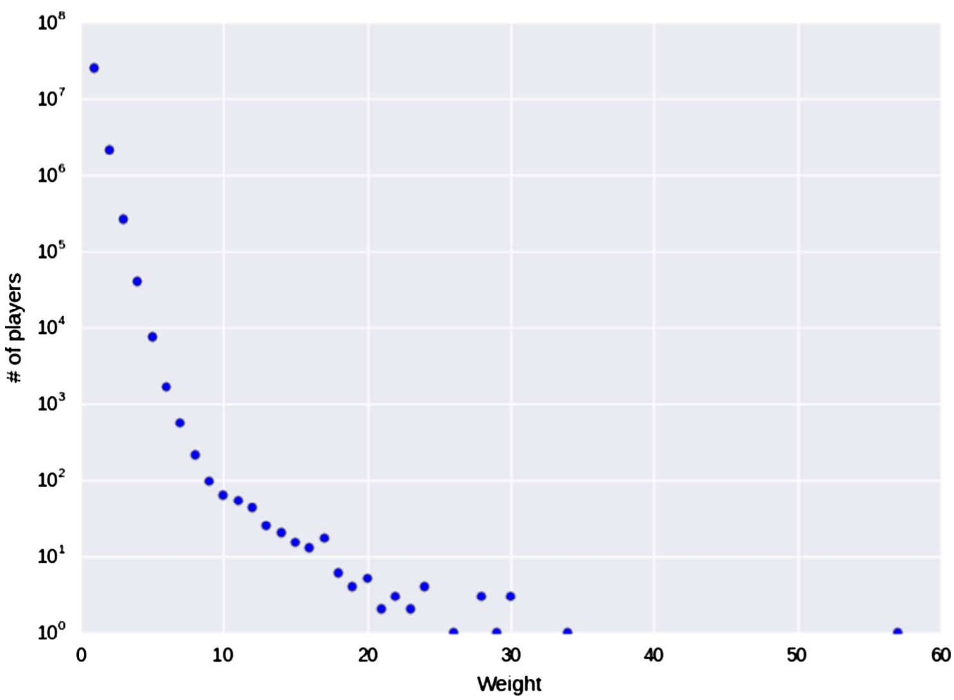
Table 7
Comparison of network node degrees.

Degree	Same Team (T)	Opposite Team (O)	Same Match (M)
0–2	1477	1990	12
3–5	54,812	128,146	1747
6–10	1,627,084	1,502,516	145,872
11–20	1,004,600	991,962	1,703,801
21–30	322,135	377,496	617,112
31–40	129,651	170,993	318,234
41–50	56,783	82,109	193,247
51–60	26,379	41,892	123,064
61–70	12,987	22,646	80,429
71–80	6766	12,535	52,356
81–90	3726	7152	35,120
91–100	2160	4479	23,848

Largest Connected Component (LCC) The largest connected component (LCC) is the largest self-contained sub-graph of the main network. As shown in Table 6, the number of nodes and links of the LCC differs only slightly from the main graphs. This means that the players are very well connected through the matches and a specific close examination of the LCC is not important for the analysis.



(a) Playing on the same team.



(b) Playing against other players.

Fig. 5. Comparison of edge weight distributions between players playing on the same team and players as opponents.

8. Analysis

In this paper, we focus on answering the following five main questions:

1. *RQ1. Do player relationships/interactions relate to the win/loss ratio in multi-player PvP matches?*
2. *RQ2. Do player relationships/interactions relate to combat performance (measured by kill/death ratio)?*
3. *RQ3. Do player relationships/interactions relate to combat performance (measured by time/match ratio)?*
4. *RQ4. Do player relationships/interactions relate to engagement (measured by number of matches played and total playtime)?*
5. *RQ5. Does clan membership correlate with the performance and engagement of Destiny players?*

To answer these questions, we first have to distinguish between players who are playing regularly with the same players (*Player Group 1: Focused Players*), and players who play more frequently with different/random players (*Player Group 2: Open Players*). We created a

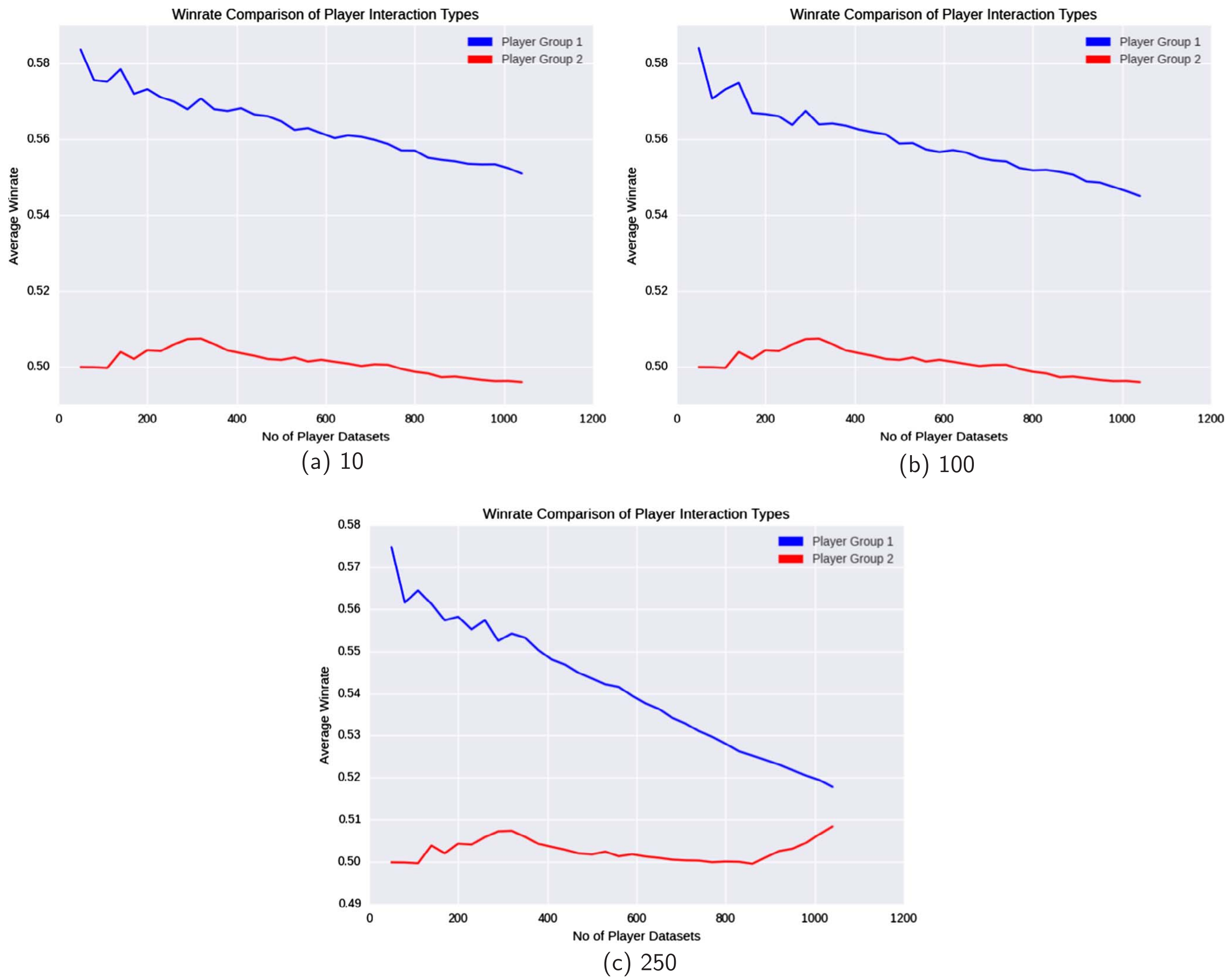


Fig. 6. The winrate comparison of player groups playing *Crucible* matches. The X-axis describes the number of player datasets extracted from the focus-ranking.

metric to rank the players based on their interaction with each other. If a player interacts with the same group of other players many times, the player will receive a higher score than a player who always plays with different team members. For this metric we examined a non-thresholded version of the team network (T) graph to ensure unbiased results for the ranking. The second part of the equation serves to eliminate a score penalty that very active players would have received otherwise.

$$FocusedPlayer = \frac{Sum\ of\ weights}{degree} \cdot \frac{\#matches\ played}{\#matches}$$

In the equation, weights describe the number of matches played by the same person and the degree describes the number of links (through matches played together) to other players. Matches played is the number of matches a player participated in and matches is the number of all matches available in the dataset.

8.1. RQ 1. Do player relationships/interactions relate to the win/loss ratio in multi-player PvP matches?

Fig. 6 compares the winrate of the two different player groups in *Crucible* matches. The three sub-figures refer to the number of matches players must have played in order to be included in the analysis. The x-axis relates to the number of player datasets extracted from the focus-ranking (see above). Player Group 1 therefore describes the top players according to the ranking and the average winrate for a certain amount of players. The results indicate that players who play more with same players have a higher winrate compared to players who play more often with random players. The average winrate in Player Group 1 was 0.559 while in the Player Group 2 the average winrate was 0.501. The results are significant for both samples: the top 100 samples ($t = 6.2$; p .001) as well as the top 500 samples ($t = 11.26$; p .001).

8.2. R2. Do player relationships/interactions relate to combat performance (measured with kill/death ratio)?

To measure the combat performance, we use a ratio between the kills and deaths of the players. A kill/death ratio greater than 1 relates to more active kills in a match. Higher numbers can be related to a better player performance. As Fig. 7 illustrates, players with a higher rate of playing regularly with the same players demonstrate again a slightly higher performance based on kill/death ratio compared to the players who prefer to play with random players. The average K/D ratio of Player Group 1 is 1.167, that of Player Group 2 is 1.034. The results are significant for both samples: the top 100 samples ($t = 3.80$; p .001) as well as the top 500 samples ($t = 6.06$; p .001).

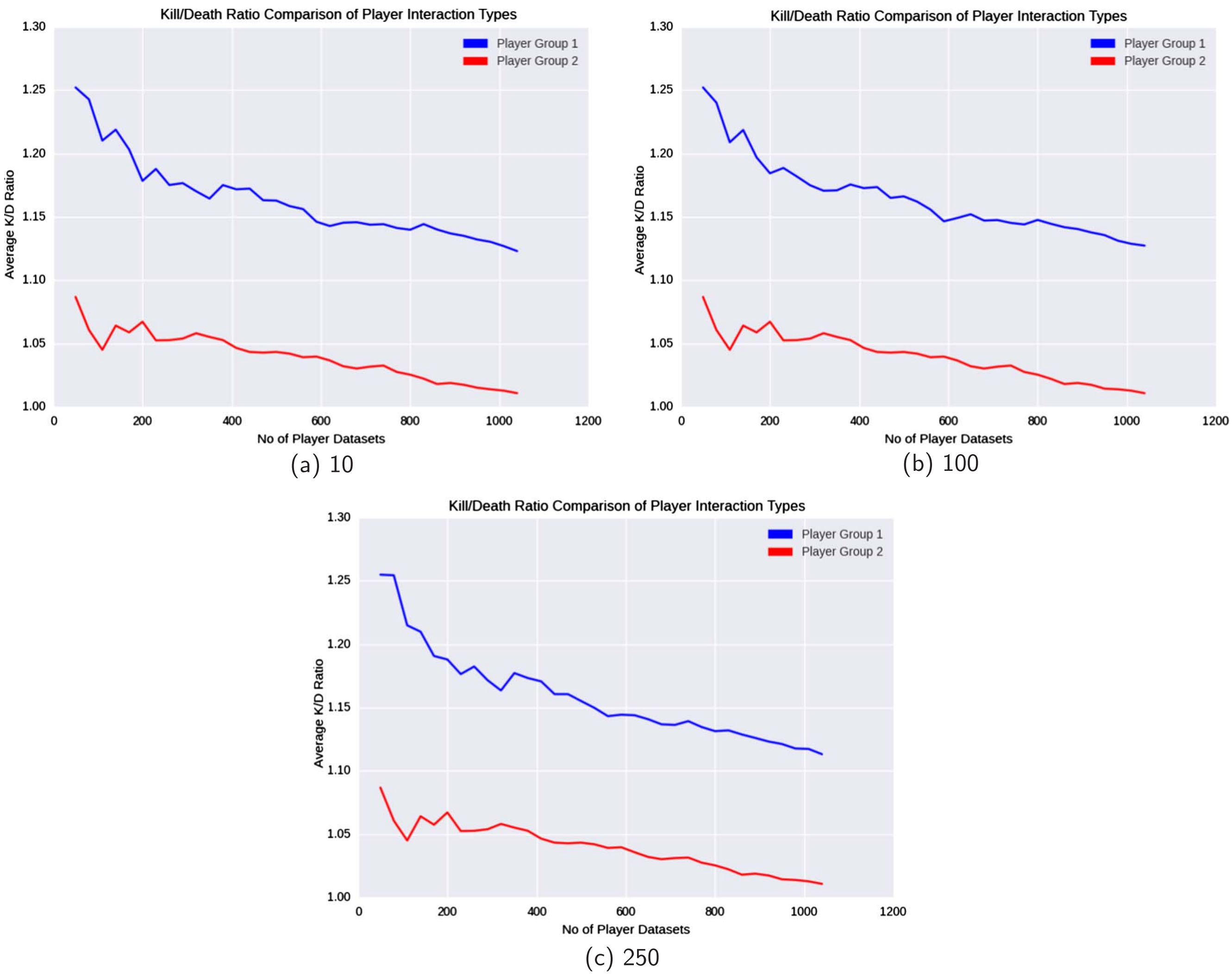


Fig. 7. Kill/Death ratio comparison of player groups in *Crucible* matches. The X-axis describes the number of player datasets extracted from the focus-ranking.

8.3. RQ3. Do player relationships/interactions relate to combat performance (measured with time/match ratio)?

In *Destiny*, players who are more successful tend to have a shorter playtime per match (see Fig. 8). This can be related to faster playstyle and more experience in matches. Fig. 8 also illustrates that the time/match of elite players (top 100 players) is significantly lower compared to average players and other successful players. The results are significant for this sample: the result for the top 100 samples is (t = 3.54; p .001).

In Fig. 9, the playtime per match of the two different player groups in *Crucible* matches is compared. Similar to the previous analysis, the two sub-figures refer to the number of matches players must have played in order to be included for the analysis. The results indicate that players who play more often with same players need less seconds per match compared to players who play more often with random players. This can again relate to a higher in-game performance. The results are only significant for the bigger sample, the top 500 samples (t = 2.31; p .021), but not for the top 100 samples (t = 1.71; p .09).

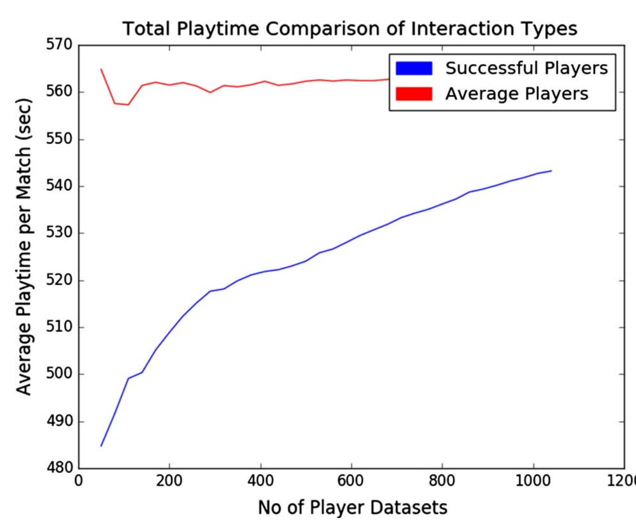


Fig. 8. Comparison of playtime in seconds of successful and average players. The X-axis describes the number of player datasets extracted from the focus-ranking.

8.4. RQ4. Do player relationships/interactions relate to engagement (measured with number of matches played and total playtime)?

To answer this question we relate player engagement to the number of *Crucible* matches played and total playtime. Figs. 10 and 11 illustrate the difference in those metrics between players who play more often with same players (Player Group 1) and players who play more often with random players (Player Group 2). Based on total playtime and number of matches played, the Player Group 1 - players playing more often with the same players - can be described as more engaged. For

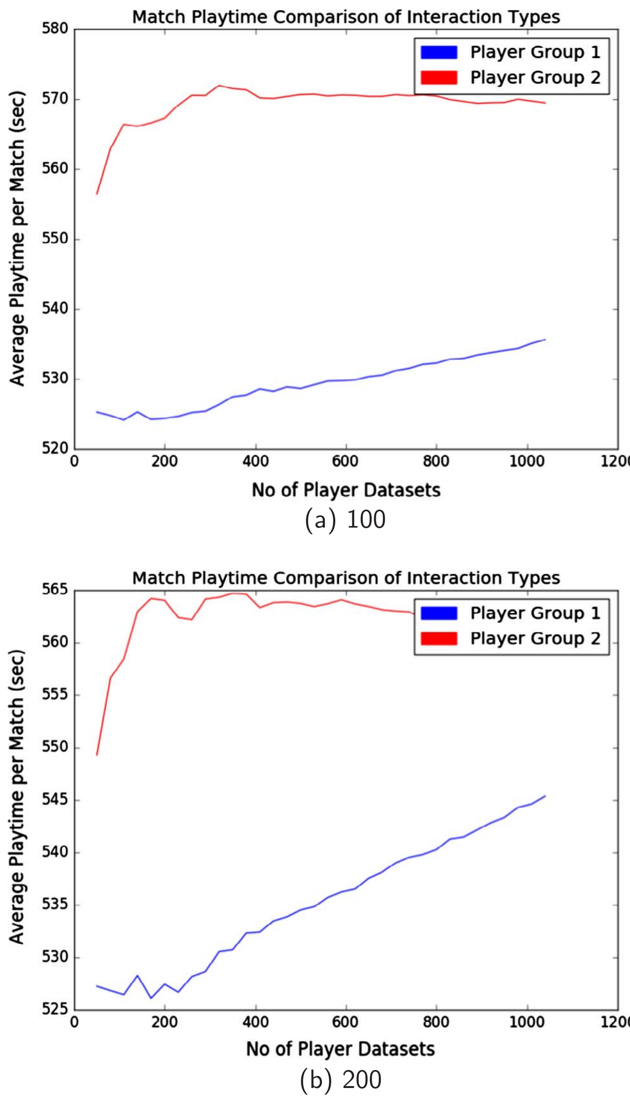


Fig. 9. Comparison of the average time per match between the player groups playing *Crucible* matches. The X-axis describes the number of player datasets extracted from the focus-ranking.

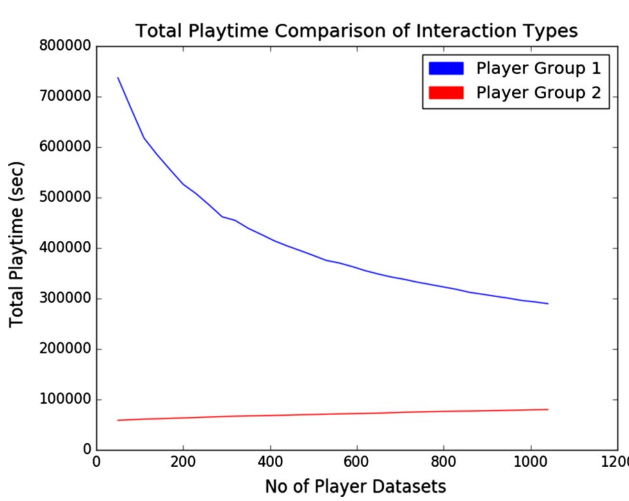


Fig. 10. Total playtime in seconds. The X-axis describes the number of player datasets extracted from the focus-ranking.

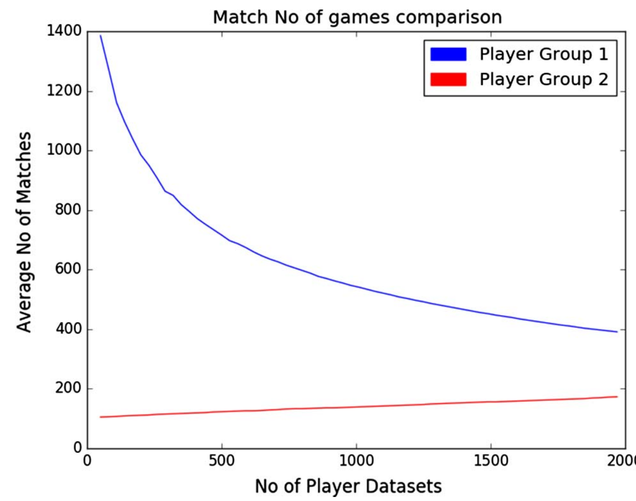


Fig. 11. Number of matches played. The X-axis describes the number of player datasets extracted from the focus-ranking.

total playtime, the results are significant for the top 100 samples (t = 1.93; p .054) but not for the top 500 samples (t = 2.74; p .006). For the number of matches played, the results are significant for the top 100 samples (t = 1.93; p .058) but not for the top 500 samples (t = 2.50; p .012).

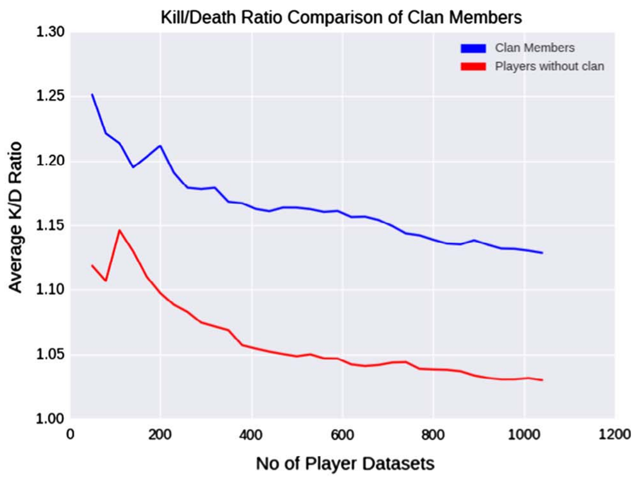
8.5. RQ5. Does clan membership correlate with the players' performance and engagement?

To answer this question, we construct two similar analyses as performed in the first two research questions. Both take a look at measurements that determine a player's success. The list of players is now split into two lists, one with players who are identified as clan members, and another one consisting of players without clans. Players are identified as clan members if they played at least 90% of their games as part of a clan, illustrating that players may need to play a few games before joining or being recruited by a clan, but still having the majority of their activity with the clan. If they played 90% of their games without a clan they are identified as clan-less players. After applying a threshold of a minimum of 100 games played, only 76 players out of 6222 do not fit into this metric. Fig. 12 illustrates that the performance of clan members exceeds that of players without a clan. The K/D ratio of players with a clan is significantly higher than the K/D ratio of players without a clan (t = 6.3; p .001 for the top 100 samples and t = 12.34; p .001 for the top 500 samples). Also, the winrate is significantly higher of players in a clan (t = 13.35; p .001 for the top 100 samples and t = 19.56; p .001 for the top 500 samples). The group of focused players (Player Group 1) is also 24.42% more likely to include clan members than the average player, and the open player group (Player Group 2) is 14.94% less likely to include members of a clan.

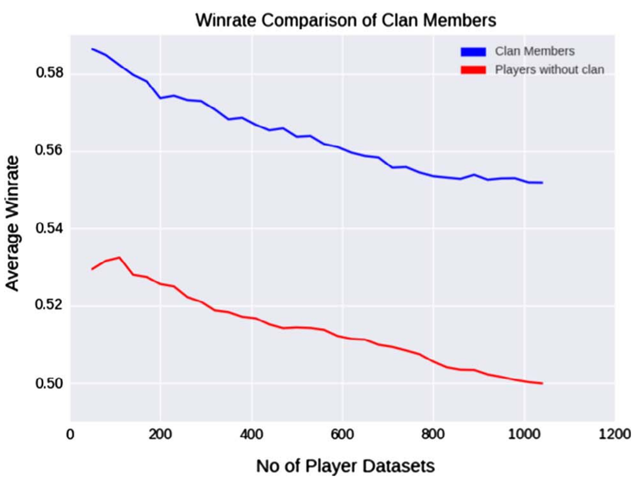
We also compared the playtime and number of matches played. Fig. 13 illustrates that individuals who are member of a clan on average play more matches compared to players who are not part of a clan. The playtime/match of clan members is shorter, which can be again related to a better in-match performance and a faster playstyle.

9. Conclusion and discussion

As multi-player online games become more and more popular but also more complex, it is crucial to find new ways for analyzing the player behavior in these games, which are capable of taking into account multiple viewpoints on the activity of the player base [2,1,18]. In this paper, this problem has been targeted by combining game-based social networks and behavioral analytics: We have developed and

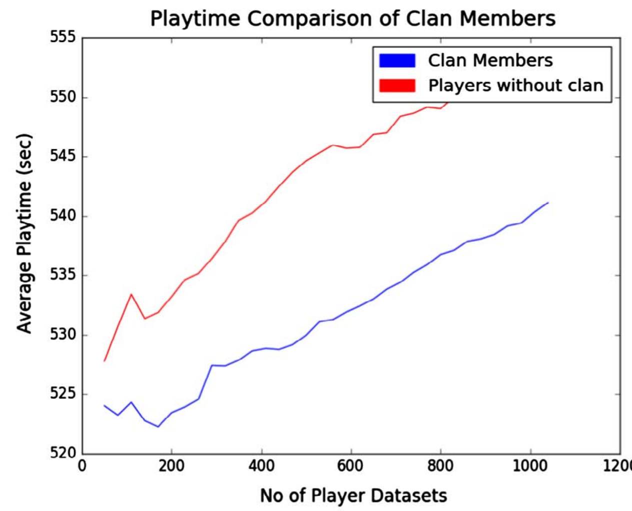


(a) Kill & Death ratio comparison when players are part of a clan

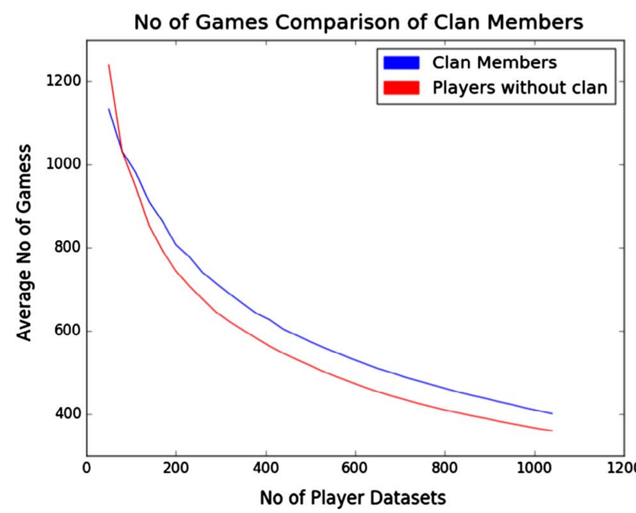


(b) Winrate comparison when players are part of a clan

Fig. 12. Clan membership. The X-axis describes the number of player datasets extracted from the focus-ranking.



(a) Comparison of average playtime per match when players are part of a clan



(b) Comparison of average number of matches played when players are part of a clan

Fig. 13. Clan membership. The X-axis describes the number of player datasets extracted from the focus-ranking.

presented a social network from the major commercial title *Destiny* and combined the network with behavioral features of the players in the paper, permitting analysis across social behavior and gameplay performance.

We present techniques from Social Network Analysis [27] and discuss and present the relevance for player networks based on match data - competitive networks - to analyze aspects such as player performance. In the above, competitive networks were developed based on data from the hybrid online shooter game *Destiny*. The networks provide information about the tendency of players using PvP game modes in the game, to play either with the same people or with random groups. In addition, behavioral telemetry concerning the individual behavior of the players was tied in, enabling the evaluation of player performance with the context of the network.

The focus in this paper has been on exploring the developed networks of the players along different performance and social vectors: (a) Match wins via win/loss ratio, (b) Performance, via k/d ratios (c) Performance via playtime/match, (d) Engagement via total playtime and number of matches played, and (e) Clan influence, i.e. whether being a member of a clan correlates with the tendency of a player to play with the same people, as well as with performance and engagement. Results indicate that players with stronger social interactions, i.e. with a tendency to play with the same people, have a higher performance based on win/loss ratio, kill/death ratio, and time/match ratio. They also play more matches on average and have played for a longer time in total. Players who are part of a clan seem to perform slightly better across all the PvP modes of *Destiny*, as compared to those who are not part of a clan.

With this analysis we want to demonstrate the potential of SNA in the context of game data analysis to gain a deeper understanding of social structures within games, and how to improve those structures. As many games also lack features that indicate the social behavior of players, the involvement of social metrics could be another way to promote collaborative or competitive gameplay and can even be used to enhance team-building recommender systems.

The results presented here are based on network features and behavioral features (e.g. K/D ratios) that can be found in other team-based online shooters such as major esports and commercial titles like *CounterStrike* and *Battlefield*. This facilitates the application of the presented techniques in games other than *Destiny*, and possibly also the further application of the behavioral results presented in this work. This needs to be verified by an analysis of the social networks for these games, but previous qualitative work such as [42] indicates that similar patterns exist for social behavior and performance in the games, as shown in other multi-player online genres [6,41,16].

Our results only scratch the surface of the potential of analyzing this giant multi-user online system to better understand players and their social behavior. The work presented here indicates several venues for future work: A wealth of performance measures exist in *Destiny*'s PvP modes (over 1400 metrics are recorded by Bungie, the developer of the game) and similar competitive multi-player FPS games such as *Team Fortress 2* and *CounterStrike*; and these measures can be combined with player networks, for example performance with specific weapon classes, or across specific PvP game modes. Furthermore, given the high dimensionality in the data, implementing behavioral profiling [13,8] as a prior step to network analysis would be useful to reduce dimensionality and define playstyles which can then be correlated with social behavior. Additionally, temporal information can be employed to explore the evolution of networks in *Destiny* as a function of time, and also player performance data can be tied into permit time-series analysis about players and networks. This analysis can furthermore serve as the basis for behavioral prediction modeling, which is an issue of direct interest in game development due to the trend towards more persistent games on the market [7,2,18]. As important avenue for future work, the many factors influencing metrics such as engagement and performance also suggest the creation of different models to test.

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