With great power comes great accountability: Network positions, victimization, perpetration, and victim-perpetrator overlap in an online multiplayer game

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3 authors:

Mingxuan Liu
University of Southern California

Qiusi Sun
University of California, Davis

Dmitri Williams
University of Southern California

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With great power comes great accountability: Network positions, victimization, perpetration, and victim-perpetrator overlap in an online multiplayer game

Mingxuan Liu
University of Macau, China

Qiusi Sun
Syracuse University, USA

Dmitri Williams
University of Southern California, USA

Abstract

Can players' network-level parameters predict gaming perpetration, victimization, and their overlap? Extending the Structural Hole Theory and the Shadow of the Future Effect, this study examines the potential advantages and accountability conferred by key network metrics (i.e., ego network size, brokerage, and closure) and their behavioral implications. Using longitudinal co-play network and complaint data from 55,760 players in an online multiplayer game over two months, the findings reveal that higher network size is associated with greater perpetration and reduced victimization. Network closure is linked to reduced involvement in both perpetration and victimization, while network brokerage is linked to increased involvement in both. The overlap of perpetration and victimization is predicted by higher network size and lower closure. Theoretically, this study complements existing research on gaming toxicity from a structural perspective.

Corresponding author:
Mingxuan Liu, Department of Communication, University of Macau, Macao 999078, China.
Email: mxliu@um.edu.mo

Practically, the findings underscore the importance of considering network elements, particularly network closure, in designing interventions to mitigate gaming toxicity.

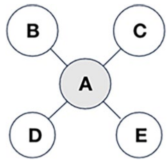
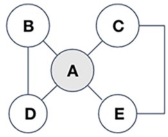
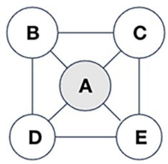
Keywords
Gaming toxicity, network brokerage, network closure, network size, perpetration–victimization overlap, shadow of the future, structural hole

Online multiplayer video games have become a global phenomenon, connecting millions of players in the virtual worlds (Entertainment Software Association, 2023). However, this vast interconnectedness also fosters an environment where interactions can turn sour, leading to player complaints of victimization and perpetration—commonly referred to as gaming toxicity (Shen et al., 2020). Toxicity refers to behaviors that are deemed disruptive and harmful to the experience, health, or well-being of others, regardless of their intent (Kordyaka et al., 2020). The perpetration of toxic behavior involves acts that impose such toxicity on others, while victimization refers to the experience of being the target of others' toxicity (Vandebosch and Van Cleempu, 2009). According to the Anti-Defamation League (ADL) (2022) survey, in 2021, 72% of players have witnessed gaming toxicity, while 68% have experienced it themselves. The deleterious consequences of gaming toxicity extend beyond financial losses to the gaming industry and disruption to social norms of online communities (Grandprey-Shores et al., 2014) to encompass the health and well-being of those affected, including the perpetrators themselves (ADL, 2022) and their families (Eisenberg et al., 2015; Marchiondo et al., 2020).

The perpetration of toxic behavior is fundamentally a social phenomenon that emerges from human interactions within specific relationships and contexts (Pauksztat and Salin, 2021). Different network positions result in an unequal distribution of status and social power, leading to disparities in how individuals experience protection from or vulnerability to harmful behaviors (Lamertz and Aquino, 2004). Structural Hole Theory (SHT; Burt, 2001) sheds light on these disparities from a socio-structural perspective. SHT suggests that individuals serving as "brokers" between otherwise unconnected groups—a phenomenon known as network brokerage—enjoy greater informational advantages than those less connected to diverse groups. Similarly, individuals integral to tightly-knit communities, demonstrated by a high level of network closure, experience unique positional advantages. These advantages include access to diverse information and a wider support network, providing them with informational and emotional leverage over others. Conversely, individuals positioned at the periphery of their networks, or those with fewer connections—described by their low network size—often find themselves at a disadvantage. This power imbalance, inherent to the dynamics of bullying (Pauksztat and Salin, 2021), underscores the impact of network positions on individuals' experiences in networked gaming environments.

While individuals in key network positions enjoy certain advantages compared with their less connected counterparts, they also face heightened accountability due to their close integration within the network. Drawing on principles from evolutionary and game theory, individuals are inclined to engage in competition and cooperate only when they

Table 1. Illustration of network metrics and accountability cues.

Network metrics	Structural illustration		Accountability cues
Network size		Network size	Low deindividuation, high accountability
Network brokerage		Structural hole/ network brokerage	High deindividuation, low accountability
Network closure		Network closure	Low deindividuation, high accountability

anticipate rewards for cooperation, expect ongoing interactions, and foresee penalties for non-cooperation (Van Lange et al., 2011). This perspective is commonly referred to as the Shadow of the Future Effect (SFE; Axelrod and Hamilton, 1981). In the context of video games, players positioned in certain network locations, such as those within tightly-knit networks, tend to engage in repeated interactions with familiar peers and anticipate future interactions. While they enjoy the advantages of playing with a stable group of people, they may be more likely to regulate their behaviors due to the potential costs that others may impose on them. Taken together, distinct network positions yield varying behavioral implications for perpetration, victimization, and their overlap. An illustration of network metrics (Berto & Sunarwinadi, 2019) and their implications for anonymity and accountability can be found in Table 1.

Current research has provided valuable insights into the structural underpinnings and social dynamics of gaming toxicity. The gaming environment, embedded within everyday social experiences, often mirrors and potentially exacerbates existing inequalities (Apperley and Gray, 2020; Cote, 2020). Networked games create a nexus where technology, identity, society, and various forms of power, inequality, and discrimination intersect (Gray, 2020). Specifically, the anonymity afforded by the gaming environment (Kordyaka et al., 2020) and the zero-sum designs of many games (Adinolf and Turkay, 2018) grant certain players privileges while normalizing hostility and the exclusion of others (Paul, 2018). These dynamics overlook the fact that people's access to (the first-level digital divide) and use of games (the second-level digital divide; Hargittai, 2001) often depend on factors beyond their control, such as the time invested in gaming or access to resources. Consequently, meritocratic ideals are often celebrated in online gaming, reproducing and perpetuating social inequality and creating what Massanari (2017) defines as "toxic technocultures."

While many critical scholars have examined gaming toxicity from a socio-structural perspective, with a few exceptions (e.g., Yokotani and Takano, 2021), most social network analysis (SNA)-based works have yet to provide empirical evidence on how much weight that network carries in explaining, identifying, and predicting gaming toxicity. To address this gap in the literature, the current study utilizes large-scale, unobtrusively collected longitudinal egocentric network data and data on toxic behavior from the popular online multiplayer video game, *World of Tanks (WoT)*. *WoT* is a competitive, vehicle-based multiplayer game with cooperative elements, where players join "random" battles on one of two teams with the objective of either capturing the enemy's base or eliminating all enemy tanks. In contrast to match-based games like *League of Legends*, *WoT* does not match teams based on player skills but rather on the types and tiers of tanks they use. This often results in teams with disparate skill levels, leading to lopsided results and more emotional swings. This disparity in skill levels between and within teams is a significant source of gaming toxicity. Consequently, players are incentivized to team up with their preferred players instead of entering random battles with strangers. Given the competitive nature of the game, it serves as an ideal environment for studying gaming toxicity. In this context, the co-play network signifies the relationships individuals are typically immersed in when they experience gaming toxicity. Thus, this study examines players' positions within their co-play network to capture the dynamic relationship between network position and involvement in gaming toxicity.

By integrating SHT and SFE, this study examines how players' network positions predict their involvement in perpetration, victimization, and their overlap in an online multiplayer game. The remainder of this article is structured as follows: We first review the literature on key network metrics (i.e., network size, brokerage, and closure) and connect that with individuals' propensity to engage in perpetration and experience victimization. We then use network positions to explain the phenomenon of perpetration–victimization overlap, and conclude with an overview of the academic and practical implications that arise from this research.

Network embeddedness and perpetration

The power difference between individuals is one of the crucial predictors of toxicity (Aivazpour and Beebe, 2018), while differences in social interactions and network positions lead to differences in power (Cook and Emerson, 1978). Research has long recognized that power is not solely an outcome of formal status, but also a characteristic of one's position in a network structure, regardless of whether the individual is cognizant of their position or level of power (Cook and Emerson, 1978). Therefore, in recent years, there have been mounting calls to study online toxicity from a socio-structural perspective, using SNA to account for individuals' social ties and relationships in toxicity dynamics (Laurie-ann et al., 2021; Wegge et al., 2013). The socio-structural perspective has been applied in organizational settings (Lamertz and Aquino, 2004) and in cyberbullying research (e.g., Sun and Shen, 2021; Wegge et al., 2015). However, its application in gaming toxicity is still in its infancy, and the current study extends this perspective by studying three key network elements: network size, network brokerage, and network closure, in a popular online multiplayer video game.

While a larger number of friends tends to endow individuals with advantages over less connected others, the perceived costs and accountability influence whether individuals use their advantages for perpetration. The selective avoidance of disruptive behavior by popular members has been documented in the diffusion of innovation (DOI; Rogers, 1995, 2010) literature. Research under DOI has repeatedly found that typically, central members enjoy popularity and influence, thus facilitating the spread of behaviors through their connections. However, in circumstances where behaviors are considered risky or incompatible with existing norms, the diffusion of behaviors may occur in the opposite direction—flowing from peripheral actors to central actors (Chen et al., 2021). This tendency likely arises from the disincentives for central members to adopt non-normative and potentially threatening behaviors that could jeopardize their social status. Conversely, individuals who experience less social pressure, such as those with fewer social connections or individuals serving as brokers, are more inclined to engage in initial experimentation of risky and non-normative behaviors (Sgourev, 2013). In addition, when playing with their self-selected teammates, under the SFE, players have a lower level of anonymity and a higher level of accountability, thus tend to regulate their behavior to a greater extent than when engaging with unfamiliar counterparts. This behavior regulation arises from the desire to avoid being perceived as a toxic player, a reputation that could hinder future collaborations with friends. Therefore, it is predicted that:

H1: Individuals with larger network sizes will engage in fewer toxic behaviors.

In addition to network size, network brokerage and closure are two other pivotal network factors that are likely to predict players' involvement in gaming toxicity. According to SHT (Burt, 1992, 1995, 2007), network brokerage refers to the social structure where the ego connects structural holes, meaning that the ego links to individuals who are otherwise unconnected. Building connections across structural holes enables access to heterogeneous information and resources, which provide individuals with diverse perspectives, information, resources, and opportunities (Granovetter, 1973; Williams, 2006). On the contrary, network closure refers to the social structure where the ego is linked to individuals who are already connected with each other. With everyone connected to everyone else, members are more likely to share similar views and information and less likely to engage in deviant behaviors due to decreased anonymity and perceived sanctions from their network (Burt, 2001). These redundant strong ties connect closely-knit networks of individuals or groups that are similar to each other, thus promoting emotional support, trust, and a sense of belonging (Lee et al., 2018).

For individuals located in a broker position, on the one hand, they have access to more resources and opportunities, thus making them have more advantages compared with others. For example, in video game contexts, players in a broker position connect otherwise unconnected players and groups and thus may be perceived as resourceful by others. They also get exposed to more playing styles and team dynamics, thus may be more accustomed to different types of players and game modes, and have learned more tricks of the game. On the other hand, they are embedded in weak ties, and their friends are not closely connected with each other, making them less accountable for their actions. The

SFE also applies less to them since losing one connection does not devastate their reputation or informal power. Consequently, they may be more inclined to engage in aggressive behaviors toward others, especially in a zero-sum competitive video game where winning is the primary reward. Therefore, it is predicted that:

H2: Individuals with higher network brokerage will engage in more toxic behaviors.

Individuals occupying advantageous positions may also exhibit prosocial behavior, especially when they are part of communal relationships where individuals respond to the needs and interests of others without the primary expectation of receiving a benefit in return (Chen et al., 2001). Those with high network closure may possess a stronger sense of identification and trust within the gaming community, guiding their behavior toward seeking attachment and building trust, while discouraging engagement in disruptive behaviors. Their social groups, in turn, offer social support and protection. In addition, they may experience a heightened sense of security and safety in their interactions with other players, making them less likely to feel threatened and engage in reactive aggression.

The interrelation among ties also heightens the accountability cues, thus creating a stronger SFE. According to the Differential Self-Awareness Theory (DSAT; Prentice-Dunn and Rogers, 1982) and the SFE (Axelrod and Hamilton, 1981), if social interactions signal accountability cues that suggest the degree to which individuals will be held responsible for their actions, they will reduce deindividuation and increase self-awareness, resulting in less aggressive behavior. Similarly, if social interactions signal internal attentional cues that direct an individual's focus on themselves, they will increase self-awareness and decrease aggressive behavior. In a game setting, individuals in a redundant network may experience a reduction in anonymity and an increase in internal attentional cues and accountability cues. Because they anticipate having frequent interactions with their network in the future, there is a greater "shadow of the future" effect, and engaging in toxic behavior may result in greater social costs, such as being shunned by friends or groups, thus losing their status quo or informal power. They are more vulnerable to negative feedback, even from a single person. Compared with individuals playing with random strangers, those in a closure position are more likely to be held accountable for their disruptive behavior. As demonstrated by Burt (2001), network closure enforces the sanctioning of negative behaviors. Therefore, it is predicted that:

H3: Individuals with higher network closure will engage in fewer toxic behaviors.

Network embeddedness and victimization

While certain network positions may predispose individuals to toxic behaviors through outcome expectancy, they can also offer protection against victimization due to the advantages they provide. Research conducted in organizational settings has shown that network size precedes the acquisition of power (Burkhardt and Brass, 1990). In a school context, Mouttapa et al. (2004) explored social network predictors of bullying and victimization and found that students who received more friendship nominations were less vulnerable to victimization. Similarly, in online aggression research, scholars have noted that individuals with a greater number of connections in their personal network are often seen as more popular and wield higher informal authority, which serves as a protective buffer against victimization (Festl and Quandt, 2013).

In the context of video games like *WoT*, having a larger co-play network provides more control over choosing gaming partners, strategies, and the timing of game initiation without having to rely on random matchmaking. This, in turn, leads to increased support and reduced skill disparity during gameplay. With stronger support from their network, players are more likely to perform better, reducing the likelihood of becoming targets due to their performance. Moreover, playing alongside familiar individuals decreases uncertainty and enhances feelings of security, reducing the chances of feeling threatened by microaggressions or ambiguous situations. Consequently, this may result in fewer reports of victimization from others:

> *H4*: Individuals with larger network size will experience lower levels of victimization.

While individuals in prominent network positions typically enjoy protection against victimization, those in high network brokerage roles may be an exception. As they bridge structural holes in their network, they might encounter a more diverse array of players, manage conflicting interests and values, and become more susceptible to attacks or retaliation from a broader spectrum of players. For instance, prior research indicates that individuals with extensive networks of weak ties were more likely to experience online victimization (Bastiaensens et al., 2014; Wegge et al., 2015). Furthermore, as SFE applies less to them, they might be less concerned about the potential negative impression on their teammates when reporting others. Consequently, they may be more predisposed to initiate reports when confronted with gaming toxicity:

> *H5*: Individuals with higher network brokerage will experience an increased level of victimization.

Individuals with high network closure may have a stronger sense of identification and trust within the gaming community. Their social groups, in turn, provide them with social support and protection. They may also have a greater sense of security and safety in their interactions with other players and are less likely to feel threatened to make a report. Furthermore, from the perspective of SFE, as they anticipate a potential long-term, ongoing relationship with other players, they may be less likely to make reports that could negatively impact their reputation within the gaming community. Therefore, we predict the following:

> *H6*: Individuals with higher network closure will experience lower levels of victimization.

Network embeddedness and perpetration–victimization overlap

Recent research in cyberbullying and gaming toxicity has shown that perpetration and victimization are not mutually exclusive but rather fluid experiences (Kordyaka et al., 2023). Perpetrators can also be victims, and victims can engage in perpetration. This phenomenon, long recognized in aggression research, has been explored both in studies of offline aggression (e.g., Unnever, 2005) and cyberbullying (e.g., Festl and Quandt, 2013), where individuals involved in toxicity have been placed along a bully-victim continuum. The perpetration–victimization overlap has been characterized by the presence of "aggressive victims" (also known as bully victims or provocative victims). Unlike the typically submissive and passive victims, there exists a subgroup of victims who exhibit aggressive and hostile behavior toward bullies, referred to as aggressive victims (Unnever, 2005). This subgroup's members have received attention in school bullying research for their distinct behaviors: they bully in ways different from pure bullies and are bullied differently than pure victims. Whereas pure perpetrators' aggression is goal-driven and instrumental, aggressive victims' perpetration tends to be more reactive and impulsive. As peers tend to find impulsivity and emotionality aversive, aggressive victims often face greater social rejection than pure perpetrators, who may even enjoy popularity within their groups (Pellegrini et al., 1999). As a result, aggressive victims are more frequently victimized than pure victims. Connecting network position and incidence-based perpetration and victimization to the unique behavioral pattern of the toxicity subgroups, it is predicted that:

> *H7*: Individuals with higher network brokerage are more likely to be aggressive victims.

Method

Procedure and participants

The research site was *WoT*, a popular vehicle-based Multiplayer Online Game that has garnered a user base of over 160 million worldwide. *WoT* features tank combat between 2 teams consisting of up to 15 players, with the goal of capturing the enemy's base or eliminating all enemy tanks. Players can opt for random battles, determined by the game's algorithms, where they play with strangers with little prior interaction history. Alternatively, they can request to join a team-within-a-team called a platoon with up to two preferred players, based on their pre-existing social structures, such as players from their friend lists or clans. Clans represent a more substantial and enduring social structure within *WoT*, offering players access to a broader pool of potential teammates and the opportunity to unlock more advanced battle scenarios. On average, a battle in *WoT* lasts from 4 to 15 minutes.

In partnership with the game operator, *Wargaming Inc.*, we acquired and merged three types of telemetry data from the *WoT* North American server, namely, player co-play network data, in-game toxicity report data, and in-game behavioral log data. The co-play network was an undirected network of *WoT* players based on their co-play experience in April 2019. A co-play incident was recorded any time a player requested to play with another player, regardless of whether they were friends or not. An undirected edge between the two nodes (players) indicates that they co-played at least once during the data collection period, disregarding the request's initiation. However, if a player opted to be placed in a random battle, that would not be included in the co-play instances. Therefore, co-play represents some degree of familiarity and social acceptance.

We also compiled all toxicity report data filed in May 2019, introducing a time lag between the network structure and subsequent toxicity incidents. Players have two options for reporting toxic behavior: during a battle through an automatic reporting system or after the battle via a customer service complaint system. We merged both sources for analysis. During the data collection period, players could report toxic behavior up to 10 times per day, and being reported five times could result in a permanent game restriction. Players could categorize toxic behavior into one of four types: inappropriate behavior in chat (14% in our dataset), unsportsmanlike conduct (41%), offensive nickname or clan name (4%), and inaction/bot (41%). We chose to analyze different types of toxicity incidents collectively for several reasons: (1) Reports made during battles are often rushed, with players possibly selecting a category at random due to time constraints. (2) The definitions of each category may not have been clearly communicated to players, nor are they mutually exclusive, leading to potential overlap and inconsistency in how each type is selected. (3) Aligning with established definitions of gaming toxicity (Kowert, 2020), we view the reporting of toxicity as an expression of concern over a disrupted gaming experience, regardless of the type of disruption. Therefore, following prior research practice (Shen et al., 2020), we aggregated incidents across all types of toxicity.

Players' behavioral log data, including metrics like their seniority within the game and win rates, were collected as control variables. To establish connections between various data types, a one-way hashed key, which is mathematically irreversible, was employed. This measure ensures that the original data cannot be deduced from the hash value, enhancing data security. All personally identifiable information was removed from the data before reaching the research team.

Measures

Network size. Network size (M=103.56, SD=262.25) was measured by degree centrality, the number of edges a node has in the co-play network. It captures a player's level of connection with other players. A player who has a high degree centrality is one who has some familiarity with a lot of other players.

Network brokerage. Network brokerage was measured by normalized effective size (M=0.39, SD=0.10). Adapting the procedure of Burt (1992, 1995), network brokerage, or the structural hole, was measured as the effective size (M=40.25, SD=105.26), normed by the ego's actual network size. Consider an ego i's ego network, we say there is a bridge between i and alter j when j has no connection with any other alters that i has. It can also be considered as the non-redundancy, measured by the following formula

$$\sum_j (1 - \sum_q p_{iq} m_{jq}), q \neq i, j$$

In the formula, p_{iq} is the proportion of an ego i's investment in a connection with an alter q, and m_{jq} is the normalized tie strength of the connection between j and q. In an unweighted and undirected network (Borgatti et al., 1997) such as our co-play network, m_{jq} simply represents the relation between j and q, and a simplified formula is

$$n - \frac{2t}{n}$$

In the simplified formula, t is the number of ties within the ego network, not including ties toward the ego, and n is the number of nodes, excluding the ego. This measure quantifies the size of an ego's actual network, adjusted by the average connectivity that each alter maintains with other alters. Given the sparsity typical of our co-play network in online multiplayer video games, where an ego's alters are unlikely to know each other, effective size can be very close to network size. Thus, we normalize the effective size of an ego's network by its actual size to determine the proportion of the ego's ties to its neighborhood that are non-redundant.

A larger value of normalized effect size means that the ego is central to facilitating connections among alters who would not otherwise be directly linked, indicating their influence in enabling information or resource flow between different parts of the network. In the context of this study, players with higher network brokerage are those who play a central role in connecting different groups or players within the network who are not directly connected. Such players are likely seen as central hubs within the gaming community, often contributing to the dynamics of team formation and social interaction. Conversely, a low level of network brokerage implies that the ego has a limited role in connecting disparate groups or individuals within the network. These players might be more peripheral in the social structure of the game, engaging in a more insular or localized set of relationships, without acting as a conduit for broader inter-player connections.

Network closure. Following the procedure of Burt (1992, 1995), we operationalize network closure as a network constraint (M=0.43, SD=0.36), using the following formula

$$C_{ij} = (p_{ij} + \sum_q p_{iq} p_{qj})^2, q \neq i, j$$

where p_{ij} is the proportion of an ego i's investment in a connection with an alter j. This constraint measures the interconnectivity between the ego i and a specific alter j; in other words, it measures i's dependence on j, representing the trust, time, and other resources i invested into the relation with j. A larger value for network constraint indicates a higher degree of dependence or interconnectedness between the ego and the alters.

Perpetration count and victimization count. The frequency of toxic behavior perpetration and victimization was measured by calculating the perpetration count (M=3.16, SD=3.87) and victimization count (M=3.04, SD=7.19) for each player, respectively. The perpetration count represents the total number of instances a player was reported as

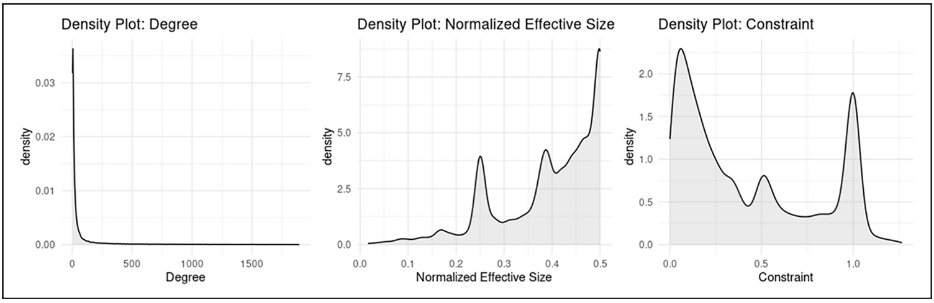


Figure 1. Density plots of key network variables.

the initiator of toxic behavior. The victimization count represents the total number of times a player reported experiencing disruptive behavior by others in the game.

Perpetration–victimization overlap. Based on individual-battle level perpetration and victimization, the perpetration–victimization overlap was categorized by identifying the number of players who are aggressive victims—those who have both reported others and been reported themselves (N=20,659). Players who did not play any battles during the study period were excluded (N=6,009).

Control variables. Battle count (M=355.79, SD=272.85) was the total number of battles in which a player participated between January and April 2019. Win rate (M=49.39, SD=6.01. Note that ties are possible.) was calculated as the ratio of battles won by a player during this period to the total number of battles, indicating player skillfulness. Clan membership was a dummy variable representing whether a player was part of a clan during the data collection period. Including battle count, win rate, and clan membership as control variables in our regression analyses allows us to account for variations in the dependent variables caused by player experience (indicated by battle count), performance (indicated by win rate), and group membership (indicated by clan membership). This adjustment enables us to draw more accurate and reliable conclusions about the impact of network-related variables on gaming toxicity, by isolating the effects of these variables from other factors that could influence the outcomes.

Analysis

The dataset comprises 55,760 players, with each row representing an individual's involvement in toxic behaviors in May 2019, along with their network measures in the co-play network from April 2019. To mitigate biases from outliers, the data were trimmed at the 99th percentile. Figure 1 illustrates the distribution of key network variables. Table 2 presents the parameter estimates and the goodness-of-fit statistics for the models. The Cragg-Uhler (Nagelkerke) Pseudo-R^2 was employed to assess the goodness of fit of the model, with higher values indicating a better fit. To test *H1-H6*, Poisson regression

Table 2. Predictions of perpetration count, victimization count, and perpetration–victimization overlap.[a]

	Perpetration count			Victimization count			Perpetration–victimization overlap		
	Rate ratio	SE	*p*	Rate ratio	SE	*p*	Odds ratio	SE	*p*
Intercept	1.5928	0.0257	***	2.1037	0.0270	***	0.0375	0.0941	***
Network size	1.0000	0.0000	***	0.9999	0.0000	***	1.0002	0.0000	***
Network brokerage	1.1428	0.0260	***	1.1443	0.0262	***	0.9551	0.0927	
Network closure	0.8935	0.0080	***	0.9421	0.0081	***	0.8981	0.0291	***
Clan membership	1.0234	0.0053	***	1.0028	0.0054		1.2102	0.0198	***
Win rate	1.0086	0.0005	***	1.0149	0.0005	***	1.0427	0.0017	***
Battle count	1.0010	0.0000	***	1.0008	0.0000	***	1.0016	0.0000	***
Pseudo *R*-squared		0.3438			0.3287			0.0907	

[a]The output of the Poisson regression models is expressed in parameter estimates of rate ratios, which represent the multiplicative change in the expected count of the dependent variable for a one-unit increase in the predictor variable. For example, a rate ratio greater than 1 indicates that the event rate increases with an increase in the predictor, while a rate ratio less than 1 indicates a decrease in the event rate. The output of the logistic regression model is expressed in parameter estimates of odds ratios, which represent the multiplicative change in the odds of the outcome occurring for a one-unit increase in the predictor variable. An odds ratio greater than 1 suggests that the odds of the outcome increase with an increase in the predictor, whereas an odds ratio less than 1 suggests a decrease in the odds of the outcome.
***$p < .001$.

models were utilized with the perpetration count and victimization count serving as dependent variables. Independent variables included players' network size, brokerage, and closure in the co-play network. The models also controlled for battle count, win rate, and clan membership. Hypothesis *H7* was tested using logistic regression models with the probability of a player being an aggressive victim as the dependent variable. The same independent variables and control variables used in the Poisson regression models were included. The results are presented in Table 2. The analysis was conducted in R version 4.1.3. The igraph package (Csardi and Nepusz, 2006) was used to compute network measures. The code used in the analyses can be found on OSF (https://osf.io/bqw4x/?view_only=bcd291f46ca14ff19b77f0b60fc8df7a).

Results

For a summary of the hypotheses and the results of hypothesis testing, refer to Table 3. *H1* investigated whether a player's popularity in a co-play network is associated with their engagement in toxic behaviors, while *H4* explored whether a player's popularity is associated with their experience of victimization. Controlling for battle count, win rate, and clan membership, network size was positively associated with both perpetration count (rate ratio = 1.000048, $p < .001$) and victimization count (rate ratio = 0.9999, $p < .001$). *H1* was rejected and *H4* was supported.

Table 3. Summary of hypotheses testing results.

Hypotheses	Results
H1: Individuals with larger network sizes will engage in fewer toxic behaviors.	Not supported
H2: Individuals with higher network brokerage will engage in more toxic behaviors.	Supported
H3: Individuals with higher network closure will engage in fewer toxic behaviors.	Supported
H4: Individuals with larger network sizes will experience lower levels of victimization.	Supported
H5: Individuals with higher network brokerage will experience an increased level of victimization.	Supported
H6: Individuals with higher network closure will experience lower levels of victimization.	Supported
H7: Individuals with higher network brokerage are more likely to be aggressive victims.	Not supported

H2 tested whether a player's network brokerage is associated with their engagement in toxic behaviors, while *H5* examined whether a player's network brokerage is associated with their experience of victimization. The results showed that network brokerage was positively related to the perpetration count (rate ratio = 1.1428, $p < .001$) and victimization count (rate ratio = 1.1443, $p < .001$), supporting *H2* and *H5*.

H3 tested whether a player's network closure is associated with their engagement in toxic behaviors, while *H6* examined whether a player's network closure is associated with their experience of victimization. The results showed that network closure was negatively related to perpetration count (rate ratio = 0.8935, $p < .001$), and victimization count (rate ratio = 0.9421, $p < .001$). Both *H3* and *H6* were supported.

H7 predicted that a player's network brokerage is positively associated with their likelihood of being an aggressive victim. Results showed that network brokerage was not associated with the likelihood of being an aggressive victim (odds ratio = 0.9551, $p = .620$). *H7* was not supported. Follow-up analyses showed that network size was positively associated with one's likelihood of being an aggressive victim (odds ratio = 1.0002, $p < .001$), while network closure was negatively associated with one's likelihood of being an aggressive victim (odds ratio = 0.8981, $p < .001$).

Discussion

Given the pervasive influence of online multiplayer video games in people's daily lives, the issue of gaming toxicity has emerged as a mounting concern for various stakeholders, including game companies, gaming communities, policymakers, educators, and parents (Neto et al., 2017; Shen et al., 2020). Although scholars have investigated the structural dimensions of gaming toxicity, the relationship between network positions and experiences of perpetration and victimization remains largely unexplored by SNA scholars. This may stem from challenges in accessing data on players' social relationships and other confounding factors within their gameplay, which complicates the task of distinguishing the impact of network factors from other influences, such as player experience and performance. The limited studies that have delved into structural factors have suggested that network-related variables exhibit greater robustness in anticipating online deviant behaviors than individual factors (Festl, 2016).

This study has examined three critical network metrics and their implications on behavior within toxicity dynamics. As predicted, there is a negative correlation between network size and victimization, indicating that players with more co-playmates are less likely to make a complaint. This might be because playing with acquaintances reduces the risk of being matched with unfamiliar players who may not cooperate or exhibit significant skill disparities (Shen et al., 2020). Playing with known others provides a protective shield, reducing exposure to toxicity and offering a sense of security that diminishes the urge to complain, even when encountering gaming toxicity.

Contrary to the prediction that teaming up with familiar players would diminish anonymity and deindividuation while enhancing accountability, the study found a positive correlation between network size and perpetration. This may suggest a homophily effect in selecting co-play friends, where players are more likely to play with others who have a similar playing style, thus experiencing less pressure to regulate their behavior. However, it is important to note that a rate ratio of 1.000048 indicates a very slight increase in the expected count of perpetration with each additional network connection, and the significance of these results may be influenced by the large sample size.

In addition to examining network size, this study also delved into network brokerage and closure. As predicted, this study revealed a positive correlation between network brokerage and the incidence of both perpetration and victimization in video games. Several plausible explanations exist for this positive association. First, players with higher network brokerage may enjoy increased access to information about other players and their strategies. Previous studies have shown that higher network brokerage can lead to improved task performance in video games (Shen et al., 2014), potentially providing players with an advantage in the game and raising the likelihood of engaging in aggressive behaviors. Similarly, research on social network sites has indicated that having numerous connections on platforms like with Facebook with those who are not offline friends increases the risk of cyberharassment and cyberbullying (Wegge et al., 2015). Perpetrators in online networks often possess a disproportionately higher number of weak ties, which may suggest that they hold a higher social status than victims. Furthermore, because the friends of their friends often do not know each other, the social consequences of their behavior are reduced, and their level of deindividuation remains relatively high, potentially leading to increased perpetration.

Furthermore, network brokerage is positively correlated with the incidence of victimization. While brokers who span structural holes often possess greater bridging social capital (Burt, 2017), regular members of different teams may perceive these brokers as out-group members, potentially leading to increased hostility toward them. Research on cyberbullying on social network sites also suggests that connecting with a large number of unfamiliar individuals is a risky practice that heightens the likelihood of being exposed to negative attention from potential perpetrators (Dredge et al., 2014). It is worth noting that while network brokerage significantly predicts the frequency of gaming perpetration and victimization, the effect size is minimal. Specifically, a 1-unit increase in network brokerage contributes to only a 0.14% and 0.15% increase in the frequency of gaming perpetration and victimization, respectively.

Compared with the effect size of network brokerage, network closure exhibits a more substantial correlation with a reduced frequency of gaming perpetration and victimization. This aligns with prior research indicating that network closure fosters emotional support and trust (Lee et al., 2018), which serves as a protective factor against victimization and a deterrent to perpetration (Aquino and Lamertz, 2005; Evans and Smokowski, 2016). Individuals with higher network closure have more at stake regarding their reputation, and they face a greater social cost for engaging in deviant behaviors. For instance, a study by Ganley and Lampe (2009) observed that network closure positively predicts users' reputation on Slashdot, a popular online community. Since players' co-play friends tend to be interconnected, the potential reputational cost may discourage individuals with higher network closure from engaging in deviant behaviors. Burt (2012) and Shen et al. (2014) also explored network closure in virtual worlds, discovering a positive association with the level of trust within groups. In video game settings, the trust associated with network closure may diminish players' propensity to report others as toxic and decrease the likelihood of being reported themselves when facing negative game feedback, such as losing a game.

Of particular interest in the study is the perpetration–victimization overlap. Traditional delinquency research has typically treated perpetrators and victims as distinct groups (Chan and Wong, 2015). However, recent research has revealed significant commonalities between these groups, with many victims also becoming offenders themselves (DeCamp and Newby, 2015). Aggressive victims, in particular, have garnered substantial attention due to their distinct psychological profiles and behavioral patterns. As noted by Reiss (1981), "any theory that assumes no overlap exists between populations of victims and offenders or that they are distinct types of persons distorts the empirical research" (p. 711). Recent research on gaming toxicity has identified the fluid roles players assume within toxicity dynamics (Kordyaka et al., 2023). The results of this study support the fluidity of roles among players involved in gaming toxicity, suggesting that perpetration and victimization should not be viewed as polar opposites on a spectrum but rather as interdependent constructs. While network brokerage positively predicts both gaming perpetration and victimization, individuals with higher network brokerage are not necessarily more or less likely to be aggressive victims. Conversely, while both network size and network closure negatively predict gaming perpetration and victimization, individuals with larger network sizes are more likely to be aggressive victims, while individuals with higher network closure are substantially less likely to be categorized as aggressive victims, exhibiting perpetration–victimization overlap.

One potential explanation for these findings is that individuals with larger network sizes, although generally regulating their toxic behavior, may be more prone to engaging in retaliatory or deviant behavior when victimized, leading to the observed overlap between perpetration and victimization. In contrast, individuals with high network closure are substantially less likely to become aggressive victims. Even if they encounter gaming toxicity, they are less inclined to engage in toxic behavior themselves. This could be due to the social sanctions against disruptive behaviors within their close-knit network or their enhanced sense of security and confidence in their relationships, stemming from their supportive network. Individuals with a higher brokerage, on the contrary, may be less inclined to engage in retaliatory behavior, possibly because they have witnessed a diverse range of behaviors and anticipate no future interactions with toxic players, making them less motivated to retaliate. The results of the study contribute to a more comprehensive understanding of the perpetration-victimization overlap and highlight the importance of building strong social ties to reduce individuals' vulnerability to victimization.

Extending previous research that underscores the digital divide in accessing and utilizing Information and Communication Technologies (ICT), this article expands the discourse on the structural inequalities in networked gaming environments and the toxic meritocracy of video games (Paul, 2018). The findings indicate that the digital divide concerns not just the amount of time people spend on games and their gaming skills but also their online social interactions. An important question for the broader academic community is the formation of in-game social networks: Do they reflect and exacerbate offline social structures? Certain groups, more vulnerable to gaming toxicity, might choose to limit their in-game networks to safer circles. This decision can reduce their opportunities to seek informational and emotional support from the broader gaming community, potentially leading to a self-perpetuating cycle of power imbalances within virtual environments.

Theoretically, SHT and SFE act as complementary frameworks that together offer insights into the behavioral patterns and gaming experiences based on the benefits and risks associated with players' positions within in-game networks. SFE, drawing from evolutionary and game theory perspectives, predicts individuals' motivations for engaging in either aggressive or cooperative behaviors. In recent years, it has been utilized to explain the psychological mechanisms behind video game players' aggressive actions (e.g., Shen et al., 2020). The current study's findings further bolster SFE by illustrating how accountability cues play a pivotal role in the toxic technoculture of sociotechnical networks, such as online gaming. Specifically, our results show that players in positions lacking accountability cues—typically those interacting with strangers and therefore enjoying high levels of anonymity—are more likely to exhibit toxic behaviors. Conversely, individuals in closely-knit networks, which are characterized by a lower level of anonymity and higher accountability, are less inclined to engage in or become targets of toxicity. This evidence lends empirical support to Massanari's (2017) argument that toxic technoculture thrives in environments with minimal accountability and high anonymity.

SHT has been applied and received support in contexts beyond face-to-face interactions, extending to online environments (Shen et al., 2014). It offers tools to assess the distinct opportunities and risks linked to individuals' network positions, both online and offline. Prior research indicates that attacks on one's identity within gaming contexts can lead to a diminished sense of self or heightened external insecurity (Gray, 2012). By weaving together these two theoretical frameworks, this study underscores the replication and perpetuation of power imbalances and social inequalities within digital spaces (Gray, 2020). Recognizing vulnerable players is a critical step toward implementing targeted interventions designed to protect them from the harmful impacts of gaming toxicity.

In the context of online video games, the punishment for toxic behavior is designed to apply uniformly to all players. However, the efficacy and impact of these punitive measures are likely to vary among individuals, potentially due to differences in perceived cost and severity of the sanctions. As noted by Massanari (2017), the design and algorithms of technology may inadvertently support "toxic technocultures." Although games like *WoT* have a graduated system of penalties culminating in bans, the relative ease of creating a new account undermines the system's effectiveness, potentially exacerbating the situation for victims. Moreover, while the ease of creating new accounts offers a superficial workaround for banned players, it does not mitigate the loss of valuable in-game assets. Consequently, the repercussions of bans are likely to be felt more acutely by players of lower economic status, for whom the loss represents a more significant financial and emotional investment. The uniform approach to addressing toxic behavior, juxtaposed with the varied perceptions of these punishments' severity among players, again underscores the reflection of offline social inequalities in online realms. Consequently, game developers and designers are encouraged to explore mechanisms that increase the difficulty for previously banned players to create new accounts. Moreover, there is a call for the video gaming industry to reevaluate its policies and approaches toward community governance, aiming to address gaming toxicity in a more substantial and meaningful manner.

This study also has methodological implications for employing network analysis to identify and mitigate toxicity in both academic research and the gaming industry. Recent research has leveraged players' in-game behavior and SNA to detect key cyberbullies effectively (Canossa et al., 2021; Choi et al., 2021). Building on this body of work, the current study provides further insights into the underlying factors that make network analysis predictive in proactively identifying influential and vulnerable players, showing that network-level factors play crucial roles in shaping player behavior and should be accounted for when explaining and predicting their behavior.

The current study marks an initial effort to compute various network measures for each player, paving the way for further incorporation of network analysis into behavioral research. First, by examining individuals' network positions and their behavior over time, we can delve deeper into the dynamics of behavior diffusion, identifying key players in the spread of both prosocial and toxic behaviors, as well as those who are most susceptible. Second, utilizing the findings from this study, gaming companies can conduct A/B tests (experiments) within the player community to assess the efficacy of network-based interventions aimed at reducing toxicity. For instance, game designers might investigate social features that promote co-playing with known contacts to foster in-game network closure. This could involve recommendation algorithms that suggest friends of friends for players to connect with or initiatives that encourage team-building within clans, which may, in turn, help curb gaming toxicity and retaliation. If an intervention effectively reduces the spread of toxicity by an individual, it can be considered successful. Moreover, the process of constructing an individual-level network could be automated and applied across various networked games, enabling live operations teams to monitor the health and financial status of the game community through a dashboard. This tool serves two purposes: it supports the A/B testing mentioned earlier and provides ongoing metrics that allow managers to benchmark over time. These metrics are not only valuable in isolation but also in comparison with previous periods or for year-over-year and seasonal analyses.

While the results of this study are noteworthy, there are several limitations that warrant attention. First, the data were collected from one game, and it is unclear whether the results would be applicable to others, particularly those from diverse genres. While the competitive nature of the game was appropriate for examining gaming toxicity, the unique mechanisms of various games may engender distinct forms of toxicity. In addition, the network structure of this online multiplayer game may differ from other types of games. For example, social games with a focus on family and friend co-play may have a much denser structure than this network. Future research should replicate these findings across various games, genres, and networks to test the generalizability of the results. In addition, since the data for this study were obtained from the North American server, it is unclear whether the findings would be consistent across different cultural and geographical contexts. Research in other cultures and regions is needed to address this gap. Moreover, while the current study employed a longitudinal design to predict lagged gaming perpetration and victimization based on network positions, it is important to note that this is not an experimental or quasi-experimental design and cannot establish causality. Future research may consider experimental designs or inferential network analysis to uncover the causal links between network positions, gaming perpetration, and victimization. Finally, this study aggregated various types of toxicity incidents into a single category due to the challenges of non-mutually exclusive toxicity types in *WoT* and the inconsistent categorization by players. Future research could explore the consistency of players' report categorization under different time constraints and examine how network positions relate to various types of toxicity incidents.

As we navigate these complexities, it becomes clear that tackling the multifaceted problem of gaming toxicity requires a holistic approach. Addressing the issue of gaming toxicity and empowering marginalized and vulnerable players would benefit from complementary in-depth critical and qualitative research into the relationship between socio-structural factors and individual network selection decisions. Because gaming may exacerbate existing inequalities (Apperley and Gray, 2020; Cote, 2020), and because these are anonymous environments (Kordyaka et al., 2020), ethnographic approaches would complement the more broad-scale and generalizable findings made possible in large-data designs like ours. It would be valuable to get more nuanced insights into the perceptions and types of players involved, which might in turn shed more light into the process of toxicity. Looking at different game mechanics and design types (Adinolf and Turkay, 2018) would also be valuable for nuance and generalizability. Then, additional quantitative studies could explore those possible findings at scale.

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Data availability statement

The data belong to Wargaming and were provided to the authors under a nondisclosure agreement (NDA). For replication requests, please contact the corresponding author, who will forward the request to Wargaming for consideration.

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ORCID iD

Mingxuan Liu https://orcid.org/0000-0002-3108-314X

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Author biographies

Mingxuan Liu, is an assistant professor in the Department of Communication at the University of Macau. Her research explores how emerging technologies shape user behavior, health, and well-being, and vice versa. She also makes causal inferences on user behavior change using observational data, panel surveys, natural experiments, and psychophysiological experiments.

Qiusi Sun is a postdoctoral research fellow at Syracuse University. Her work focuses on negative phenomena associated with technology affordances, especially online deviant behaviors such as trolling, incivility and toxicity, health misinformation, and polarization.

Dmitri Williams is a professor at the Annenberg School for Communication, focusing on the social effects of technology, including games.