Influencers in Multiplayer Online Shooters

Evidence of Social Contagion in Playtime and Social Play

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ABSTRACT

In a wide range of social networks, people's behavior is influenced by social contagion: we do what our network does. Networks often feature particularly influential individuals, commonly called "influencers". Existing work suggests that in-game social networks in online games are similar to real-life social networks in many respects. However, we do not know whether there are in-game equivalents to influencers. We therefore applied standard social network features used to identify influencers to the online multiplayer shooter *Tom Clancy's The Division*. Results show that network feature-defined influencers had indeed an outsized impact on playtime and social play of players joining their in-game network.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **Empirical studies in collaborative and social computing**;

KEYWORDS

social network analysis, influence, games-as-services, live games; online communities

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1 INTRODUCTION

With the current paradigm shift of the game industry towards games as a service [9, 37, 62], player retention has become one of the most important design goals and metrics. Entertainment value is, in fact, measured in hours of playtime. To accommodate for these shifting values, commoditization strategies have begun revolving around subscription-based models, free to play games with premium content, free updates, premium DLC, and season passes. In an interview, Anne Blondel-Jouin, Vice President of Live Ops at Ubisoft, explained that: *"...games as a service, or live games, refer to games that offer an evolving long-term, entertaining experience for our players. They often have a focus on online competitive multiplayer experiences such as Tom Clancy's The Division but they can also include other types of game experiences like The Crew. 'Live' refers to all the activities and interactions created for the game community including pre- and post-launch as well as regular updates, new content, and events both in-game and out-of-game, etc. throughout the game's lifespan"* [64].

As shown by the longevity of games such as *World of Warcraft* or *League of Legends*, social connections foster prolonged retention. One of the most important tools that the industry uses to investigate social connections, especially in social and online games, is Social Network Analysis (SNA). Increasingly, social network analysis methods are being used in games [e.g., 3, 20, 24, 43, 44]. Similar to the literature on online communities [35], it suggests that there are key members who contribute to keeping the community alive.

In this paper, we apply methods from SNA to the game *Tom Clancy's The Division* (TCTD) to identify potential influencers, here defined as players that engage with the multiplayer component of the game in a way that makes them highly centralized (as defined by SNA measures). Subsequently, we compare relevant features of influencers with two other populations, power users and random players, to investigate if there are other differences besides the way in which the three populations utilize multiplayer components. To gauge whether playing with influencers has an impact, we investigate changes in playtime and time spent playing in groups for the social circles of the influencers, power users, and random players. This work contributes to understanding the social dynamics and providing evidence for social contagion in online social game networks and provides a deeper understanding of the role and impact that influencers in these networks may have.

This paper is organized as follows. We first ground and motivate this work within the existing literature by discussing influence in social networks, what has been done with SNA in games, what is known about social contagion in this context, and what we generally know about influencers and how to identify them. Then, we describe how we conducted our study using a sample of PC players from TCTD and SNA. The paper ends by presenting and discussing the results.

2 BACKGROUND

Influence in Social Networks

Social Network Analysis (SNA) is a family of methods for formally describing and analyzing relations between people as graphs with nodes (people) and edges (relations), with broad applications in offline and online social networks [41].

A major topic of SNA research is *social influence*, as expressed for instance in behavioral and social contagion theory [15, 39, 61]: behaviors (like physical activity or prosocial behavior) and their consequences (like obesity or happiness) cluster and spread within networks [e.g., 6, 15]. Methodologically, social influence is often hard to disentangle from homophily, namely where similarity is the primary cause for connections [15, 40]. Still, there is now good evidence for contagion processes in social networks via social-psychological mechanisms such as modeling or norm-setting [17, 18]. Put differently: Not only do similar behaviors attract connections; being connected causes more similar behavior.

As online social networks have become major means of communication, social influence has become subject to intense interest in communication and marketing as well as computer science and human-computer interaction (HCI) communities, especially computer-supported collaborative work and learning, Internet research, or informatics [16, 48, 53]. Practitioners have been chiefly concerned with finding ways to maximize the spread of desired information and behaviors through networks, and to reliably measure the impact of particular actions and actors [38].

In the following sections, we will describe the work that is done on SNA and social contagion in the context of games. Then, we will turn to what we know about influencers in general before we discuss what our research involves.

Social Network Analysis in Games

With the rise of multiplayer online games like *World or Warcraft* and social network games (sic) like *FarmVille* in the mid- to late 2000s, social graphs of players became more readily digitally trace-able. As a result, researchers became interested in applying SNA to online games.

The analysis of social connections and social networks is found in a variety of physical and online environments. Online social networks has facilitated large-scale SNA to be performed, notably on platforms such as *Facebook* and *Twitter*, which provide immense datasets to SNA research. This body of research has highlighted the usefulness of network analysis to identify the formation and evolution of social connections between users, and by extension how to cater to the interests of—and influence—those users [10]. The state of the art in SNA is substantial. Focusing on previous work in games, limitations of space require a focus on previous research most directly related with the current project.

Previous research on social connections and networks in games suggests that social connections and social interactions are important motivational drivers for playing games [20, 63]. This gives the games industry a direct interest in how social networks are formed and evolve in games in terms of the impact this has on the user experience [2].

SNA has been employed as a method for investigating social interaction between players primarily since the introduction of social network games, played on top of a social network platform such as *Facebook* [31]. With the popularity of persistent online games and mobile games, SNA began to be employed here as well. Social networks in games have been investigated using qualitative methods and ethnographic approaches [19], as well as using quantitative SNA [26, 63]. The available SNA work is focused on massively multiplayer online games and other shared online virtual environments, using in-game social features such as friend lists to construct networks. For example, Ducheneaut et al. [20] and Shen [49] examined social interactions in these types of games, with similar conclusions concerning the social life of players in massively multiplayer games being less prevalent than anticipated. Surveys have also been used as a method for collecting information about the social connections of players, e.g. Shen and Chen [50] who studied the sociodemographic, socioeconomic, and gameplay patterns of different networks across players. Furthermore, Szell and Thurner [54], studied the structure of friend, enemy, and communication networks, noting that friend and enemy networks were different topologically. Player-generated structures such as guilds have also been investigated, e.g. by Ducheneaut et al. [21] who used SNA metrics such as density and centrality to map the properties of player guilds in World of Warcraft. Chen et al. [14] followed up this work by categorizing guilds based on their underlying characteristics.

More limited attention is given to other game genres, e.g. esports, with one exception being Iosup et al. [25] that looked at social networks in *DOTA 2* and *StarCraft II*, using matchmaking as the baseline for building edges between players.

Similarly, Rattinger et al. [45] used matchmaking-based connections between players in the online First Person Shooter game *Destiny* to build networks between players in the game, thereby overcoming the limitation of the lack of explicit friendship features in the game. The authors noted that the most heavily engaged and longest retained players were characterized by having large social networks. Following up on this work, Schiller et al. [47] analyzed a social matchmaking service for *Destiny* players operating outside the game itself.

Summarizing, SNA as applied to games has been focused on the associations that form between players during and around the playing activity [20, 26, 45]. There is more limited work on social structures formed around games [47], not only for external services, but also distribution platforms such as *Steam* and *Uplay*. The work presented here forms a concrete extension of previous work applying SNA in games contexts, not only by integrating information about social connections from the *Ubisoft* distribution platform *Uplay*, but also in its continuation of the work by e.g. Rattinger et al. [45] on using SNA to identify players with specific properties across in-game behavior and network behavior.

Social Contagion in Games

With respect to social contagion, there has been some evidence in online games, such as generosity (gifting in-game money) [27, 66], purchasing of in-game goods [23], and cheating such as bot usage [65], including initial exploratory attempts at identifying "spreaders" or influencers with an outsized impact on cheating behavior [29]. However, research suggests that online in-game interaction network structures and dynamics are highly context-sensitive, meaning different kinds of interactions and relations (friending, trading, messaging, etc.) show very different structures and dynamics [51]. Thus, the existence of social contagion for gift-giving does not immediately generalize to e.g. team play, as different kinds of interactions have different strategic and other utilities and thus bring in different considerations and social-psychological mechanisms [51].

Influencers

There is no agreement on what is an influential person [46]. However, two types of influencers can be distinguished in previous work: (1) an individual who impacts the spread of information or behavior, people who influence people [59]; and (2) an individual who exhibits some combinations of desirable attributes such as trustworthiness and expertise or network attributes (connectivity or centrality) [28]. The first group of influencers are often referred to as opinion leaders [22], prestigious innovators [13], key-players [8] and spreaders [32]. The second group of influencers are often referred to as celebrities [52], evangelists [4] or experts [28], such as a journalist at BBC or a professor at Harvard.

Here we focus on measuring and quantifying the influence of an influencer of the first type, for two reasons. First, because they may touch a large scale of audience with a very small marketing cost [34, 36, 55]. Second, because their tendency to spread desirable behavior may be key to keep healthy communities alive for a longer time [13, 32].

Centrality measures have been proven to be relevant indicators in the analysis and comprehension of influencers in a social network [5, 33]. The most utilized measures of centrality are: in- and out- degree, betweenness, eigenvector and closeness; they are all measures of an actor's prominence in a network [58]. Valente et al. [56] investigated correlations between these most common measures of centrality. The researchers found that there are strong but varied correlations among the centrality measures presented here. The average of the correlations was 0.53 with a standard deviation of 0.14, indicating these measures are distinct, yet conceptually related. Since the centrality measures examined are not mutually excluding members but have slight different selection criteria, in order to identify the players with most influence we will utilize all the centrality measures and select only players that are ranked at the top for each measure.

Research Question and Contribution

To summarize, there is good evidence for social contagion and the existence of influencers in social networks more generally. Prior work in games has shown the existence of in-game social network structures similar to other domains. However, there is as of yet little data on social contagion or influencers in in-game social networks, which is the focus of the present study. Specifically, the question remains whether influencers in online games have an outsized influence not just in terms of the *quantitative reach* of their ego network, but also in terms of their *qualitative impact* on behavior. Since standard influencer definitions are based on social network features, reach-based claims are somewhat tautological: individuals with a large network *by definition* will touch a large network. Hence, instead of asking, "Do influencers influence *more people*?", we asked: "Do influencers influence people's behavior *more strongly*?" Given the game industry's interest in *playtime* as a major relevant design goal and prior work on influencers' specific *social behaviors*, we focused on these two aspects to measure the influence that influencers may have on other players.

While operationalizing playtime is straightforward, social behaviors are less so. Because the clearest form of exhibiting social behaviors is playing together, we decided to operationalize this aspect as *social play*, specifically the percentage to which one plays a multiplayer game collaboratively with others versus alone. Put as a research question: *Do influencers* *in online games affect connected players' playtime and social play more strongly than average?* Given prior findings in the SNA literature, we hypothesized that

(1) **Social contagion effect:** If a player joins the in-game network of an influencer, it will increase the player's playtime (H1a) and social play (H1b).
(2) **Impact of Influencers:** If a player joins the in-game network of an influencer, it will increase the player's playtime (H2a) and social play (H2b) *more* than joining the in-game network of another player.

The first hypotheses test if a social contagion effect occurs as a result of playing with an influencer; the second hypotheses seek to determine whether an influencer has more influence than other socially active players or, in other words, to rule out that playtime and/or social play can explain for the effect on other players. By testing these hypotheses, we are making a twofold contribution to the literature: (1) We are establishing whether basic tenets of social contagion in offline social networks transfer to online, in-game networks, extending the evidence base from larger-sized, longer-lifetime guilds to short-term, small-sized pick-up groups. (2) We are deepening the general understanding of influencers in online social networks by establishing to what extent their influence supercedes other network members not just in network reach, but also per-individual behavioral impact.

3 METHOD

Material

To avoid potential confounds by homophily, we looked for instances where we could quasi-experimentally observe changes in player's playtime and social behaviors before and after joining another player's social network, and compare influencers to the average player population. We found such an instance in the group mechanic in the game *Tom Clancy's The Division* (TCTD). TCTD is an online-only open world RPG shooter, set in a near future New York City in the aftermath of a smallpox pandemic. The player, an agent of Strategic Homeland Division, must help the group rebuild its operations in Manhattan, investigate the nature of the outbreak, and combat criminal activity in its wake. Released March 2016, TCTD accumulated more than 20 million players to date, becoming the fastest selling new IP of all times. As of April 2017 (time of initial data collection for this paper), there were more than 2 million active monthly players.

TCTD is structured with elements of role-playing games combined with collaborative Player versus Environment (PvE) and Player versus Player (PvP) online multiplayer activities. It is split in two zones: PvE, where players cannot kill each other (called "coop"), and PvP, where they can. We use the terms "competitive" and "cooperative" to indicate coop vs. PvP. It is possible to play and replay all the story missions and side missions with up to four real players in coop (PvE). Alternatively, it is possible to enter a PvP area called the Dark Zone and challenge other players.

All activities, both in PvP and PvE, can be completed solo or in groups. Groups are composed of the group creator and up to three other players. Groups can be created through quickmatch with random players or with players already connected as friends to the profile through Xbox Live, PlayStation Network (PSN), or Uplay accounts. Players invite and accept friend invites by using Uplay IDs. Upon acceptance, players show up in each other's menus as someone they can add to a group play session. Uplay is a multiplayer and communications service for PC, used exclusively by first-party Ubisoft games. Groups can be created or joined at safe houses and social hubs scattered around the game area or right before beginning any given activity.

A playtime segmentation report showed that active players are spending more than 35% of their time playing in groups, while players that quit the game spent less than 30% of their time in groups. Based on that and the existing literature, we hypothesized that social dynamics have a massive impact on player retention. Therefore, SNA would be an important tool to use on the data from this game to identify and isolate influential players.

Dataset

We had access to data collected by both the Uplay platform and the TCTD game. To reduce the computational time for this analysis, instead of working with the whole dataset from more than 14 million players (at the time of polling), we polled an initial random sample of 200,000 PC players from TCTD, and then included all other players that the initial sample interacted with in the game either by being invited or by inviting to a group. This led to a sample of 246,041 players. This will be referred to as the initial sample. This initial sample was polled on April 24th, 2017. We chose PC players only because our access to account data was limited to the Uplay service. Including PS4 and Xbox players would have required special permission from Sony and Microsoft. In addition, we made sure to include individuals that players in the original sample interacted with since we were interested in exploring communities generated by group forming behavior and not including these last players would have imposed an incomplete network. The total population at the time of polling was 14,716,507 players. Therefore, the initial sample is 1.7 percent of the entire population at that time.

The dataset consists of two tables. The first table has the IDs of the group creators, the time of group creation, the IDs of players invited to each group and their status (friend on Uplay or quickmatched). The second table has, for every player (group creators and not), various statistics, such as their total and daily playtime, number of friends, etc.

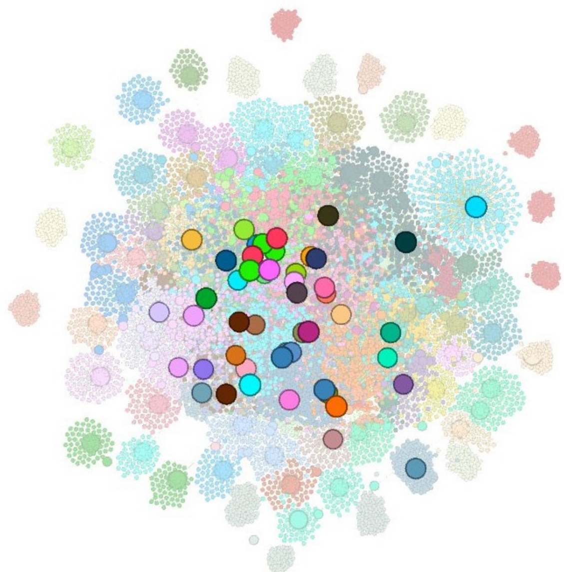

Figure 1: The 49 identified influencers mapped on the supergraph using conventional SNA techniques.

Identifying Influencers

We used conventional SNA techniques to identify influencers in our data set, a practice that has been done before in the context of both social networks at large [7, 32] and multiplayer games specifically [30]. Given that there is no agreement on which individual measure to utilize when identifying influencers, we used six different measures of centrality: closeness, betweenness, eigenvector, in-degree, out-degree and pagerank. All the sets of players identified by each centrality measure are intersected with each other to identify the players that are considered central for each of the six measures. In this work, we define influencers as players that satisfy all these six conditions.

We then plotted the resulting influencers onto a network graph where the nodes represent the players and the color of a node indicates the community (module) the node belongs to. The resulting supergraph is depicted in Figure 1. The size of the nodes is proportional to the importance of a player, hence influencers display a much bigger size than normal players. Details of our method are described below.

Identifying Most Central Influencers. We first computed centrality measures, which aim to quantify the "influence" of a particular node within a network. Our aim was to identify within each community which player may be influential. To accomplish this, we considered the following measures:

(1) **Closeness centrality:** how easily accessible a node is to all other players, represented as the length of the shortest path. The speed by which a player accesses all other players ranges between 0 and 1. We selected all nodes with values > 0, resulting in 182 players.
(2) **Betweenness centrality:** it represents the number of shortest paths to other players, or how likely a player is the most direct route between two other players. The range fell between 0 and 168. We selected all nodes with values > 0; resulting in 78 players.
(3) **Eigenvector centrality:** while degree centrality counts all connected nodes equally, eigenvector centrality treats connected nodes differently based on their "importance," or how well a player is connected to others. The range is between 0 and 1. We selected all nodes with values > 0.05; resulting in 198 players.
(4) **In-Degree (prestige):** number of connections to a node from others. These are players invited most often to groups. Range is between 0 and 5 and we selected all nodes with values => 2, resulting in 371 players.
(5) **Out-Degree:** number of connections from a node to other nodes. These are group creators that frequently invite other players. Values range between 0 and 630 and we selected all nodes with values > 0, resulting in 165 players. In- and out-degree together tell us how many players a certain player can reach directly.
(6) **Pagerank:** what fraction of players can be reached via directed paths. It uses links as a measure of importance. Each node is assigned a score based on its number of incoming links (its "in-degree"). These links are also weighted depending on the relative score of its originating node. The result is that nodes with many incoming links are influential, and nodes to which they are connected share some of that influence. The scores range between 0.000063 and 0.000059. We selected all nodes with values > 0.00006, resulting in 178 players.

Choosing Influencers. The intersection between the 182 players with highest closeness centrality, the 78 players with the highest betweenness centrality, the 198 players with the highest eigenvector centrality, the 371 players with the highest in-degree centrality, the 165 players with the highest out-degree centrality, and the 174 players with the highest pagerank score returned 49 players. These 49 players will be referred to as influencers from now on. It is important to note how intersecting across the six measures of centrality gives us a very conservative selection of players since in order to be considered influencers they must satisfy all six criteria. Furthermore, as Figure 1 shows, these 49 players map to a very large extent onto the sub-communities that form the heart of the network.

Sampling Comparison Players

After we identified the influential players, we sampled a group of comparison players to get a better understanding of who these influencers are. Because we hypothesized that playtime and/or social play alone cannot explain the effect on other players, for this comparison group we selected the most engaged players in the whole population—generally known as "power users." It is important to note that power users is an already existing category of players; within Ubisoft they are known as "star players" [1]. Ubisoft routinely invites "power players" to special events and sees them as an important resource for community building. With this in mind, it is legitimate to wonder whether "power players" could count as another influencer type (the "celebrities, evangelists, or experts" mentioned earlier). There may be some overlap of these categories. However, as our data offers no good, easy indicator of popularity and status within the player community, we cannot test this assumption. In the context of TCTD, power users are defined as players with:

(1) **At least 70 hours playtime.** The whole player population has an average playtime of 67 hours and 20 minutes.
(2) **At least 10 friends on Uplay.** On average players have 8.60 friends.
(3) **Gearscore in the top 5%.** Gearscore is an indicator for how well-equipped players are. Every weapon or piece of gear found after reaching level 30 (the level cap) has a Gearscore value. The higher an item's Gearscore, the stronger the item is, making it a more valuable field asset. The overall Gear Score of players defines their progression after the "end-game" (i.e., completing all the story missions). We selected only the top 5 percent.
(4) **At least played twice in groups in the week before we polled the sample.** We added this criterion to ensure that the power users made extensive use of the multiplayer functionalities of the game.

Applying these criteria to our initial sample led to 2,102 power users (less than 1% of the sample). It is interesting to compare infuencers to power users because we made no effort to remove influencers from the initial sample, yet no influencer was found amongst the power users. A third comparison was carried out with the total population.

Additionally, we intended to compare longitudinally the impact that influencers, powers users, and random players from the general population may have on others. For that purpose, we needed to extend our samples. First we selected all players that engaged with the 49 influencers (n = 16,742), all players that engaged with 49 power users randomly selected from the 2,102 initial power users sample (n = 1,346), and all players that engaged with 49 random players from the initial sample (n = 560). For the latter sampling, we excluded players with less than 1 week of total playtime and excluded all power and influential users.

Lastly, we examined if there was behavior transfer from influencers to the players they interacted with by running again the influencer identification method from the section "Identifying Influencers." For this we needed to extend the three samples. We selected all players that interacted with the 49 influencers and that were still active a year later (n = 3,901) and added all players that interacted with them (n = 99,672); we also selected all players that interacted with the 49 power users and that were still active a year later (n = 390) and added all players that interacted with them (n = 8,725); and finally we selected all players that interacted with the 49 random players and that were still active a year later (n = 28) and added all players that interacted with them (n = 302).

Constructs and Measures

As discussed before, to evaluate our hypotheses we focused on two constructs: playtime and social play. Playtime acts as a proxy for retention; social play will reveal a tendency to value the social dimension of play more, which, as we hypothesized based on the TCTD data and the existing literature, is a good indicator for how long a player will be engaged with a game—and is therefore another proxy measure of retention. Both constructs are measured as follows:

(1) **Playtime (DV1).** Average daily playtime calculated only for days of activity.
(2) **Social Play (DV2).** Ratio of solo and group play.

Both measures were chosen in the context of TCTD. For example, we chose to use playtime and not days played because it fits better with the game's monetization model: players need to play "enough" every day to see value in and buy upgrades or subscriptions, and the longer they play in this active fashion, the more they pay over time. Days played would not offer this level of granular information.

4 RESULTS

Descriptive statistics

Table 1 shows an overview of the three groups: influencers, powers users, and the total population. The comparison is based on the lifetime of players. On average, it turns out that the powers users are indeed the powers users we would expect with more sessions played, more daily playtime, but especially far more playtime, kills, skill kills (i.e., killing enemies with particular abilities), and items extracted compared to the influencers and the total population. For example, power users (454 hrs) played almost four times more than the influencers (119 hrs) and seven times more than the general population (67 hrs). The influencers, on the other hand, have on average far more friends (208) compared to the power users (26.5) and general population (8.60), but especially interact with others (342) more in group play than power users

(27) and the general population (11). Interestingly, both influencers and power users spent about two-thirds of their time in group play, whereas this is the reverse for the general population. Another interesting observation is that for performative measures (e.g., kills, skill kills, and items extracted) the influencers perform similar to the general population.

As for group play, power users spent only marginally more time in group vs. solo play and competitive vs. cooperative play, but especially have created (205) and joined (173) many more groups compared to influencers and the average players. However, these numbers are somewhat deceiving. When we consider their total playtime, it turns out that on average power users create 0.45 and join 0.38 groups per hour; the average player creates 0.38 and joins 0.30 groups per hour; and influencers create 0.74 and join 0.39 groups per hour. Therefore, it shows that power users are only marginally more engaged per hour than the average player and that influencers take far more initiative in creating groups.

In terms of group play, it is also interesting to consider with whom both influencers and powers have played with. On average, power users play with 27 other players in their lifetime. This is interesting because the number of players that power users interact with in groups (27) is very close to the number of friends (26.5), indicating that power users tend to play almost exclusively with their friends. At the same time, each influencer plays on average with 342 other players, a larger number compared to the already large number of their friends (208), indicating that influencers play in groups with considerably more players than just their friends. Therefore, while power users spend on average about equal amount of time in group play, they are more likely to play with friends rather than strangers.

Testing Hypotheses

To assess our hypotheses, we took the following three steps:

(1) We isolated all players that played with influencers (16,742), the selected power users (1,346), and the selected random players (560) at least twice in the week before polling the data.
(2) We split data regarding their communities in two: data regarding play behavior corresponding to the two weeks before joining the community (operationalized as being added as friends on Uplay) and data regarding play behavior for the two weeks after joining the community.
(3) We compared daily playtime and social play ratio two weeks before and two weeks after joining the communities of the influencers, power users, and random players, respectively.

Results are shown in Table 2. There is a clear change and impact on the behavior of players that join the community of the influencers: the daily playtime increases considerably, from a number very close to the general population average to a number very close to the influencers themselves; the amount of time spent in groups increases from the total population average to almost the same amount of the influencers. For playing with power users, in contrast, both the daily playtime and social play do not change drastically. The numbers are also similar to the powers users themselves, suggesting that not only do power users play together with their (limited) group of friends (see Table 1), they are likely to play together with other power users. Engaging with random players does not change behavior and, as expected here, the statistics are similar compared to the total population.

Paired-samples t-tests were conducted to compare daily playtime (DV1) and social play (DV2) in two weeks before joining a community (condition1) and two weeks after (condition2). As for the playtime (DV1), there was a significant difference for the daily playtime of players interacting with influencers before (M = 1.78, SD= 1.41) and after (M = 2.21, SD = 1.36) they joined the influencers' community; $t(16{,}741)$ = 28.83, p = .001, r = .22. No significant effect on daily playtime was witnessed for players interacting with power users two weeks before (M = 3.39, SD = 2.43) and after (M = 3.36, SD = 2.35) joining their community; $t(1345)$ =-0.26, p = .796, r = .007. For the random sample of players, there was also no significant effect on daily playtime, two weeks before (M = 1.6, SD = 1.49) and after (M = 1.61, SD = 1.42) joining their community; $t(559)$ = 0.14, p = .885, r = .005. These results support hypotheses H1a and H2a: joining a group with an influencer did, in fact, increase the daily playtime of players (H1a), at least in the first two weeks after joining, while the same could not be stated of power users or a random sample of players during the same period (H2a).

As for social play, joining an influencers's community significantly changed the ratio from two weeks before (M = 0.41, SD = 0.27) to after (M = 0.59, SD = 0.16); $t(16{,}741)$ = 74.32, p = .001, r = .50. This ratio change was also significant for players joining a power user's community compared to their situation two weeks before (M =0.6, SD = 0.23) and after (M = 0.65, SD = 0.27) joining them; $t(1{,}345)$ = 4.79, p = .001, r = .13. For a random sample of players, two weeks before (M = 0.39, SD = 0.29) and after (M = 0.38, SD = 0.27) joining groups, it did not significantly change their social play ratio; $t(560)$ = -0.54, p = .588, r = .002. These results support hypotheses H1b and H2b: the ratio of playing in groups significantly increased for players joining an influencer's community (H1b), at least in the first two weeks after joining. While a significant increase in group play happens with joining power users as well, their impact is less. The effect size for influencers is large (.50) resulting in an average increase on of 18% in group play, whereas the effect size for power users is small (.13) resulting in an average increase of only 5% of group play (H2b).

Table 1: Comparison of the three populations: Influencers, power users, and total population.

	Influencers	Power Users	Total Population
Total # players	49	2,102	14,716,507
# Sessions, *M* (*SD*)	178.27 (313.94)	213.71 (258.13)	44.54 (442.50)
# Kills, *M*(*SD*)	7,353 (5,286)	26,937 (55,374)	6,849 (10,738)
# Skill kills, *M*(*SD*)	1,172 (1,719)	5,385 (4,261)	1,041 (3,247)
# Items extracted, *M*(*SD*)	437 (328)	1,561 (3,566)	513 (1,895)
# Friends, *M*(*SD*)	208.07 (104.59)	26.51 (32.42)	8.60 (36.35)
# Groups created, *M*(*SD*)	87.94 (90.82)	205.03 (301.12)	22.36 (138.46)
# Groups joined, *M*(*SD*)	47.19 (148.42)	173.40 (137.21)	20.38 (52.17)
# Players interacted with in group play, *M* (*SD*)	341.89 (229.47)	27.05 (274.69)	10.72 (306.43)
Total playtime in hrs, *M* (*SD*)	119.63 (98.51)	454 (172.37)	67 (217.38)
Daily playtime in hrs, *M* (*SD*)	2.56 (1.64)	3.39 (1.96)	1.56 (1.47)
Time spent in group–solo play	61%–39%	67%–33%	38%–62%
Time spent in coop–competitive play	53%–47%	46%–54%	49%–51%

Table 2: Changes in the influencers', power users', and random players' communities two weeks before and two weeks after engaging with influencers, power users, and random players.

	Influencers		Power Users		Random Players	
	Before	After	Before	After	Before	After
Daily playtime in hrs, *M* (*SD*)	1.78 (1.41)	2.21 (1.36)	3.39 (2.43)	3.36 (2.35)	1.60 (1.49)	1.61 (1.42)
Social play ratio	41%–59%	59%–41%	60%–40%	65%–35%	39%–61%	38%–62%

Retention and Influencer Conversion

For testing our hypotheses, we limited our observations to two weeks before and after. A question remains what kind of influence influencers may have on other players beyond this period. For this analysis, we first considered if players are still actively playing TCTD. In our previous analyses we used playtime and social play as measures because these can indirectly tell us something about retention: more engaged players and players engaged in the multiplayer aspects of a game tend to stick around longer. To calculate retention here, we looked at which of the players who joined the communities of the influencers, power users, and random players were still active after one year. Table 3 shows the retention results. After 1 year, 23% of the influencers' community is still active, whereas this is 29% of the power users' community and only 5% of the random players' community.

The second consideration is more ambitious. We considered which of the players from these communities may have become an influencer themselves. As we have demonstrated, influencers have an impact on other players and so if these players are converted into influencers they, on their turn, can influence others—and thereby keep the community alive, even if certain influencers decide to leave the game. For this analysis, we first applied the same method for identifying the original 49 influencers except a year later (see Methods section). Then, we considered which of the newly identified influencers mapped onto the players from the initial population that the original influencers, power users, and random players engaged with.

Table 3 shows the conversion results, which are remarkable. From the community of the random players only 2 players were identified as an influencer a year later, which is a conversion rate of 1% based on the still active players in that community. The influence of power users is greater: from their community 22 players are identified as an influencer resulting in a rate of 6%. However, from the community of influencers we identified a staggering number of 1,002 influencers, which corresponds to a rate of 26%.

5 DISCUSSION

Using conventional Social Network Analysis (SNA) techniques we identified key members that are very engaged with the game *Tom Clancy's The Division* (TCTD) but also with other players. The question that we investigated is whether these so-called influencers *really* influence other player's behavior, as measured in their playtime (H1a) and social play (H1b), and if they do this *more* than other players (H2a and H2b). Our results provide supporting evidence

Table 3: Players interacting with influencers, power users, and random players that continue to be active and have become influencers themselves after 1 year. Note: conversion rate is based on active population after 1 year.

	Initial population	Active after 1 yr	Retention	Influencer conversion	Conversion rate
Influencers' community	16,742	3,901	23%	1,002	25.7%
Power users' community	1,346	390	29%	22	6%
Random players' community	560	28	5%	2	1%

that influencers do indeed impact other players and more so than others. We discuss here our findings on social contagion, retention, and player differences before explaining the limitations and implications of this study.

Influencers are Socially Contagious

Our results highlight that the identified influencers seem to have a very tangible impact on the people they play with: these other players begin playing longer and spend more time in groups. We observed a significant increase with a small to medium effect size (r = .22) on playtime (H1a) and a large effect size (r = .50) on social play (H1b). Compared to interacting with an influencer two weeks before, players' daily playtime increased on average with 24% and their social play ratio completely reversed in favor of being more social (from 41%–59% to 59%–41%) two weeks after (Table 2). We contrasted the impact of influencers with those of power users and average users and found that interacting with these users does not yield any significant differences in playtime (H2a) and only a significant but with a smaller effect size (r = .13) on social play (H2b) for power users. Therefore, a strong social contagion effect is unique to the influencers.

Homophily is always a possible confound in social contagion work [15]. For this reason, we ran a quasi-experimental analysis comparing playtime and social play ratio pre/post joining the team of an influencer vs. power player vs. normal player (Table 2). Homophily (i.e., influencers attract already-social and already-active players) would predict higher overall playtime and social play ratio among influencer team members, but not the significant changes that we observed. This makes us confident in claiming causality that influencers are socially contagious.

Influencers are Important for Retention

Retention is a key measure for success in the game industry. Our results suggest that not only are influencers socially contagious, they are also important for retention. We measured if players continue to be active players one year after interacting with influencers, power users, and random players (Table 3) and found that players who interacted with influencers (23%) and power users (29%) are more likely to be active compared to a random player (5%). While the retention is higher for power users, it should be kept in mind that influencers are able to retain ten times the number of players and that power users tend to engage only with similar users, so their influence is more of a reinforcing feedback loop than having an impact on the community at large.

What is most striking, however, is that players who have interacted with influencers may become influencers themselves after a year (26% chance). Such influence is not as noticeable with power users (6%) or random players (1%). This data suggests that the social contagion effect of influencers may go as far as converting a significant portion of the players they interact with into influencers. Because we did not (quasi-)experimentally test this, or observed whether these new influencers exhibit the same kind of impact, we cannot claim causality here neither can we fully illustrate what impact this has on the community. However, these results provide further evidence of the important role that influencers play in online game communities, especially with the issue of retention in mind. In fact, as the sustained lifetime of a game depends in large measure on a healthy, lively community of players engaged with the multiplayer aspects of the game, these players seem to form the invisible social backbone of a game community.

Influencers are Different Players

Our results show that influencers are different from other players (Table 1). Influencers create groups much more than the average player. They play many more sessions (34 times more), have many more friends (21 times more), and spent relatively more time in group (23% more) and coop play (4% more) than the average player. More importantly, they seem to be the ones who initiate group play and invite others to join (4 times more). Power users, on the other hand, spent many more hours playing (4 times more), but while they engage considerably in group activities, even at a similar ratio as the influencers, they tend to start groups relatively less and seem to play mostly with their much more limited number of friends (8 times less) who are likely to be power users too and less so with strangers.

Important to observe as well is that the selected power users are indeed power users: compared to the average player, they have far more kills (4 times more), skill kills (5 times more), and items extracted (3 times more), and play more competitively (3%). Interestingly, the statistics for influencers on these performative metrics are with the exception of competitive play (7% less than power users) fairly similar to the average player. Therefore, what defines influencers in contrast to power users is that they have a wide-reaching and solid network of friends and an active engagement with the multiplayer aspects of a game rather than an elite performance in the game. Influencers are the social butterflies.

Although these metrics highlight the differences between influencers vs. power users vs. average players, it is important to note that these metrics are not sufficient to identify influencers. When applying one or a combination of metrics, it was impossible to achieve the same result. Therefore, SNA seems to be required to identify influencers. The approach we have taken here is to define influencers on the basis of combining six centrality measures and then inspecting the results visually for verification (see "Identifying Most Central Influencers"). Future research is needed to further refine this approach and examine how it generalizes to other contexts.

Furthermore, neither the SNA or the metrics tell us *really* who these influencers are and how it is possible that they can convert others into influencers. Because explanations such as that influencers are inherently social, a suggestion supported by evidence that there are similarities between virtual and real world personalities and behavior [11, 12, 57, 68], or are a different type of player, more into social play [e.g., 42, 67], cannot fully explain the results we observe here. It may be that those converted are socially inclined people and that interacting with another socially inclined person but already socially active player (i.e., an influencer) activates how they can and want to play. Regardless, our quantitative, hypothesis-testing approach is inherently limited in generating detailed explanatory portraits of players and the dynamics we observed. Future qualitative and mixed-methods work, where influencers and the players they interact with are interviewed or closely followed over a period of time, can provide further evidence on understanding who these players are and why they have such influence on others beyond being socially active as described with the metrics here.

Limitations and Generalization

Our presented work has several limitations. First, the work focused on a single game. Although there are differences between TCTD and other online multiplayer games, the type of game, its game mechanics, and especially its management of group play is similar to other online games. The most important difference in terms of group play compared to other online games is that it is limited to up to four players at a time, meaning that player ties may be closer than in other games and that there are more loosely connected communities than in other games. More importantly, influencers who initiate group play may be more influential as they are the ones who make connections across the network, whereas in games where guilds and factions play a role there are other (social and cultural) mechanisms of how players join groups.

Second, we sampled only one degree of ties after the initial sample of 200,000 PC players (1.7% of the population) by including all the players the initial polled sample interacted with. This was a necessary step because we aimed to investigate their social networks based on who they play with. However, there is a question how representative the sample is in terms of the whole population. Depending on the study design and situation, different techniques for sample size estimation exists. Assuming normally distributed variables in the population, Z-scores can be used to define the confidence interval and sample size. In the current case, with a 1% margin of error and a 99% confidence level (Z score = 2.576), the required sample size for the whole population would be about 9,600 players using random sampling. The sample used here is roughly 20 times larger. Nevertheless, aside from replicating the work in other game contexts, future work could operate with the entire network and/or samples that have up to three degrees of ties similar to what others have done while utilizing SNA on game communities [44, 45].

Third, while we made deliberate decisions—based on literature, closely examining our data, and definitions used by *Ubisoft*—on how to identify influencers, define power users, and examine the impact of social contagion choosing a different set of criteria may have led to different results. As future work will consider this phenomenon more closely, more robust standards and definitions will be established and the results presented here can be (dis)affirmed.

Fourth, in order to rule out the possibility that a particular metric can explain for the impact we observed, it would be necessary to perform a propensity sample where we compare the influencers to a sample with similar characteristics.

Implications

The current work has important implications for HCI researchers and industry. For HCI researchers, we have established here how social contagion or influence occurs in online, in-game networks, specifically in the context of short-term, small-sized pick-up groups. While we need to be cognizant of this particular context, this work advances the field at large. Where previous SNA work on influencers in games and social media focused on network features only [e.g., 60], our work highlights how influencers *act differently* from others and the *extent of their impact* on others and the community over time. Additionally, as it remains an ongoing discussion on how to identify influencers in social networks using SNA metrics [46], our work suggests a combination is necessary and that measures of activity and popularity are not good metrics. This latter is relevant for the community management for every game or social media, which generally tend to be most interested in active users, as well "celebrities, evangelists, or experts" such as power users. Our data suggests that for TCTD at least, the "most central" users may be the most important for engaging, and retaining other users. Therefore, community managers should tap into SNA to identify such influential users, then leverage them for feedback or to reach a large part of the community.

6 CONCLUSION

In this paper, we studied if influencers in online games affect connected players' playtime and social play more strongly than average. We studied this in the context of *Tom Clancy's The Division*, a popular multiplayer online shooter. Our findings show that influencers do indeed impact other players and more so than power users or the average player, thus providing evidence for a social contagion effect and the important role influencers have in these online social networks.

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