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Birds with more feathers gather their flocks together: The power of status in information-sparse environments

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ABSTRACT

Human interactions are often shaped by social structures and individual traits, yet the mechanisms of influence in such settings remain poorly understood. This study investigates social influence within the online game *Sky: Children of the Light*, focusing on the roles of network centrality and status cues in the absence of traditional communication signals. By combining network analysis on 1,175,390 players with a large survey (n = 7858), we measured Social Value (SV) and cross-examined these results with individual traits (i.e. player typology, psychological needs satisfaction, and perceived social capital). Our findings reveal that network centrality, specifically out-degree centrality and betweenness, are the strongest predictors of social influence. Status, as indicated by the number of outfits a player possesses, significantly correlates with higher influence and overlaps with network centrality measures. Additionally, we observed that players categorized as Socializers and Competitors have the highest SV, while Completionists exhibit the lowest. Contrary to expectations, psychological needs, such as perceived relatedness and competence, did not show significant effects on influence. These results highlight status as a proxy for social connections in cue-sparse environments, where visual signals carry greater weight due to the lack of direct communication. Our study contributes to understanding how social influence operates in anonymized digital worlds and offers insights into how status and network structures shape behavior in virtual environments.

1. Introduction

At the risk of the obvious, interactions with other people are an important part of the human experience. We need each other to survive as a species, as well as for relationships. The 75-year Harvard Grant and Glueck study (Curtin, 2017) has demonstrated that relationships and social ties are critical for health and well-being. It is taken as an active assumption that we influence each other, and that collectively these impacts are important. This assumption sits at the core of all social science (Backhouse & Fontaine, 2014), and is evidenced in myriad theories, including those covering the influence of one person on another, such as social proof (Cialdini, 1993), which has been found to extend even online (Marwick, 2013). However, measuring human-to-human causal ties has remained challenging, in part due to the complexity of human relationships and the difficulty of tying them to actual behavioral records. Indeed, "how" and "why" other people impact us are among the most complex issues of the social sciences, and even "how much" has been challenging to quantify.

In a recent article, Williams et al. (2023), produced a falsifiable (Popper, 2002), scalable method that addresses the causal issue of "how much" one influences their social connections (Williams et al., 2023), and has also been recently applied to donation behavior and other games (Yang & Williams, 2026; Zeng et al., 2026). This measure is called "Social Value" (SV). The SV method, while accurate, offers a "black box" to issues of theory and process–we can measure who influences who else, and how much, but nothing about why, how, or who is more likely to be that influential person.

This study attempts to address two of those gaps, in one initial context. By examining behaviors in an online system, and by adding survey data on the individuals, this study begins to address the "who" and the "how". We suggest that this early research will accompany others that will use this method to examine other groups in other spaces, and in so doing will eventually begin to fill out a picture–and a theory–of how influence occurs, and how it may vary across context.

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In a consciously limited scope, we investigate the composition of high influence in an online space. Much like the initial discovery setting of SV in the original paper, this one uses the data-rich environment of an online game. It does so because of the relative ease of acquiring the challenging data necessary to collect SV and compare it to correlates, and because it offers a substantially different setting than the original study, thereby allowing for possible speculation into generalizability or comparison across a second context. As we will note in the Discussion, we assume that future research will need to test across more varied contexts with varied affordances (Gibson, 1977) for greater generalizability. Different affordances make generalizability vastly more complex than when comparing effects from a medium even as varied as television.

To that end, the game used here is as different as possible as the original title (World of Tanks) in which SV was first derived and validated. We put significant emphasis on the role of status. Games and virtual worlds have served as fertile ground for research on human interactions, where variables such as the laws of interaction and appearance can be modulated. The game used here is *Sky: Children of the Light*, which differs from Tanks in terms of platform, genre, goals, aesthetics, and player community. Crucially, players are anonymized, cannot communicate verbally with each other, and only perceive visual cues from each other. These features are critical for understanding how they might operationalize theories of influence and communication, and so why we might expect to have different SV outcomes from title to title.

People generally seek to model their behaviors, sense of identity, and norms on others' (Bandura, 2009). The lack of typical offline cues such as faces and their expressions, voices and speech creates a setting in which players have fewer social signals to which they would typically react. In such cue-sparse settings, research grounded in the Social Identity Model of Deindividuation Effects (SIDE) framework (Spears, 2017) (details below) has shown that the social cues that *do* remain carry more weight. These visual cues are a central feature of the tests below. While SIDE emphasizes the contextual conditions under which reduced cues shape social influence, we also draw on the Structured Influence Process (SIP) framework (Contractor & DeChurch, 2014) to address complementary questions: who within the network is more likely to exert influence, and what types of players are most likely to be influential.

Our paper proceeds as follows: We first measure social influence by using Social Value, and attribute individual-level value (Williams, 2018). We then cross-section these Social Value scores with a survey (n = 7858), which exposes users' player typology, psychological needs satisfaction, and perceived social capital. We find they are motivated predominantly by socialization and expertise in a game, and posit that status signaling in information sparse environments elevates the influence of high performers.

2. Literature

2.1. Virtual worlds and games for social scientific investigations

Games and virtual worlds have served as fertile ground for research on human interactions dating back at least to early work around early arcades (McClure & Mears, 1984) and later online spaces (Crookall, 1999), with methods improving as the data from these spaces has become more accessible alongside parallel improvements in large-scale data-driven computational communication (Williams et al., 2011). Whether being used as objects of interest because of their sheer scale, as "mapping" (Williams, 2010) analogs for the more "real" offline life, or as "petri dishes" for experiments on human behaviors not feasible offline (Castronova, 2006), games are a vibrant research space. Indeed, games are now the primary entertainment activity of the planet, surpassing all other media in terms of both time and money spent during the pandemic (Wijman et al., 2020). Additionally, unlike many other media, games tend to be socially interactive spaces, offering a wide range of affordances (Gibson, 1977) and settings that allow researchers to observe social dynamics. This has allowed researchers to study games to examine their educational potential (Annetta, 2008), to study economic behavior (Castronova et al., 2009), to model complex cognitive processing (Tamborini & Bowman, 2010), sexuality (Tang & Fox, 2016) and identification issues (Liu, 2023), and many other topics. The upshot of this work is that gaming is highly complex, with many cognitive and social processes taking place across a vast range of settings that may have an effect on the individuals independent of whether the player selected the space. Working in this space therefore invites both precision and conservatism: research must be theoretically grounded and unusually aware of the different mechanisms at play and how they may or may not generalize to other game settings or to "IRL" (in real life).

2.2. SIDE: Social identity model of deindividuation effects

In the computer-mediated environment, the Social Identity Model of Deindividuation Effects (SIDE) suggests that visual anonymity can lead to deindividuation, causing a diminished awareness of one's and others' individuality (Spears, 2017). Similarly, in online gaming environments, the absence of prior interactions between users fosters depersonalized, category-based perceptions of others (Dai & Shi, 2022; Postmes et al., 2002). In such settings, the remaining social cues carry more weight and foster stronger group identification (Lea et al., 2001; Walther et al., 2010). In the context of *Sky: Children of the Light*, SIDE theory is relevant because the game environment limits players' ability to access traditional cues, such as faces, voices, or direct messages, creating a cue-sparse setting.

In this study, we argue that the absence of typical offline cues in Sky heightens the significance of the remaining social signals, with clothing serving as one of the most prominent cues in the game. All players begin with the same default outfit, but they know that more distinctive and attractive options can be obtained through in-game currency or real money. Acquiring and displaying outfits is a central source of enjoyment in gameplay. Experienced players often update their appearance — such as by purchasing seasonal outfits — and these visible signals are readily perceived by others. In a cue-sparse environment like Sky, such markers draw peers' attention, reflect in-game resources, and in turn confer higher social status compared to players who rely on basic outfits or seldom change their look. Due to the scarcity of traditional social indicators such as facial expressions or spoken language, players frequently rely on observable features like outfits to model their behavior, identity, and social norms to align with and adapt to the game's social environment.

H1: Individuals with more in-game outfits, which indicate higher in-game status, are more likely to influence others.

2.3. Social influence process: Networks and social capital

The scientific community has examined social influence from various perspectives. Research on social networks explores how individuals' network positions shape their capacity to stimulate behavior change within a community. Concurrently, psychological research investigates the fundamental human motivations underlying social influence processes. Building upon these two strands of research on social influence, the Structured Influence Process (SIP) framework (Contractor & DeChurch, 2014) leverages network positions to identify "who" the influential and receptive individuals are, and human motivations to understand "how" the direction and/or intensity of a person's attitudes and behaviors depend on those of others in their social networks.

Taking a network approach toward social influence, SIP proposes that individuals' attitudes and behaviors are co-shaped by key opinion leaders and other individuals in their social networks. Considerable research has identified key opinion leaders from a social network perspective and found that individuals central in the network are more likely to be influential, either because they are connected to many others or because they are connected to those who are influential. Therefore, individuals central in a network have the most potential to induce change. From the social network perspective in SIP, this study predicts:

H2: Individuals with higher network centrality are more likely to influence others.

In addition to network positions, we consider the perceived benefits and resources gained from these social relationships—social capital (Adler & Kwon, 2002). Scholars have made a distinction between bonding and bridging social capital (Putnam, 2001), which are linked to different types of tie strength. The strength of social ties is characterized by "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services" (Granovetter, 1973). Specifically, bonding social capital represents the resources accrued from tightly knit connections called "strong ties" such as emotional support, whereas bridging social capital refers to the resources gained from loose connections called "weak ties" such as access to diverse information (Granovetter, 1973; Williams, 2006). We include these as additional controls for network structure.

Homophily, the tendency for individuals to associate with similar others (McPherson et al., 2001), also stand to influence network formation. In information-sparse environments where traditional markers of similarity (e.g., demographics, verbal self-disclosure) are unavailable, observable status cues like clothing may serve as the primary basis for selective association, in combination with SIDE. Players who signal higher status through their visual appearance may preferentially attract and be sought out by similarly engaged players.

2.4. Social influence process: Individual traits

Beyond the network perspective, SIP framework emphasizes how individual attributes shape both influence and susceptibility. Prior research has shown that such attributes not only influence how networks form but also contribute to differentiated status outcomes within them (Breiger et al., 2025). The SIP framework identifies two fundamental motivational drivers underlying these processes: the need for accuracy and the need for affiliation (Contractor & DeChurch, 2014). In gaming contexts, the need for accuracy motivates players to follow those who demonstrate expertise or success, as their behaviors signal effective strategies for performance. Conversely, the need for affiliation leads players to be influenced by socially central individuals whose connectedness fosters belonging and recognition. Together, these dynamics suggest that influence in online games arises not only from structural position but also from individual attributes that signal competence (accuracy) and relatedness (affiliation).

Expanding on the SIP framework, this study explores individual traits, such as player typologies that define gaming motivations, alongside the psychological needs fulfilled through gameplay, to predict players' social influence. The investigation of player typology can be traced back to Bartle's (1996) taxonomy of Multi-User Dungeon (MUD) players. Following this seminal work, Kahn et al. (2015) identified six distinct player motivations: Socializers, Completionists, Competitors, Escapists, Story-driven individuals, and Smarty-pants. The current study focuses on Socializers, Completionists, and Competitors, as these player types align closely with the game's affordances. Both Bartle (1996) and Kahn et al. (2015) define socializers are players who prioritize interaction and relationships with others. Socializers tend to engage in frequent communication with fellow players and are thus more likely to benefit from these interactions. In contrast, competitors are driven by a strong desire to win and regard victory as paramount. Completionists are characterized by their determination to explore every aspect of the game in meticulous detail.

Sky emphasizes collaboration over victory. Progression requires players to unlock functions through communication and cooperation, making social engagement central to advancement. Within this context, socializers and completionists are expected to exert greater social influence, as their motivations align with the game's cooperative affordances. Although all players may adjust their behavior to conform to the game's collaborative norms, prior research suggests that dispositional tendencies persist across contexts (Burt, 2012). Accordingly, we expect that Socializers will be more responsive to the collaborative norm and consequently occupy higher-status positions. Conversely, because the game does not involve direct competition, competitors are unlikely to shape social influence. Extending the SIP framework, we further argue that alignment between individual traits and the fulfillment of basic psychological needs—particularly relatedness and competence, increases influence over others. By integrating the game's affordances with the SIP framework, this study hypothesizes:

H3: Socializers will be more likely to influence others.

H4: Completionists will be more likely to influence others.

H5: Competitors will not influence others.

H6: Individuals with high perceived competence are more likely to influence others.

H7: Individuals with high perceived relatedness are more likely to influence others.

2.5. Research context

In this study, we draw on two complementary theoretical frameworks: SIDE and SIP. SIDE explains why visible cues become especially influential when other communication signals are scarce, guiding our prediction about the role of status markers such as outfits (H1). SIP provides two interrelated dimensions of influence. The structural dimension emphasizes how network embeddedness shapes influence, captured through measures of network position (H2), and the motivational dimension, underscoring how individual motives shape social interaction. We extend this aspect of SIP into the gaming environment by considering player typologies as reflections of motives that align with the goals and affordances of the game (H3–H7). In Sky, where progression depends on cooperation, players who embody these motives — such as Socializers, Completionists, or those demonstrating competence and high relatedness, rather than purely competitive orientations — are positioned to become opinion leaders. By aligning their actions with the game's design, we hypothesize that these players both model desired behaviors and exert greater influence on others.

Sky: Children of the Light (Sky) is a mobile MMOG developed by *thatgamecompany* that allows players to embark on a journey through a mystical kingdom, where their objective is to reunite fallen stars with their respective constellations. The central theme of the game is collaboration and compassion where players do not compete against one another but rather build relationships by flying together, and explode fireworks together (Martens, 2019). Players begin the game with limited communication options but as they progress and socialize with other players, communication options upgrade as the friendship develops. Also, the friendships allow players to unlock abilities in the game. But, compared to other games, it is relatively difficult for players to speak directly. The majority of communication between strangers is merely seeing each other or gesturing, at least until the relationship is formed and progresses substantially within the game's pre-set paths. This lack of direct communication is both "feature and bug" in the sense that it artificially reduces normal communication patterns in an online space. That reduction makes the generalizability lower, while offering researchers a unique opportunity to examine how players influence each other in an information-sparse environment. Sky's interpersonal cues are extremely limited compared to other titles.

Applied to this environment, the Social Value paradigm measures whether players cause each other to play more, or less, but it does not specify the process of that influence. At heart, Social Value is a test of the difference between situations when a focal person either does or does not do something, and its effect on those around them. It is

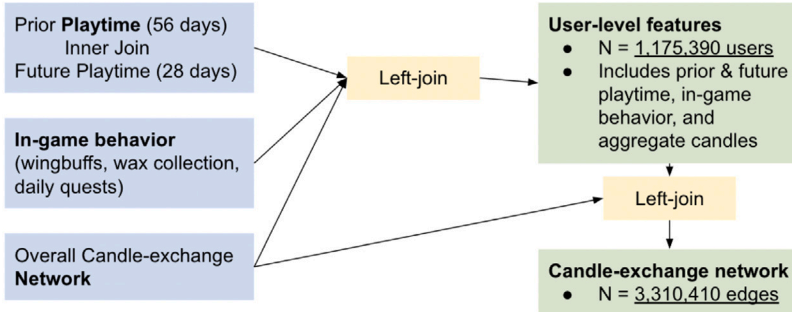

Fig. 1. Flow-chart of data preparation for user-level and edge-level table aggregations.

a test of whether a given Sky player's presence and actions result in others around them playing more, compared to times when that first player is not present. When the focal player is present, we know that in this particular environment, the social cues are limited in comparison to other online games that feature text and voice chat. Without those cues, the strength of the ties in the network are likely weaker than in communication-rich environments. So we expect Social Value to be lower than in a more cue-intense social environment, as noted by Williams (2018). Nevertheless, that signal, however attenuated, is likely to be driven by different player motivations.

3. Methods

Computing Social Value consists of three steps. First, data preparation by transforming raw traffic data (as a behavioral log) into two tables. Second, training a machine-learning model that predicts on the DV. Third, attributing the DV to social and asocial features, and to each user.

As mentioned prior, especially in the early game, there is a sparsity of information and communication. We focus on a few parameters: wingbuffs, wax collection, and daily quests as metrics for in-game engagement directly with the game. Lastly, we also extract playing time—which serves as our primary dependent variable. We provide summaries of these in-game features below:

Candles serve as the primary in-game currency in Sky. Players need to exchange one candle to make friends with other players. Candles can be used to unlock in-game items and social features, and purchase cosmetics for customizing their avatars. This is the primary indicator for social exchange and reciprocity. **Wax** represents pieces of light that players can collect to forge candles. Wax can be found at various locations in the Sky realm. This is largely an asocial feature, generated by interacting with the digital environment.

Each day, players receive four **Daily Quests**, which might involve interacting with friends or finding the light. Players will be awarded with one candle per completed quest. This is an indicator for completionist tendencies. Lastly, **Wing Buffs** are critical to Sky. Flying and co-flying with friends offer unique and tranquil experiences within Sky, a world defined by exploration. Navigating this world heavily depends on a player's flight capabilities. When entering Sky, players begin to earn their wings in the form of a cape. Players can upgrade their cape to fly higher and longer. One way to do this is by collecting winged light from the children of light as they explore the Sky world. However, there is a limit number of wings that players can collect this way. Wing buffs are additional wings that players can acquire using more advanced candles. Acquiring wing buffs not only improves players' flying abilities but also unlocks higher-priced cosmetics, which serve as status symbols within the information sparse environment.

3.1. Data processing

The Social Value algorithm relies on two core tables. First is a user-level aggregation which includes the dependent variable–in our case playtime– and the features used to build a machine-learning model. The second table is an edge list that accounts for social actions between two users, in this case candle exchange. Fig. 1 shows the pipeline used to produce the tables. We produced both the user-level and edge-level tables by aggregating in two time periods. First, between 06/01/2022 to 07/26/2022 (8 weeks/56 days) for the features and then second, between 07/27/2022 to 08/24/2022 for time played (DV). As a caveat, we used an inner join which prevents churners. We then merged their in-game actions and candle exchange over the first 8 week period and arrived at the two tables. The user-level features table includes 1,175,390 users and the candle exchange 3,310,410 edges. Note, we also log transform the playtime.

3.2. Data descriptions

Before building the machine learning model, we show some basic descriptives of the underlying data. Fig. 2(a) shows the distribution of playtime in the prior and future period. Both have clear bimodal distributions on the log scale. Fig. 2(b) shows the distribution of four user actions–Wing Buffs, Daily Quests, Wax Farmed, and Candles Collected. Here, we see Candles Collected (red) and Wax Farmed (green) have clear power law distributions, with wax farmed having a longer tail. This suggests a greater supply for in-game actions (rather than social actions). DailyQuests (orange) has a discontinuity– first increasing slightly then diminishing to 0 quickly. This is likely because there is a limited supply–as there are only 4 possible daily quests per day, most users approach that upper bound. Few attain the maximum.

3.3. Training the regressor

Gradient Boosting Decision Trees (GBDTs) are a class of ensemble methods that combine multiple weak learners — typically decision trees — into a single, strong predictive model (Friedman, 2001). Each tree is trained to minimize the residual errors of the previous trees, iteratively improving predictive accuracy. This approach captures non-linear relationships and high-order interactions without explicit feature engineering, making it particularly effective for structured data (Ke et al., 2017; Prokhorenkova et al., 2018). Among modern GBDT implementations, *CatBoost* (Prokhorenkova et al., 2018) introduces algorithmic innovations that address several limitations of earlier boosting methods. It employs an "ordered boosting" technique to prevent target leakage, incorporates efficient handling of categorical variables through target statistics, and supports GPU acceleration.

To interpret the contribution of individual features in the trained model, we employ *SHapley Additive exPlanations* (SHAP) (Lundberg & Lee, 2017). SHAP builds on cooperative game theory to attribute each feature's marginal contribution to the model prediction, ensuring consistency and local accuracy. For each observation, the SHAP value represents the average marginal contribution of a feature across all possible feature coalitions. This yields both global importance (feature-level contribution to overall predictions) and local interpretability (feature influence for individual cases). This combination of GDBTs and

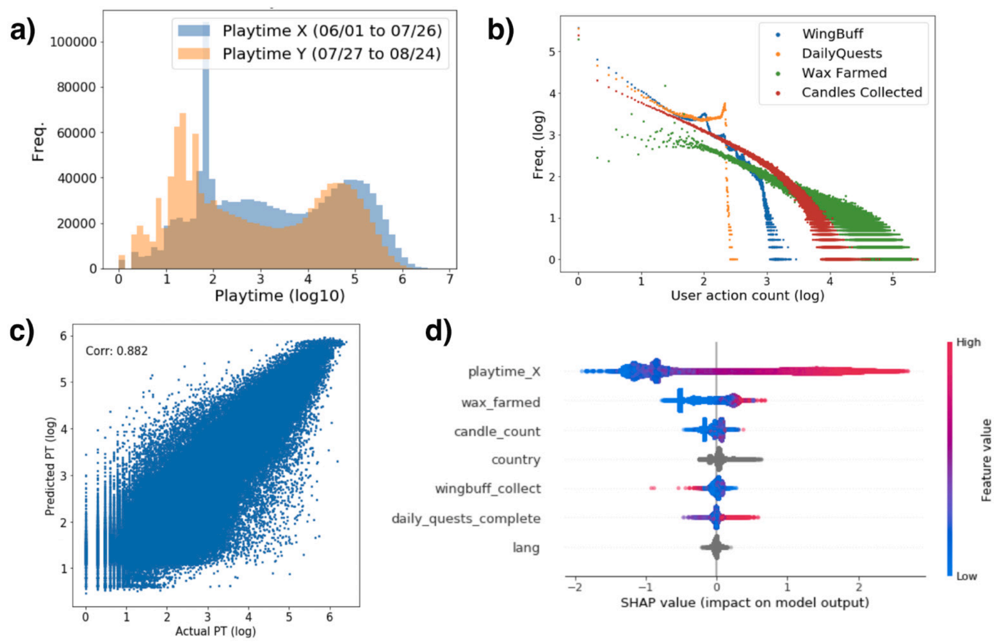

Fig. 2. Descriptives of the user-level feature space. Fig. 2(a) shows a bimodal distribution playtime for both the prior and future time periods. Fig. 2(b) shows a log–log distribution of in-game user actions. Fig. 2(c) shows the correlation of predictions versus actual playtimes. Fig. 2(d) shows results of Shapley value analysis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

feature explainers have become popular in both the scientific and social scientific literature (Ahneman et al., 2018; Chang, 2025b; Chang, Druckman et al., 2025; Hyl et al., 2020).

With the data tables produced, our next step is to generate a machine learning model to estimate future playtime. Whereas the original Social Value algorithm uses a random forest model, we use CatBoost, a gradient boosting model that supports native categorical features. This is immensely useful as we account for countries and language as features. To train the model, we used 2000 iterations, a learning rate of 0.03, depth of 7, and l2 leaf regularization of 7. We performed a 80-20 training-testing split to prevent the possibility of overfitting.

3.4. Computing social value

Finally, we utilize Williams et al. (2023) to compute the Social Value. The final output includes six variables:

- Social Value: The amount of behavior the influencer causes among others. This amount would not occur without their presence in the system.
- Non-Social Value: The amount of behavior not caused by the influencer(s). This is what the person would do without them, and can also be seen as the value of the system itself.
- Receptivity: The inverse of Social Value. This is the amount of extra behavior caused by others on to the focal person. This would not occur without the influencer's presence.
- Network Power: The sum of a person's own Non-Social Value and their influence on others. If the person were to leave the system, this is how much total behaviors would drop, from them and/or among others.

In aggregate, we find Sky has a combined Social Value of 18%, and a full table can be found in the appendix. While this number may vary slightly based on the included variables, because we are conducting user-level comparisons solely on Social Value, these will not impact the direction or significance of our results. The resultant model yields a R2 of 0.88 (Fig. 2c) on the test set. We show these features as, based on the regressor's Shapley values (Fig. 2d). As expected, previous playtime and in-game activity like wax farmed, candle count, and completed daily quests correlate positively.

3.5. Network analysis

Beyond computing Social Value using the underlying network, we also compute centrality measures for each user. Fig. 4 shows a visualization of the candle-exchange network using a physics-based spring algorithm.

In particular, we compute the betweenness centrality, in-degree centrality, out-degree centrality, Katz centrality, and PageRank centrality. Betweenness centrality is a measure of a node's importance in a network based on the concept of the "betweenness" of that node. It quantifies how often a node acts as a bridge or intermediary in the shortest paths between pairs of other nodes in the network. Nodes with high betweenness centrality are crucial for maintaining efficient connectivity in the network, and frequently serve as a proxy for bridges. In-degree centrality is a centrality measure in a directed network that describes the number of incoming connections a node receives. In our case, it means the number of candles received. Out-degree centrality, the opposite of in-degree centrality, assesses the number of outgoing connections from a node; here, it represents the number of candles given.

3.6. Survey deployment

Procedure. Through the collaboration with ThatGameCompany, we distributed a survey within the game Sky between November 20, 2020, and November 30, 2020. This survey was specifically targeted at players who had completed the final realm in the game. Completion of this realm signifies the players' completion of the game's main storyline, involving a journey across seven realms. The survey's distribution in the last realm allows researchers to reach players with a basic understanding of the game's mechanics, such as the use of candles and hearts, fostering reciprocal behaviors in Sky. This approach aimed not only to investigate the social and asocial behaviors of users but also to involve both novice and seasoned players randomly as survey participants.

This study was approved by the University of Southern California Institutional Review Board (Study ID: UP-20-00363), which determined the research to be exempt from 45 CFR 46 under §46.104(d), categories

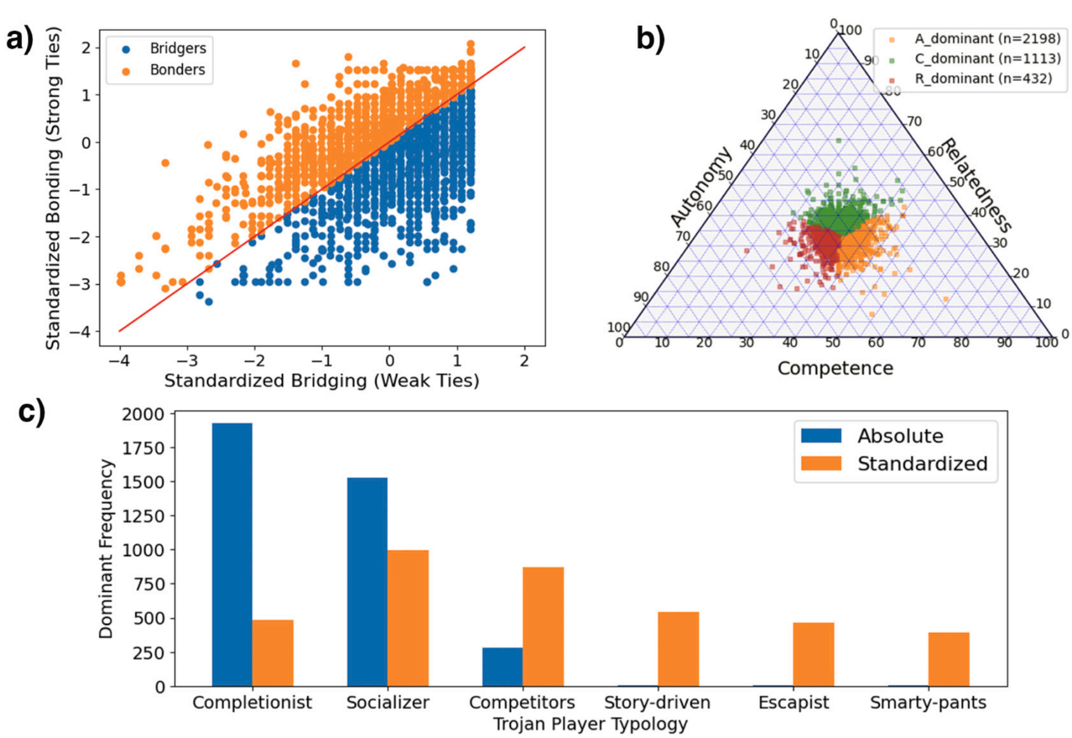

Fig. 3. Distribution of the survey results. (a) shows the bonding and bridging social capital, (b) shows the dominance of one of autonomy, competence, and relatedness, and (c) the dominance of each of the Trojan Player Typologies.

(2) and (4). The study procedures were limited to secondary data analysis and survey completion with adult game players. Informed consent was obtained from all survey participants prior to participation, following the IRB-approved information sheet.

Participants. After running attention checks and excluding incomplete answers, we included 3783 participants in our analysis. Demographics are redacted for privacy concerns. The survey participants were asked to answer questions regarding the Trojan Player Typology, psychological needs, and social capital.

3.6.1. *Measures*

Social Capital. Social Capital Scales (SCS) was adjusted to evaluate the social capital of players (Williams, 2006). 10 items each were used to evaluate bridging and bonding capitals. Using a 5-point Likert scale (ranging from “I disagree completely” to “I agree completely”), participants reported their agreement with statements about their Sky gameplay experience. Bridging social capital was measured using scale items such as “Interacting with people in Sky makes me interested in things that happen outside of my town in real life” and “Interacting with people in Sky makes me want to try new things”. Bonding Social Capital was measured using scale items such as “There are several people in Sky I trust to help solve my problems” and “There is someone in Sky I can turn to for advice about making very important decisions”. These are used as additional controls for network structure.

Trojan Player Typology. Trojan Player Typology scale was modified from Kahn et al. (2015). Socializers, completionist, and Competitors were measured using three items each, and escapist, story-driven, and smarty-pants were measured using two items each. Using a 5-point Likert scale (ranging from “I disagree completely” to “I agree completely”), participants reported their agreement with statements about their Sky gameplay experience.

- Socializer. Socializer was measured using scale items such as “I like to chat with other players while playing Sky (either through the game or some outside method)” and “I like to use some voice system to talk with other people when I play Sky”.
- Completionist. Completionist was measured using scale items such as “I like to master every part of the Sky experience” and “I like to figure out all of the small details of Sky”.
- Competitor. Competitor was measured using scale items such as “I play Sky to accomplish more than others” and “It is important to me to be the most skilled person playing Sky”.
- Escapist. Escapist was measured using scale items, “I like to do things in Sky that I cannot do in real life” and “Sky allows me to pretend I am someone else”.
- Story-driven. Story-driven was measured using scale items, “I like the feeling of being part of the story” and “I like the storylines that play out during Sky”.
- Smarty-pants. Smarty-pants was measured using scale items, “Playing Sky makes me smarter” and “I play Sky to enhance my intellectual abilities”.

Psychological Needs. To examine psychological needs of Sky players, we ask participants to respond to each statement from the Basic Psychological Need Satisfaction Scale (La Guardia et al., 2000) by indicating how true it is for them using a 5-point Likert scale (ranging from “I disagree completely” to “I agree completely”).

- Need for Competence. Need for competence was measured using items such as “When I am playing Sky, I feel like a competent person” and “When I am playing Sky, I feel very capable and effective”.
- Need for Relatedness. Need for relatedness was measured using items such as “When I am playing Sky, I feel cared about in the gaming community” and “When I am playing Sky, I feel a lot of closeness in the gaming community”.

The distributions for these indicators can be summarized in Fig. 3. These distributions indicate good levels of heterogeneity across the different traits– predilection for certain types for strong ties and weak ties, deviance toward a particular psychological need, and primary driver for game play.

We matched players' survey data with their in-game behavior data using a unique player ID. The combination of digital trace data and surveys is a powerful contemporary tool to link mechanistic-level measurements with observational behavior, including in games (Choi et al., 2023; Kim et al., 2022; Liu et al., 2024) and social media (Burke et al., 2011; Nyhan et al., 2023).

All player IDs were anonymized with an encrypted hash function before reaching the research team. It is a one-way hashing function that is used to protect the integrity and privacy of exchanged data (Mohammed et al., 2016). This encryption method has also been applied in recent video game research that linked players' survey responses to their in-game data (Johannes et al., 2021). The team never saw personally identifiable information or player IDs. As our data collection was conducted through a partnership with the game operator, *thatgamecompany*, the dataset is subject to a non-disclosure agreement. This arrangement prevents us from making the raw data publicly available, as doing so could compromise user privacy and would conflict with the company's data governance policies. However, we are happy to pass along any requests to the company for consideration.

4. Results

Fig. 4 shows the CatBoost regression results for our independent variables against Social Value. Fig. 4a shows the results of network centrality, number of outfits, social capital, and psychological needs. We find, in both cases, betweenness and out-degree are the most significant and correlate positively. Importantly, out-degree is not just significantly more important than in-degree for predicting Social Value, but correlates positively. In-degree correlates negatively. This indicates embedded altruism strongly determines social influence. The number of outfits is the third most important, indicating status quite significantly predicts social influence, followed by the Trojan Player Typology. However, compared to centrality measures, they do not exhibit clear directionality. While the importance of network centrality for social influence may seem tautological, these measures are not observable to normal users. In other words, our inclusion and exclusion here serves as a control for status serving as a proxy for network connections.

Although a clear directionality from the regression is not apparent, we can still demonstrate the extent of explained variance using hierarchical regression, where we build regression models based on the different power sets of variables. Fig. 5 shows the r^2 values under these different combinations. In particular, we delineate individual factors (the Trojan Player Typology, psychological needs, and perceived social capital) with social factors (network centrality scores and clothing).

In Fig. 5(a), only training on social capital and psychological needs as individual traits yields an r^2 of 0.46 (blue). Adding in the number of clothes increases that by 0.16 to 0.62 (green). Adding network measures yields the greatest increase of 0.28, moving to 0.77 (orange). Crucially, when adding the number of clothes to this last set, there is only an increase of 0.06. This indicates significant overlap between the number of clothes and network measures. In other words, signals of status can encode for one's position in the network.

This finding remains consistent when using Trojan Player Typology (Fig. 5b) as individual traits. Individual traits yield an r^2 of 0.55. Adding status increases this by 0.2, whereas adding centrality scores increases this by 0.34. Importantly, adding status to individual traits and network measures increases r^2 by another 0.07. These results suggest the inclusion of status may act in a similar fashion to network measures directly.

Again, it is important to note, by design, Sky is an information sparse environment. Users can only see the visuals of other players. In other words, in absence of communicative cues within the game, status can be perceived as network ties. At the same time, status also increases the predictive model marginally, indicating elements from status alone can also increase influence. This demonstrates **H1**.

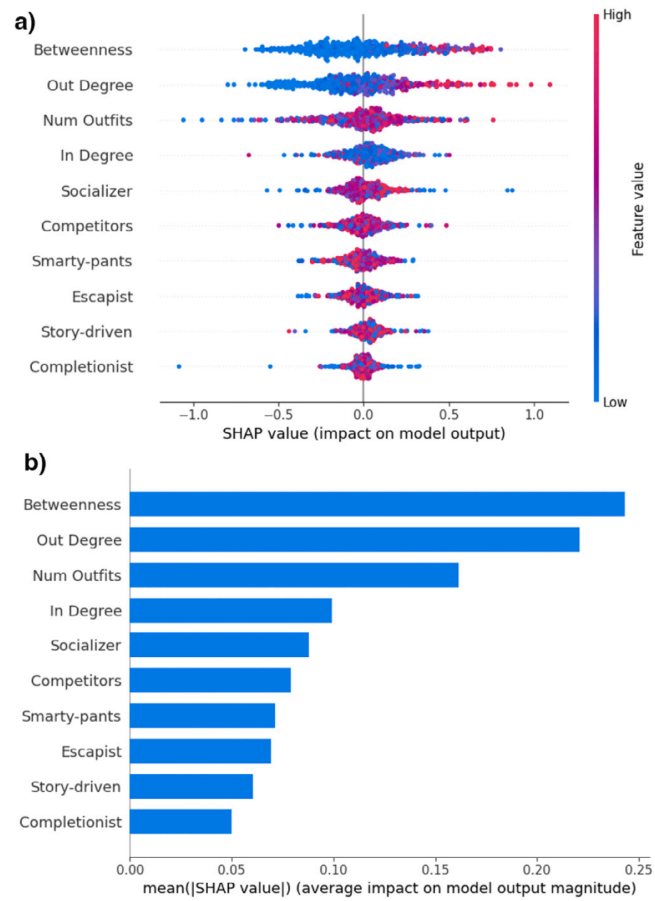

Fig. 4. Modeling results for predicting Social Value. (a) Shapley values for centrality values with social capital, number of outfits, and psychological needs and (b) their overall importance, with $r^2 = 0.96$.

Lastly, we directly consider if there are differences in Social Value across the categories of psychological needs, perceived social capital, and Trojan Player Typology. Only Trojan player typology yields significant differences in Social Value. Fig. 6 shows Social Values grouped by the dominant player type after standardization. Overall, Socializers and Competitors have the highest Social Value; Completionists have the lowest Social Value. This is well within expectation. Players that like to socialize have more social influence; players who play in order to finish the game have less social influence. In other words, there is a clear distinction between players who stress the social dimension versus the affordance dimension of game play.

Interestingly, we find Socializers (H3) to have the highest influence. Contrary to expectations, Competitors also highly influence others (H4), whereas Completionists have the lowest Social Value (H5) across all Trojan Personality Types. Both H6 and H7 do not demonstrate sufficient statistical significance. We summarize all of these findings in Table 1.

5. Discussion

In this study, we investigate social architectures and influence dynamics within online digital environments, using the game "Sky" as a rich, naturalistic case. While computational approaches such as the Social Value algorithm can identify influential members within a network, they fall short of explaining why influence emerges or which individual and structural factors drive it. Addressing this critical gap requires both large-scale behavioral data and psychometric measures—resources rarely available in tandem. Leveraging a unique collaboration

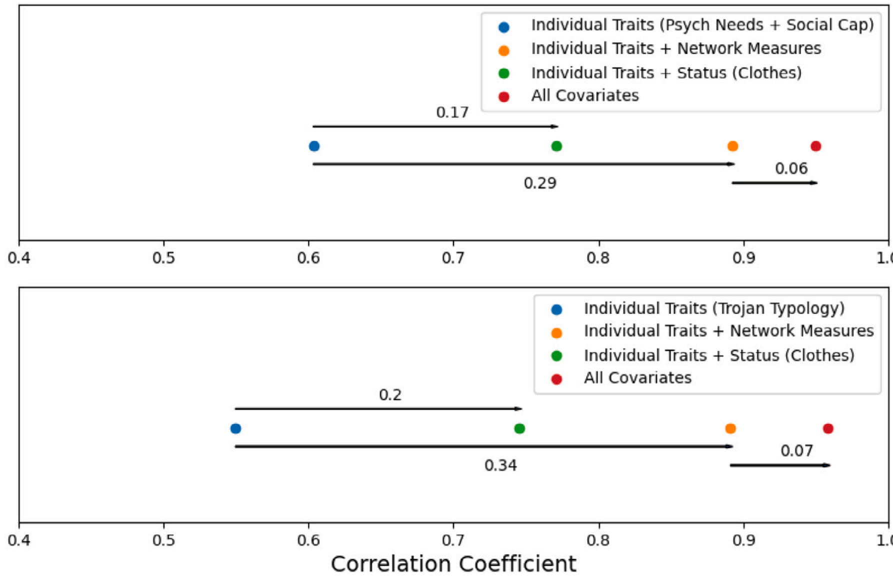

Fig. 5. Correlation coefficients from power sets of variable groups. Fig. 5(a) shows social capital and psychological needs (blue), with network measures (orange), with the number of clothes (green), and all features (red). Fig. 5(b) shows Trojan player typology (blue), with network measures (orange), with the number of clothes (green), and all features (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of hypotheses and empirical support.

Hypothesis	Supported?
H1: Individuals with more in-game outfits, which indicate higher in-game status, are more likely to influence others.	Yes.
H2: Individuals with higher network centrality are more likely to influence others.	Yes; specifically, betweenness and out-degree are the most significant and correlate positively.
H3: Socializers will be more likely to influence others.	Yes. Socializers and Competitors have the highest Social Value.
H4: Completionists will be more likely to influence others.	No. Completionists have the lowest Social Value.
H5: Competitors will not influence others.	No. Socializers and Competitors have the highest Social Value.
H6: Individuals with high perceived competence are more likely to influence others.	Not statistically significant.
H7: Individuals with high perceived relatedness are more likely to influence others.	Not statistically significant.

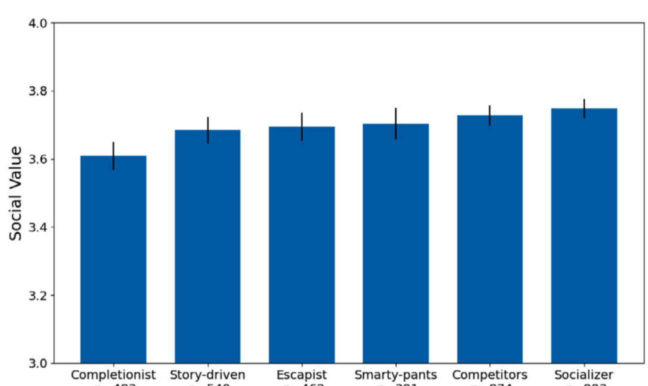

Fig. 6. Social Value by Trojan player typology.

with the game publisher, *thatgamecompany*, the present study integrates network analytics with psychological profiling to unpack the mechanisms underlying digital influence. Guided by the SIDE and SIP frameworks, we show that influence arises from the interplay between network position and individual characteristics. Moreover, in the cue-sparse context of Sky, players rely on a salient symbolic cue — avatar outfits — as a cognitive shortcut for recognizing social status and influence. Together, these contributions advance theoretical understanding of online influence while demonstrating the empirical power of combining large-scale behavioral data with in-depth psychometric measures.

Network centrality is critical to social influence, with the most altruistic (out-degree) and embedded (betweeness) having the highest Social Value. We do not find evidence of increased social influence across psychological needs, but we do find higher levels of influence amongst Socializers and Competitors, and the lowest amongst Completionists. Crucially, we validate our principal hypothesis regarding SIDE theory— in absence of visible social networks and anonymization of individual features, status (i.e. clothing) serves as a proxy for these connections. Practically, designers of social platforms can optimize how such cues are presented to reduce bias and enhance meaningful interaction, especially in cue-sparse environments. Developers and community managers can also identify and empower constructive influencers — those who model cooperative or inclusive behaviors — to sustain positive social climates.

In *Sky*, cosmetics serve as the primary means for players to express their individuality and character. These cosmetics can be purchased and customized, with fancier options generally requiring more in-game currency. Players can obtain the necessary currency through sustained effort (e.g., candle farming) or through monetary purchase, meaning that one's outfits reflect both resource commitment and motivational orientation. Players driven by achievement and competition often take pride in accumulating cosmetics, signaling expertise and dedication through distinctive, diverse outfit choices that attract others' attention and deference. Conversely, given that Sky emphasizes social progression over competition, players motivated by socializations may adopt popular or seasonal outfits to enhance sociability, attract new friends, and strengthen their social standing. Collectively, these patterns illustrate how signaling mechanisms in information-sparse environments can amplify the influence of high-performing or socially attuned individuals, making visual self-presentation a key driver of digital influence. Results also support the application of SIDE and SIP in a digital gaming context.

Our findings also bear similarities with the framework of Network Ecology (Doehne et al., 2023; McFarland et al., 2014), which frames features as the proximal environment which moderate tie-formation mechanisms, which spans even financial and geopolitical networks (Chang et al., 2023; Chang, Herbert et al., 2025). Sky's distinctive ecology channels relational dynamics in ways that amplify the salience of status cues, consistent with the framework's prediction that contextual affordances shape which social signals stabilize into durable relations and influence.

There are a few possible limitations. First, while gradient-boosting trees such as CatBoost are powerful machine learning regressors, they are also prone to overfitting. While the training-test split we performed should mitigate this, robustness checks using different regressors (i.e. XGBoost (Chen & Guestrin, 2016)) or even building canonical models can improve future evaluations (Chang, 2025a). Second, reliance on proprietary data means replicability is difficult. Additionally for methodology, Selection bias could also influence our subset of users, as we only include users who have progressed past the tutorial. However, this is in some sense a more meaningful subset of users, who have full access to the full modality of communication and features. While data sharing agreements with companies are growing increasingly prevalent (Burke et al., 2011; Liu et al., 2024; Nyhan et al., 2023), this data cannot be shared as is the associated demographic data, in order to protect the privacy of users. However, new methods in differential privacy — representative transformations to the underlying data that preserve distributional metrics — may pave a way for more open data sharing paradigms (Abadi et al., 2016).

As future work, studies focused on the progression of communication could be of immense interest. In Sky, each pair of players progresses through nonverbal and verbal communication features (e.g., unlocking the chat or hugging functions) through mutual investment of in-game resources. Consequently, there is considerable within-person and dyadic variation in communication development. Future work that tests how the diversity of unlocked communication options affects social value is of critical interest. It is plausible that players who have unlocked more social features with their network experience greater enjoyment and are more likely to remain in the game—and, in turn, influence others to do the same.

While our study focused on *Sky*, similar social environments and influential dynamics may exist in not just other gaming platforms, but emergent organizations: contingent on the environment, influential individuals must possess not only good people skills but also high competence. Engaging with long-standing debates around mapping of findings from virtual worlds to real-world scenarios becomes crucial. Further research will help compare this speculation against similar titles and contrast it with different social architectures as the field develops and can slowly begin to make more generalizable claims. We view our study in a Popperian sense –if the data cohere with our predictions, that means the continued accumulation of evidence for media richness and influence processes.

CRediT authorship contribution statement

Ho-Chun Herbert Chang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mingxuan Liu:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Sukyoung Choi:** Writing – review & editing, Writing – original draft, Validation, Investigation, Conceptualization. **Eu Gene Lee:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation, Conceptualization. **Dmitri Williams:** Writing – review & editing, Writing – original draft, Validation, Investigation, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors have nothing to declare.

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Data availability

The authors do not have permission to share data.

References

Abadi, M., Chu, A., Goodfellow, I., McMahan, H. B., Mironov, I., Talwar, K., & Zhang, L. (2016). Deep learning with differential privacy. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security* (pp. 308–318). http://dx.doi.org/10.1145/2976749.2978318.

Adler, P. S., & Kwon, S.-W. (2002). Social capital: Prospects for a new concept. *Academy of Management Review*, *27*(1), 17–40. http://dx.doi.org/10.5465/amr.2002.5922314.

Ahneman, D. T., Estrada, J. G., Lin, S., Dreher, S. D., & Doyle, A. G. (2018). Predicting reaction performance in C–N cross-coupling using machine learning. *Science*, *360*(6385), 186–190. http://dx.doi.org/10.1126/science.aar5169.

Annetta, L. A. (2008). Video games in education: Why they should be used and how they are being used. *Theory into Practice*, *47*(3), 229–239. http://dx.doi.org/10.1080/00405840802153940.

Backhouse, R. E., & Fontaine, P. (Eds.), (2014). *A historiography of the modern social sciences*. Cambridge University Press, http://dx.doi.org/10.1017/CBO9781139013741.

Bandura, A. (2009). Social cognitive theory of mass communication. In *Media effects* (pp. 110–140). Routledge, http://dx.doi.org/10.4324/9780203877111-8.

Bartle, R. (1996). Hearts, clubs, diamonds, spades: Players who suit MUDs. *Journal of MUD Research*, *1*(1), 19.

Breiger, R. L., Lomi, A., & Pallotti, F. (2025). Culture as configurations of categories: Analyzing peer effects via dual-to-regression modeling. *Poetics*, *111*, Article 102014. http://dx.doi.org/10.1016/j.poetic.2024.102014.

Burke, M., Kraut, R., & Marlow, C. (2011). Social capital on facebook: Differentiating uses and users. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 571–580). http://dx.doi.org/10.1145/1978942.1979023.

Burt, R. S. (2012). Network-related personality and the agency question: Multirole evidence from a virtual world. *American Journal of Sociology*, *118*(3), 543–591. http://dx.doi.org/10.1086/667856.

Castronova, E. (2006). On the research value of large games: Natural experiments in Norrath and Camelot. *Games and Culture*, *1*(2), 163–186. http://dx.doi.org/10.1177/1555412006286686.

Castronova, E., Williams, D., Shen, C., Ratan, R., Xiong, L., Huang, Y., & Keegan, B. (2009). As real as real? Macroeconomic behavior in a large-scale virtual world. *New Media & Society*, *11*(5), 685–707. http://dx.doi.org/10.1177/1461444809105346.

Chang, H.-C. H. (2025a). Measuring social influence with networked synthetic control. http://dx.doi.org/10.48550/arXiv.2505.13334, arXiv preprint arXiv:2505.13334.

Chang, H.-C. H. (2025b). Pet ownership ties as indicators for giving behavior. *Anthrozoös*, 1–12. http://dx.doi.org/10.1080/08927936.2025.2544418.

Chang, H.-C. H., Druckman, J. N., Ferrara, E., & Willer, R. (2025). Liberals and conservatives share information differently on social media. *PNAS Nexus*, *4*(7), Article pgaf206. http://dx.doi.org/10.1093/pnasnexus/pgaf206.

Chang, H.-C. H., Harrington, B., Fu, F., & Rockmore, D. N. (2023). Complex systems of secrecy: The offshore networks of oligarchs. *PNAS Nexus*, *2*(3), Article pgad051. http://dx.doi.org/10.1093/pnasnexus/pgad051.

Chang, H.-C. H., Harrington, B., & Rockmore, D. (2025). Secrecy strategies: Global patterns in elites' quest for confidentiality in offshore finance. *PLoS ONE*, *20*(7), Article e0326228. http://dx.doi.org/10.1371/journal.pone.0326228.

Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785–794). http://dx.doi.org/10.1145/2939672.2939785.

Choi, S., Liu, M., Sun, J., & Huang-Isherwood, K. M. (2023). Who benefits from directed communication? Communication directionality, network structures, and perceived social capital in an online game. *Computers in Human Behavior*, *147*, Article 107825. http://dx.doi.org/10.1016/j.chb.2023.107825.

Cialdini, R. B. (1993). *Influence: The psychology of persuasion*. Quill.

Contractor, N. S., & DeChurch, L. A. (2014). Integrating social networks and human social motives to achieve social influence at scale. *Proceedings of the National Academy of Sciences*, *111*(supplement_4), 13650–13657. http://dx.doi.org/10.1073/pnas.1401211111.

Crookall, D. (1999). Editorial: Internet simulation/gaming. *Simulation & Gaming*, *30*(1), 5–6. http://dx.doi.org/10.1177/104687819903000101.

Curtin, M. (2017). This 75-year harvard study found the 1 secret to leading a fulfilling life. https://www.inc.com/melanie-curtin/want-a-life-of-fulfillment-a-75-year-harvard-study-says-to-prioritize-this-one-t.html. (Accessed 27 August 2024).

Dai, Y., & Shi, J. (2022). Vicarious interactions in online support communities: The roles of visual anonymity and social identification. *Journal of Computer-Mediated Communication*, *27*(3), Article zmac006. http://dx.doi.org/10.1093/jcmc/zmac006.

Doehne, M., McFarland, D. A., & Moody, J. (2023). Network ecology: Tie fitness in social context(s). *Social Networks*, *76*, 159–178. http://dx.doi.org/10.1016/j.socnet.2023.09.003.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5), 1189–1232. http://dx.doi.org/10.1214/aos/1013203451.

Gibson, J. J. (1977). The theory of affordances. In R. Shaw, & J. Bransford (Eds.), *Perceiving, acting, and knowing: Toward an ecological psychology* (pp. 67–82). Erlbaum.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. http://dx.doi.org/10.1086/225469.

Hyland, S. L., Faltys, M., Hüser, M., Lyu, X., Gumbsch, T., Esteban, C., Bock, C., Horn, M., Moor, M., Rieck, B., Zimmermann, M., Bodenham, D., Borgwardt, K., Rätsch, G., & Merz, T. M. (2020). Early prediction of circulatory failure in the intensive care unit using machine learning. *Nature Medicine*, *26*(3), 364–373. http://dx.doi.org/10.1038/s41591-020-0789-4.

Johannes, N., Vuorre, M., & Przybylski, A. K. (2021). Video game play is positively correlated with well-being. *Royal Society Open Science*, *8*(2), Article 202049. http://dx.doi.org/10.1098/rsos.202049.

Kahn, A. S., Shen, C., Lu, L., Ratan, R. A., Coary, S., Hou, J., Meng, J., Osborn, J., & Williams, D. (2015). The trojan player typology: A cross-genre, cross-cultural, behaviorally validated scale of video game play motivations. *Computers in Human Behavior*, *49*, 354–361. http://dx.doi.org/10.1016/j.chb.2015.03.018.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. *Vol. 30*, In *Advances in neural information processing systems* (pp. 3146–3154).

Kim, S. S., Huang-Isherwood, K. M., Zheng, W., & Williams, D. (2022). The art of being together: How group play can increase reciprocity, social capital, and social status in a multiplayer online game. *Computers in Human Behavior*, *133*, Article 107291. http://dx.doi.org/10.1016/j.chb.2022.107291.

La Guardia, J., Ryan, R., Couchman, C., & Deci, E. (2000). Basic psychological needs scales. *Journal of Personality and Social Psychology*, *79*(3), 367–384. http://dx.doi.org/10.1037/0022-3514.79.3.367.

Lea, M., Spears, R., & De Groot, D. (2001). Knowing me, knowing you: Anonymity effects on social identity processes within groups. *Personality and Social Psychology Bulletin*, *27*(5), 526–537. http://dx.doi.org/10.1177/0146167201275002.

Liu, Y. (2023). The proteus effect: Overview, reflection, and recommendations. *Games and Culture*, *20*(3), http://dx.doi.org/10.1177/15554120231202175.

Liu, M., Choi, S., Kim, D. O., & Williams, D. (2024). Connecting in-game performance, need satisfaction, and psychological well-being: A comparison of older and younger players in world of tanks. *New Media & Society*, *26*(2), 692–710. http://dx.doi.org/10.1177/14614448211062545.

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Vol. 30*, In *Advances in neural information processing systems* (pp. 4765–4774).

Martens, T. (2019). The player: With 'sky,' thatgamecompany's Jenova Chen wants to fix what's broken with games. https://www.latimes.com/entertainment/herocomplex/la-et-hc-sky-thatgamecompany-20190709-story.html. (Accessed 27 August 2024).

Marwick, A. (2013). *Status update: Celebrity, publicity, and branding in the social media age*. Yale University Press.

McClure, R. F., & Mears, F. G. (1984). Video game players: Personality characteristics and demographic variables. *Psychological Reports*, *55*(1), 271–276. http://dx.doi.org/10.2466/pr0.1984.55.1.271.

McFarland, D. A., Moody, J., Diehl, D., Smith, J. A., & Thomas, R. J. (2014). Network ecology and adolescent social structure. *American Sociological Review*, *79*(6), 1088–1121. http://dx.doi.org/10.1177/0003122414554001.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. http://dx.doi.org/10.1146/annurev.soc.27.1.415.

Mohammed, E. A., Slack, J. C., & Naugler, C. T. (2016). Generating unique IDs from patient identification data using security models. *Journal of Pathology Informatics*, *7*(1), 55. http://dx.doi.org/10.4103/2153-3539.197197.

Nyhan, B., Settle, J., Thorson, E., Wojcieszak, M., Barberá, P., Chen, A. Y., Allcott, H., Brown, T., Crespo-Tenorio, A., Dimmery, D., et al. (2023). Like-minded sources on facebook are prevalent but not polarizing. *Nature*, *620*(7972), 137–144. http://dx.doi.org/10.1038/s41586-023-06297-w.

Popper, K. R. (2002). *The logic of scientific discovery*. Routledge, http://dx.doi.org/10.4324/9780203994627.

Postmes, T., Spears, R., & Lea, M. (2002). Intergroup differentiation in computer-mediated communication: Effects of depersonalization. *Group Dynamics: Theory, Research, and Practice*, *6*(1), 3. http://dx.doi.org/10.1037/1089-2699.6.1.3.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: Unbiased boosting with categorical features. *Vol. 31*, In *Advances in neural information processing systems* (pp. 6638–6648). http://dx.doi.org/10.48550/arXiv.1706.09516.

Putnam, R. D. (2001). *Bowling alone: The collapse and revival of American community*. Simon & Schuster.

Spears, R. (2017). Social identity model of deindividuation effects. *The International Encyclopedia of Media Effects*, 1–9. http://dx.doi.org/10.1002/9781118783764.wbieme0091.

Tamborini, R., & Bowman, N. D. (2010). Presence in video games. In C. C. Bracken, & P. Skalski (Eds.), *Immersed in media: Telepresence in everyday life* (pp. 87–109). Routledge, http://dx.doi.org/10.4324/9780203892220.

Tang, W. Y., & Fox, J. (2016). Men's harassment behavior in online video games: Personality traits and game factors. *Aggressive Behavior*, *42*(6), 513–521. http://dx.doi.org/10.1002/ab.21646.

Walther, J. B., DeAndrea, D., Kim, J., & Anthony, J. C. (2010). The influence of online comments on perceptions of antimarijuana public service announcements on YouTube. *Human Communication Research*, *36*(4), 469–492. http://dx.doi.org/10.1111/j.1468-2958.2010.01384.x.

Wijman, T., Fernandes, G., & Doan, L. (2020). Global games market report: April 2020 update. https://newzoo.com/insights/trend-reports/newzoo-global-games-market-report2020-light-version. (Accessed 27 August 2024).

Williams, D. (2006). On and off the 'net: Scales for social capital in an online era. *Journal of Computer-Mediated Communication*, *11*(2), 593–628. http://dx.doi.org/10.1111/j.1083-6101.2006.00029.x.

Williams, D. (2010). The mapping principle, and a research framework for virtual worlds. *Communication Theory*, *20*(4), 451–470. http://dx.doi.org/10.1111/j.1468-2885.2010.01371.x.

Williams, D. (2018). For better or worse: Game structure and mechanics driving social interactions and isolation. In C. J. Ferguson (Ed.), *Video game influences on aggression, cognition, and attention* (pp. 173–183). Cham: Springer, http://dx.doi.org/10.1007/978-3-319-95495-0_7.

Williams, D., Contractor, N., Poole, M. S., Srivastava, J., & Cai, D. (2011). The virtual worlds exploratorium: Using large-scale data and computational techniques for communication research. *Communication Methods and Measures*, *5*(2), 163–180. http://dx.doi.org/10.1080/19312458.2011.583443.

Williams, D., Khan, E. M., Pathak, N., & Srivastava, J. (2023). Social value: A computational model for measuring influence on purchases and actions for individuals and systems. *Journal of Advertising*, *52*(2), 247–263. http://dx.doi.org/10.1080/00913367.2021.2002743.

Yang, A., & Williams, D. (2026). Finding receptive donors: Unpacking the dynamics of social influence in large-scale political donor networks. *Nonprofit Management and Leadership*, 1–28. http://dx.doi.org/10.1002/nml.70051.

Zeng, W., Kumar, C., Zhou, S., Kim, D., Yang, A., & Williams, D. (2026). Capability, opportunity, and motivation in a social multiplayer online game: Player influence dynamics in sky: Children of light. *Social Science Computer Review*, Article 08944393251414170. http://dx.doi.org/10.1177/08944393251414170.