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The larger, the fitter, the better: clans' evolution, social capital and effectiveness

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Abstract

Purpose – Team social capital (TSC) has been attracting increasing research attention aiming to explore team effectiveness through within- and cross-team resource conduits. This study bridges two disconnected theories – TSC and evolutionary theory – to examine gaming clans and analyzes mechanisms of the clans' TSC building from an evolutionary perspective.

Design/methodology/approach – This research draws longitudinal data from a sample of gaming teams ($N = 1{,}267$) from anonymized player data from the game World of Tanks spanning 32 months. The authors explored teams' evolutionary patterns using hidden Markov models and applied longitudinal multilevel modeling to test hypotheses.

Findings – The results showed that teams of different sizes and levels of evolutionary fitness vary in team closure and bridging social capital. The authors also found that larger teams are more effective than smaller ones. The positive association between team-bridging social capital and effectiveness is more substantial for smaller teams.

Originality/value – This research advances the theoretical development of TSC by including the constructs of teams' evolutionary status when analyzing strategic social capital building. Adding to existing literature studying the outcome of TSC, this research also found a moderating effect of team size between TSC and effectiveness. Finally, this study also contributes to a longitudinal view of TSC and found significant evolutionary patterns of teams' membership, TSC, and effectiveness.

Keywords team social capital, Effectiveness, Fitness, Evolution, Social networks, Gaming clans

Paper type Research paper

1. Introduction

As technology has become a more integral part of daily life, virtual teams have attracted increasing research attention. Virtual teams allow us to facilitate distant collaboration, address thorny business issues, and even enhance gaming experiences (Chamakiotis *et al.*, 2021; Mysirlaki and Paraskeva, 2020; Sun *et al.*, 2021). This study focuses on a specific type of virtual team in online games that is fluid in structure – as they are self-organized around common interests and competitive goals (e.g. winning and increasing ranking) and membership is constantly changing (Shen *et al.*, 2020). These teams are crucial social

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structures that help enhance gamers' virtual experience by increasing social interactions, facilitating knowledge exchange, improving skills, and reducing loneliness.

Studying the effectiveness of virtual self-organized and competitive teams is valuable in several ways. First, we noticed that the current literature around team social capital (TSC) mostly focuses on specific types of teams, such as project teams (e.g. Bao *et al.*, 2013; Lee *et al.*, 2015) and work teams (e.g. Chau *et al.*, 2017; Linuesa-Langreo *et al.*, 2018), or on individuals' within-TSC building (e.g. Trepte *et al.*, 2012; see also Reer and Krämer, 2014, 2019). TSC building of self-organized and competitive teams as collectives has received limited research attention. Additionally, although outcomes of TSC have been extensively studied (e.g. Wei *et al.*, 2011; Yu *et al.*, 2013), the mechanisms of TSC building could be better understood. Last, previous research often treats teams as homogeneous in their evolutionary status (e.g. Benefield *et al.*, 2016; Oh *et al.*, 2004), while in reality they vary.

Therefore, to fill these gaps, the research objective of this study is to delve into self-organized and competitive teams, or gaming clans, and analyze mechanisms of their TSC building from an evolutionary perspective. By filling these gaps, this study contributes to TSC theory as it enriches the understanding of self-organized and competitive virtual teams and provides dynamic insights on factors influencing TSC building by treating teams as evolving entities.

Treating teams as evolving entities, this research also aims to add an evolutionary extension to TSC theory. Membership is one of the most important types of resource for self-organized teams (Wang *et al.*, 2013) because the maintenance of this type of team often requires a certain number of members to willingly contribute their limited time, knowledge, and work. Therefore, in this study, two factors that capture key dimensions of team membership evolution are at the center of the analysis as follows: membership size and growth momentum, which we describe below as evolutionary *fitness*. Fitness describes teams' evolutionary status in natural selection and is measured by the ratio of the number of team members at two time points (Fisher, 1930; Price, 1972). We argue that teams of various types of membership – sizes and evolutionary fitness, specifically – may differ in TSC building. The relationships between social capital and membership resource are twofold. First, social capital requires members' time and social networks to build, and in turn. Second, social capital affects teams' and members' resource access, which should influence membership recruitment. Two types of TSC are studied: within-team-bonding social capital, which is referred to as *team closure* hereafter, which unites the team, and inter-team-bridging social capital, which guarantees connections with other teams and brings in diverse information from the environment.

The research site of this study is an online multiplayer first-person game that features teams of tanks fighting in matches. These large-scale games provide valuable settings for researchers to study social processes in teams (e.g. Reer and Krämer, 2019; Shen, 2014; Williams, 2006). While some teams are formed only for temporary battles, another, more permanent type of team is the focus of this research – clans, an essential organizing structure in online multiplayer games (Benefield *et al.*, 2016). Clans are formally organized in games to connect players and often feature diverse identities, cultures, sizes, and social structures (Sun *et al.*, 2021). Clans facilitate players' ability to socialize and play, and clans also compete with each other for high in-game rankings (Shen *et al.*, 2020; Williams, 2010). This study draws on particularly deep and unobtrusively collected behavioral data from the gaming company, enabling a longitudinal study of the factors affecting TSC and effectiveness.

2. Literature review

2.1 Team social capital conduits: team closure and bridging social capital

Social capital, one of the most widely studied concepts in social science (Ellison *et al.*, 2014), has been defined in two ways – as the network structure producing effects (Burt, 2005; Granovetter, 1973) and as the outcomes of those structures, such as emotional support and information access (Williams, 2006). This study examines social capital from a structural perspective. TSC, a special type of social capital, describes the *right* forms of social network positions that allow teams to "more effectively employ other types of capital they possess (such as financial resources, knowledge, skills, and abilities) to achieve their goals than can people or teams with social connections of a different type" (Oh *et al.*, 2004, p. 861).

Two types of TSC exist: team closure and team-bridging social capital (Han, 2018; Oh *et al.*, 2006). Han (2018) suggests that these two TSCs are conduits to resources through "teams' internal and external networks" that are associated with teams' internal/external processes and effectiveness (p. 19). Team closure is defined as the "characteristics of the relationships among team members and by the overall social network properties of the team" (Oh *et al.*, 2006, p. 572). This type of relationship unites the team and brings members together (Oh *et al.*, 2004) like a "social glue" to achieve shared goals (Han, 2018, p. 19). It is often associated with within-team solidarity, trust, and a collaborative environment for information sharing among team members (Han, 2018; Han *et al.*, 2014).

Since TSC is defined not only by the structures within the teams but also by the broader team-level social structure (Balkundi and Harrison, 2006; Marks *et al.*, 2005; Oh *et al.*, 2004), it is essential to bring social activities across team boundaries into consideration. Social capital formed through the conduits of inter-team boundary-crossing connections is described as team-bridging social capital (Han, 2018; Oh *et al.*, 2004). Ties that connect across teams carry diverse information and valuable resources from outside of teams (Han, 2018; Tsai, 2001). External ties help teams gain insights, interact with the environment, and manage uncertainty more successfully (Pfeffer and Salancik, 1978).

Two research gaps exist in the current TSC literature. First, most studies focus on teams with formal organizing structures and intensive knowledge-sharing activities, such as project teams (e.g. Bao *et al.*, 2013; Lee *et al.*, 2015) and work teams (e.g. Chau *et al.*, 2017; Linuesa-Langreo *et al.*, 2018). Literature on the more self-organized (Dissanayake *et al.*, 2015) and competitive teams, such as gaming teams (Benefield *et al.*, 2016), could be enriched. Second, most previous research studies TSC as an inherent ability and emphasizes its contribution to smooth knowledge transfer and performance (e.g. Bao *et al.*, 2013; Chau *et al.*, 2017; Dissanayake *et al.*, 2015; Peng, 2009), which risks overlooking the mechanisms of TSC building. A few exceptions exist. For example, Lee *et al.* (2015) identified that knowledge and communication strongly influence TSC building in project teams. Linuesa-Langreo *et al.* (2018) found that servant leadership style in which leaders prioritize members' needs contributes to the accumulation of TSC in their study of formally structured work teams. However, factors related to self-organized and competitive teams' social capital building remain largely unexplored. Last, although some research recognizes that teams vary in evolutionary status (e.g. Chau *et al.*, 2017), studies seldom emphasize the role of evolutionary status in TSC building or analyze TSC in longitudinal models. Therefore, this research fills the gaps by analyzing gaming teams that are competitive and self-organized in nature to enrich the field of study and examines the mechanisms of TSC from an evolutionary perspective.

2.2 An evolutionary extension of team social capital theory

Evolutionary theory draws from the biological theory of natural selection to explain the evolution of human social systems (Darwin, 1859). The theory's premise is that entities, including humans, teams, and organizations, rely on limited resources to survive and grow (Campbell, 1965). Therefore, like animals in the wild, any human social system may emerge, transform, or die (Carroll and Hannan, 2004). Similarly, self-organized teams experience the life cycles of emergence, growth, maintenance, decline, and disbanding (Chen *et al.*, 2008).

Although not often applied together, evolutionary theory and social capital theory share a focus on social network structures as sources of essential resources. Resources that are socially related or made available by social interactions are referred to as social capital (Lin, 1999). Through strategic network building such as embeddedness (Granovetter, 1985) and social capital building (Walker *et al.*, 1997), entities' chances of survival can be enhanced. In addition, some evolutionary studies have already examined social capital by emphasizing that occupying the *right* position in the network and connecting with the *right* network actors bring valuable resources (Oh *et al.*, 2004, p. 861). For instance, Weber and Monge (2017) found that interorganizational connections provide organizations stability, resource access, and support, which increases their chances of survival during uncertain times. In the context of teams, scholars like Lai (2014) have also applied evolutionary theories to studying meetup teams and discovered that external network connections, equivalent to team-bridging social capital, bring resources to the teams and increase the chance of their survival. In summary, relationships "can be thought of as mechanisms for acquiring and consuming resources," and "communication and other network links can be classified as an investment" (Monge *et al.*, 2008, p. 455). Since social capital can be accumulated and accessed through networks, too (Lin, 1999), we study the strategies teams use to build social capital to understand how they are related to their fitness building and evolution. Therefore, this research posits that an evolutionary perspective expands TSC theory to examine how teams in different evolutionary phases vary in their social capital building.

One of the core inquiries of evolutionary theory is understanding the survival and fitness of entities (Doerfel *et al.*, 2010). Bridging evolutionary theory and TSC theory, this research explores how teams with different evolutionary statuses build social capital differently. Teams' evolutionary statuses can be approached from several dimensions, such as size, average expertise level, and age. As discussed, membership is a core type of team resource that is crucial for virtual teams' maintenance and survival (Wang *et al.*, 2013). Therefore, this research pays special attention to two dimensions of evolutionary statuses: *team size* and *team fitness*, which function as measures of teams' levels of membership resource and growth momentum, respectively.

Size describes the number of members in a team. Previous TSC research often includes team size as a control variable when studying formally organized work teams, and has found it is negatively associated with knowledge transfer (Wei *et al.*, 2011), and it has no relationship with team creativity (Gu *et al.*, 2013) or performance (Lee *et al.*, 2015). Size reflects abundance in team membership. Social capital offers resources but also needs resources to be built (Lin, 1999). It is reasonable to speculate that team size may also be directly associated with social capital building and may in turn influence future resource access and team effectiveness. Moreover, although many studies on the relationship between size and team closure exist (e.g. Wincent *et al.*, 2010; see also Wheelan, 2009), the relationship between size and bridging TSC has not received enough research attention. Treating team size as an indicator for teams' membership resources and an important dimension of teams' evolutionary status, this research aims to deepen the understanding of team size and different types of TSC through a longitudinal analysis.

In addition, scholars adopting evolutionary theory often bring up the concept of *fitness* to study entities' status of adaptation to the environment (Hilbert *et al.*, 2016) and describe teams' momentum of membership growth at each time point. This study creatively adds this evolutionary dimension to understanding TSC building, which has never been studied to the best of our knowledge.

3. Research question and hypotheses development

Motivated by the aim to unveil mechanisms of TSC building from an evolutionary perspective, the dynamic relationship among membership resources in clans (measured by team size and evolutionary fitness in the current research), TSC building, and team effectiveness is examined.

3.1 Team size, team social capital, and effectiveness

3.1.1 Team size evolution. For self-organized teams that have low entry and exit costs, the ability to attract new members and sustain existing members is critical. They rely upon team members' information, passion, and commitment (Faraj *et al.*, 2011) to operate and develop. Therefore, membership size reflects teams' abundance level in resources such as commitment, time, knowledge, and skills (Wang *et al.*, 2013). Evolutionary processes can occur on the population level as well as individual entities' level (Aldrich *et al.*, 2020). To understand the overall evolutionary processes of membership resources in the environment, this research explores population-level dynamics first by raising an exploratory research question of how the population, the collection of gaming teams, evolves. Given that this is an exploratory question that is not positing a relationship of team size with any construct, this is raised as a research question instead of a hypothesis.

RQ1. How does team size evolve?

3.1.2 Team closure. Researchers have extensively addressed the relationship between team size and team closure. Larger teams tend to be less cohesive (Wincent *et al.*, 2010). Members of larger teams have less perceived trust (Wheelan, 2009) and commitment within the team (Soboroff, 2012) than members of smaller teams. Moreover, according to the evolutionary framework, there exists a relational carrying capacity (Monge *et al.*, 2008) in each group, which means that relationships require time and energy to build and maintain, and these resources are limited, so that the number of linkages in the group has an upper limit. Relational carrying capacity can also be understood as teams' "upper bound on network density" (Monge *et al.*, 2008, p. 456), and network density is the common measure of team closure (Benefield *et al.*, 2016; Oh *et al.*, 2004). In fact, relational carrying capacity may be reached faster than membership growth, so that although membership is still growing for large teams, the number of linkages ceases to grow (Monge *et al.*, 2008). As a result, larger teams tend to be less cohesive. Whether such a pattern persists in the context of gaming clans is explored in this research.

H1a. Team size is negatively associated with team closure.

3.1.3 Team-bridging social capital. Research on the relationship between team size and team-bridging social capital is limited. Larger teams tend to have more external connections than smaller teams because more members potentially know someone from outside of the team (Cantner and Stuetzer, 2013). Although not explored in the evolutionary framework, it is reasonable to postulate that when teams have more membership resources, teams' relational carrying capacity to other teams may increase, since the addition of new members creates an increased amount of time, energy, and opportunity for teams to use in building external connections. With self-organized teams specifically, members often voluntarily move around different teams, bringing their social connections from previous teams with them (Sun *et al.*, 2021). Therefore, larger teams tend to have a richer reservoir of bridging connections than smaller ones.

H1b. Team size is positively associated with team-bridging social capital.

3.1.4 Effectiveness. For teams that require formal management and coordination, team size is negatively associated with team effectiveness, because management and coordination of large teams is more complicated and costly than of small ones (Wincent *et al.*, 2010). However, for clans that require less formal coordination and that are managed by members' voluntary contributions, the effect of team size might differ. In a shared environment, large teams have advantages over small ones when they compete in a shared environment because they have abundant resources (Bercovitz and Mitchell, 2007; Lee and Littles, 2020) and diverse and extensive information and ideas (Paulus *et al.*, 2013).

Among gaming clans, small and large clans have different goals and organizing structures (Williams *et al.*, 2006). Small clans often concentrate more on social bonding than in-game competition. In comparison, large clans tend to focus on competition and game performance (Williams *et al.*, 2006). This is consistent with team literature showing that large offline clans are less cohesive, but they tend to perform better than smaller ones (e.g. Bercovitz and Mitchell, 2007; Paulus *et al.*, 2013).

H2. Team size is positively associated with team effectiveness.

3.2 Evolutionary fitness, team social capital, and effectiveness

To the best of our knowledge, the application of evolutionary *fitness* is limited in TSC research. Biologists, ecologists, anthropologists, and economists often study evolutionary fitness to capture patterns of evolution. Entities with varying fitness differ in their soundness in natural selection (Fisher, 1930; Price, 1972). Fitness is usually described as the number of offspring that contribute to its evolutionary status in the next time point (Okasha, 2008). Treating evolutionary fitness as a "growth factor," it can be measured as a ratio of the number of units in a population at two consecutive time points (Hilbert *et al.*, 2016, p. 39). To study the changes in clans, we borrow this measurement to study team growth and capture teams' evolutionary status by using the number of members at time $t + 1$ divided by that at time t.

Clans with a high fitness score grow fast and attract many players in a short time. Fast expansion like this may create disruptions to teams, as existing members may not have the opportunity to get familiar with new members, which may pose challenges for fostering within-team closure. Furthermore, there may exist relationship inertia when new members have just joined, meaning these members still maintain relationships with members of their prior teams and it takes time for them to foster new relationships with peers in their current team.

It may also create opportunities, as fit clans that are growing fast attract many players, bringing external connections to other clans. Moreover, entities with superior fitness are often more adapted to the environment, as evidenced by natural selection processes (Carroll *et al.*, 2011; Hilbert *et al.*, 2016). Such adaptation can be achieved through bridging social capital building, which helps teams build relationships with their surroundings and gather information about the environment (Oh *et al.*, 2004). Therefore, fitness and bridging social capital are likely to be positively associated.

In addition, according to evolutionary theory, entities evolve through the process of variation, selection, and retention (Aldrich *et al.*, 2020). Variation describes the process when entities experience vast changes in form, selection is when some changes are selected while other variations are dropped, and retention is when some of the selections are retained and routinized (Aldrich *et al.*, 2020). Both selection and retention signal "pressures towards stability and homogeneity," inertia, and reproduction of past routines (Aldrich *et al.*, 2020, p. 39). Therefore, when fitness is large, teams are experiencing vast changes in membership, and it is likely that they are experiencing variation, whereas when fitness is small, teams may be experiencing selection and retention as membership changes are eased. When fitness is high and teams are experiencing variations, their form and composition are shifting drastically, and such turbulence can impede team closure. However, such vast variation means active exchange of membership with the external environment, which is beneficial to the building of bridging social capital. Summarizing the arguments above, the following hypotheses are raised:

H3a. Evolutionary fitness is negatively associated with team closure.

H3b. Evolutionary fitness is positively associated with teams' bridging social capital.

Fitness is a concept that reflects human entities' interaction with the environment (Hannan and Freeman, 1977). It usually indicates whether the entity has the adaptive power to grow and survive (Hannan and Freeman, 1977). As Mills and Beatty (1979) suggested, the concept is "a complex dispositional property" of human entities that describes their opportunities to survive and reproduce (p. 270). Higher fitness indicates that the team has adjusted to the environment well and is in a favorable resource position (Carroll *et al.*, 2011), and, therefore, may be related to better performance.

H4. Evolutionary fitness is positively associated with teams' effectiveness.

The relationship between TSC and effectiveness is integral to TSC theory (e.g. Benefield *et al.*, 2016; Oh *et al.*, 2004, 2006). This next section analyzes the relationship between TSC and effectiveness for gaming clans.

3.3 Team social capital and effectiveness

3.3.1 Team closure. Teams with high closure are often cohesive, and members share strong connections. Within-team closure helps foster team identification, develop trust, and provide emotional support among members (Chung *et al.*, 2011; Williams, 2006), which is also beneficial for information exchange, knowledge sharing, and collaboration within the team (Coleman, 1988). Therefore, closure is closely related to team performance (Oh *et al.*, 2006). A positive relationship between cohesion and team success has been widely supported (Evans and Dion, 2012; Mullen and Copper, 1994; Wise, 2014). High team closure is related to low friction, increased knowledge sharing, and high satisfaction (Wise, 2014). Cohesive teams also present a high level of solidarity and foster shared values faster (Tekleab *et al.*, 2009).

However, too much closure can reduce bridging and create constraints. The downside of closure, the conduit of social capital, is "insularity" and even "out-team antagonism" (Williams, 2006, p. 597). Team members may submit to the team norms, which may squelch dissent, hurting teams' openness to new ideas or change (Wise, 2014). Moreover, too much closure often indicates high redundancy in the network, which blocks diverse information from getting into the team (Granovetter, 1973). Therefore, the optimal level of team closure should be between the two extremes, and there is an inverted curvilinear relationship between within-team network density and team effectiveness (e.g. Benefield *et al.*, 2016; Oh *et al.*, 2004; Wise, 2014).

H5. An inverted curvilinear relationship exists between team closure and effectiveness.

3.3.2 Inter-team-bridging conduits. Occupying central and important inter-team network positions reflects the level of power, popularity, and activity a clan possesses (Freeman, 1978). Occupying a central network position is associated with better information access, higher perceived attractiveness, and more power, all of which contribute to better performance (e.g. Balkundi *et al.*, 2011).

H6. Clans' bridging social capital is positively associated with team effectiveness.

In this study, the relationship between bridging social capital and team effectiveness is analyzed with more nuances by considering the potential interaction effect of team size. As discussed, membership is an important resource for self-organized teams (Wang *et al.*, 2013). Large teams can provide more social opportunities and diverse resources for members and are also more self-sustaining than smaller ones. Therefore, large teams are less reliant upon external connections to achieve higher performance because their internal resources might already be adequate (Cantner and Stuetzer, 2013). In comparison, smaller teams may have an insufficient number of members to carry out tasks. Establishing external connections with outside teams is important to recruit outside members as well as to compensate for the relatively inadequate information and expertise to boost performance. Therefore, we hypothesize that bridging social capital is more important for smaller teams than larger ones to achieve effectiveness.

H7. In comparison to larger teams, the relationship between bridging social capital and effectiveness is more substantial for smaller teams.

4. Methods

4.1 Research context

4.1.1 Gaming clans. Gaming is the largest media market globally, generating a total of US$159.3bn in revenue in 2020 (Field Level Media, 2020). Lockdowns due to the COVID-19 pandemic only expanded the market (Hall, 2020). Therefore, the sheer size and omnipresence of games render research of social structures and dynamics in gaming clans important and relevant. Moreover, research has unveiled dynamics in gaming communities and suggested they mirror competitive workplaces and offer useful real-world implications (Fox *et al.*, 2018; Shen, 2014), which means that gaming research provides unobtrusive observations relevant to important social mechanisms that enhance our understanding of the real-world patterns.

This research focuses on a specific type of team: clans. The term *clan* was defined by Ouchi (1979) to describe teams that are organized by aligned goals, shared values, and prevailing norms that are reinforced by team members' social relations. He listed teams of researchers and labor unions as examples of clans. This concept has been used to study a type of organizational control called clan control, an informal type motivated by shared visions, goals, interests, and norms. Individuals strengthen their membership by voluntarily accepting the team's rules and norms (Ouchi, 1980).

Gaming clans have these features: They are a form of player organization with shared goals, coordinated action, co-play (Reer and Krämer, 2020), and clear memberships (Sun *et al.*, 2021). Players form clans to socialize, seek advice, exchange information, and advance their skills to win the game (Williams *et al.*, 2006). Clan membership also reduces players' loneliness, improves their gaming experiences (Martončik and Lokša, 2016), and facilitates individual gamers' social capital building (Reer and Krämer, 2019). Individual players join and leave clans voluntarily, and therefore, gaming clans are also organized by shared goals, norms, and voluntary membership.

4.1.2 Social architecture. The research site is World of Tanks (WoT), a global game featuring zoned servers around the world (i.e. a North American server hosts players in Canada, the United States of America, and Mexico, while another hosts players in the former Soviet states, another players in Europe, and several for players in different parts of Asia). WoT is a session-based game in which two teams of players piloting tanks fight against each other in a match that lasts no longer than 15 min. While most battles are among random strangers, a subset is dedicated to pre-set teams.

On this site, clans are groups of players who have decided to band together for the long term to socialize and compete in these matches. They are formed through self-organized processes and players join and leave at will, though there are often recruitment and vetting steps. Clans are more stable than the temporary teams that are often created for battles and disbanded immediately afterward (Benefield *et al.*, 2016). Although players are allowed to socialize with fellow clan members, clans do not limit players to only playing or communicating among themselves. Inter-clan chat and battles without clans at all are common. In fact, the most common game mode is "Random Battle," which allows a subset of no more than three players to join. Participating players can be complete strangers who are matched by the system, or invited to co-play (in a "platoon") based on existing relationships. Clan battles are also often formed based on existing relationships or clan affiliations; they are less common but are more competitive and come with more rewards. This is why membership is an especially critical resource for clans, because they cannot fight in clan-based battles unless they have enough players online at the same time. As such, clan battles require better coordination and planning, which a clan provides. The relationship being studied in this research includes voluntary co-play, which includes invited co-play and clan battles only.

Specifically, to form a platoon a player needs to send an invitation to another player, who accepts the invitation. Players communicate and coordinate with one another in the battles they fight together, transferring knowledge about the game in the process. Studies suggest that co-play encourages trust (Chen *et al.*, 2016) and supports psychological well-being (Shen and Williams, 2011). Such voluntary co-play reflects the social structures on the platform because it signals pairs of players' mutual acknowledgment of the relationship.

Like any other online space, games have significant differences in their affordances and mechanics, and so not all games generalize to all others. By noting the specific affordances in World of Tanks, we can offer a focused piece of generalizability, in which studying clans can help us understand other similar virtual and offline teams. In summary, findings of this study may be generalized to help us understand competitive and self-organized clans engaging in frequent sessions or tasks, such as self-formed sport teams and competitive problem-solving teams. They may have limited application to teams that are not very competitive (e.g. learning teams). Because of the somewhat permanent characteristics (Shen *et al.*, 2020), the generalizability cannot be extended to ad hoc teams (e.g. temporary project teams).

4.2 Data

The game publisher Wargaming provided anonymized player data for the North American servers of WoT. The data presented here are longitudinal, spanning 32 months (from September 2016 to April 2019) [1]. There were 11,404 active clans in the observed time points on the North America server. We randomly sampled 1,300 clans. After dropping clans with missing attributes, 1,267 remained for analysis.

4.3 Measures

4.3.1 Within-clan network measure. 4.3.1.1 Team closure. For each clan, at each time point, an undirected and unweighted co-play network was constructed among members who played with each other by making a pre-formed team prior to a battle. We used the R package igraph to calculate all network measures (Csardi and Nepusz, 2006). This research adopts network density to describe team closure following Oh and colleagues (2004, 2006). It was measured by the total number of existing ties over all possible ties in the within-clan co-play networks.

4.3.2 Inter-clan network measure. Inter-clan networks consist of inter-clan co-play ties. For instance, if a member of Clan i has played with a member of Clan j, there is a tie between i and j. In line with past research, boundary-crossing connections such as these can enable information exchange and knowledge transfer through member-level social networks (Benefield *et al.*, 2016; Everett and Borgatti, 2005).

4.3.2.1 Team-bridging social capital. Oh *et al.* (2006) noted that inter-team-bridging social capital can be captured by unique inter-team relationships. For each clan, at each time point, the degree centrality of the inter-clan network was calculated by counting the sum of all unique ties each clan shared. Duplicate ties were not considered. Clans' degree centrality score was used to proxy team-bridging social capital (Han, 2018). This variable was normalized.

4.3.3 Other measures. 4.3.3.1 Team size. Each month, the number of players and their clan affiliation information was collected. In other words, we only included players that had been in a clan the entire month. To measure team size, the total number of players who were affiliated with the clan over the month was calculated. When testing the moderating effect of team size, large and small clans were categorized based on team size. Clans that were larger than or equal to the mean size of each month were categorized as large and small, respectively. Small clans were coded as 0 and larger ones as 1.

4.3.3.2 Evolutionary fitness. According to Hilbert *et al.* (2016), evolutionary fitness can be measured by the number of players in $t + 1$ divided by that at time t. For example, clans' fitness score in the first month was calculated using the ratio of their size in the first month divided by their size in the second month. One caution is that, like most teams, clans do not grow indefinitely. The upper bound of all clans was 100. Therefore, for larger teams approaching the upper membership limit, their fitness score tends to be suppressed because of this constraint [2]. Although fitness is calculated by the ratio of team size for two consecutive months, *size* and *fitness* are distinct conceptually, with *size* indicating the number of members in each clan and *fitness* reflecting the momentum of growth. In fact, clans that grow fast can be large or small.

4.3.3.3 Team effectiveness. We adopt a clan's rating on competitive and public leaderboards as a proxy for team effectiveness, following Benefield *et al.* (2016). On leaderboards, teams receive points by achieving higher win rates, especially against other highly ranked teams. The leaderboard of the game ranks clans based on this rating. The range of this variable is 1–7, indicating that clans' ratings fall into the range of 1,000–7000. The game rating system considers factors including the average number of battles played by the clan members, members' performance in the battles, and average ratings of the members.

4.3.4 Control variables. 4.3.4.1 Clan age. This variable was measured by the number of years since the clan was launched. The raw data contain the number of days since the launch for each clan, and we transformed the scale to the number of years by dividing each value by 365. This variable was added as a control variable to our models.

4.3.4.2 Diversity. A plethora of literature has suggested that diversity in team composition affects team performance (e.g. Bell *et al.*, 2011; Muller *et al.*, 2019). Therefore, we added team diversity as a control variable when analyzing factors influencing team effectiveness (see Appendix 1 for a detailed account of this measure).

4.4 Analytical procedures

Longitudinal multilevel model (MLM, also called hierarchical linear model, growth curve model, or general linear mixed model) was used to test the hypotheses. For each of the 1,267 clans, there are 32 observations. Because of this data structure, longitudinal MLM is suitable, allowing analysis of two levels simultaneously. The first level models how each clan changes over the 32 time points (within-clan), and the second level examines how changes vary across clans (between-clan). The model used restricted maximum likelihood estimation, a procedure similar to maximum likelihood estimation (Dickey, 2008).

For RQ1, hidden Markov models (HMMs) were utilized on the evolution of the clans' sizes. An HMM, when applied to temporal data, can be best understood as an attempt to capture hidden dynamics in the system under study of which the research does not have explicit full knowledge. Consider the weather as an example: One may have three states, "SUNNY," "RAINY," and "CLOUDY," to describe the observed local weather for different cities from day to day. An HMM model with three states may allow us to assess empirically the probability distribution under which we will see any particular state the next day given that we observe a state on the current day (e.g. the empirical probability that we will observe "RAINY" the day after we observe "SUNNY"). As for the number of states, using four states to learn the model might prove to be more effective if the observers were unaware of a fourth "FOGGY" state. The likelihood curve can help us decide the number of states to choose from.

5. Results

5.1 Clans' evolutionary patterns

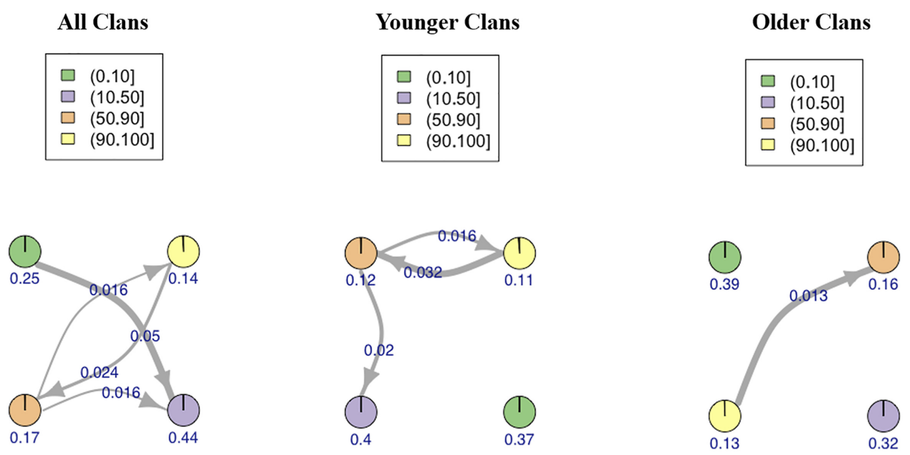
To explore RQ1, a simplified representation of the time series data of the clans was considered: We analyzed a bivariate time series containing the size and age of the clan at the start of each month. The sets of time series were split into younger and older teams according to the median age of 893 days at the initial point of the 32 time points. We then discretized the size time series of both categories into four bins: (0, 10], (10, 50], (50, 90], and (90, 100]. With these discretized time series data, we then trained an HMM for the younger clan set, for the older clan set, and for the total set of time series. To choose the number of states to use in the model, we examined a likelihood curve. We chose four states to compare the models more directly by identifying four states as being closest to the sharpest decrease in gradient for both conditions as suggested by the likelihood curves. Please see Figure 1 for the model visualization.

We observed that in the older clans, none had a population in the (0, 10] range, and that middle-sized clans tended to stay middle-sized (in terms of transition probability). Similarly, the (90, 100] range clans only tended to fall to (50, 90] but did not seem to fall further from that. This suggests some robustness in the older clans (which may be a result of a sort of survivorship bias). In comparison, the younger clans in the (0, 10] range were observed more frequently, and with relatively small probability of transitioning to the (10, 50] range. We observed that larger clans initially had lower probability, and they appeared to converge (albeit with relatively low probability) to the (10, 50] range over time. This result suggests that the younger clans manage to have some probability of attracting more than 10 members.

5.2 Factors affecting team social capital and effectiveness

Table 1 provides a summary of all variables and more details on the descriptive statistics for the first six months. Pearson's correlation table of all variables in the second month appears in Table 2.

To test the hypotheses, separate ML models were run with the three dependent variables: team closure, team-bridging social capital (see Table 3), and team effectiveness (see Table 4). First, three empty means models were fit with the each of the three dependent variables. The empty means model for team-bridging social capital showed that the intraclass correlation (ICC) was 0.2985, meaning 29.85% of the variance was due to between-clan variance. For team closure, the ICC was 0.502, which means 50.2% of the variance was caused by between-clan differences. The ICC for team effectiveness was 0.674. The unexplained variance indicated that a hierarchical model was necessary. Then, the model fitting procedure was that we first fit fixed linear models, and then random linear models. With the changes in degrees of freedom, if the chi-square change was significant and the model fit scores dropped, it means the model was of better fit when random linear models were added. A first-order autoregressive covariance structure was also fitted, and was compared with the random



Note(s): The thicker the arrow is, the higher the transition probability is

Figure 1.
HMM visualization of all clans, younger and older clans

Table 1.
A summary of variables and monthly descriptive statistics in the first six months (N = 1,267)

	Measures	Sep. 2016	Oct. 2016	Nov. 2016	Dec. 2016	Jan. 2017	Feb. 2017
1. Team closure	Within-clan network density	0.061 (0.057)	0.060 (0.569)	0.060 (0.056)	0.061 (0.056)	0.059 (0.056)	0.059 (0.057)
2. Team-bridging social capital	Inter-clan network degree centrality	0.014 (0.009)	0.014 (0.009)	0.013 (0.009)	0.012 (0.009)	0.013 (0.009)	0.012 (0.009)
3. Team size	Number of members	27.641 (21.861)	27.549 (21.674)	28.918 (22.005)	28.303 (21.841)	27.169 (21.536)	26.837 (21.226)
4. Evolutionary fitness	Clans' momentum of growth	1.165 (0.040)	1.071 (0.659)	1.132 (0.623)	1.064 (0.980)	1.007 (0.829)	1.052 (0.923)
5. Team effectiveness	Clan ratings	3.693 (1.180)	3.702 (1.186)	3.707 (1.182)	3.715 (1.182)	3.716 (1.181)	3.738 (1.174)
Control variables							
6. Clan age	Number of years since establishment	2.656 (1.465)	2.743 (1.470)	2.819 (1.467)	2.909 (1.469)	2.991 (1.474)	3.070 (1.470)
7. Diversity (Maximum tier)	Gini scores for members' maximum tiers	0.058 (0.038)	0.060 (0.38)	0.064 (0.040)	0.063 (0.039)	0.060 (0.038)	0.060 (0.039)
8. Diversity (experience point (XP) gained)	Gini score for members' experience points	0.544 (0.135)	0.547 (0.127)	0.538 (0.120)	0.542 (0.123)	0.546 (0.127)	0.553 (0.129)

Note(s): Cell entries represent means, and values in the parentheses are standard deviations linear model. For each of the three dependent variables, we reported the models with the best fit. For each model, the multicollinearity of all the fixed effects in the models was checked using the variance inflation factor and tolerance statistics (Schreiber-Gregory, 2017). There was no multicollinearity issue.

H1a posits that team size is negatively associated with team closure. It was not supported ($b = 0.0001$, $p < 0.001$). H1b proposes that team size is positively associated with team-bridging social capital, and was supported ($b = 0.0002$, $p < 0.001$; see Table 3). H2 hypothesizes that team size is positively associated with effectiveness, and was supported ($b = 0.003$, $p < 0.001$; see Table 4).

H3a suggests fitness is negatively associated with team closure. However, the relationship between fitness and team density was not significant ($b = -0.00004$, $p > 0.05$). H3a was not supported. H3b predicts that fitness has a positive relationship with team-bridging social capital. The positive and significant parameter in our model ($b = 0.0005$, $p < 0.001$) supports

Variable	1	2	3	4	5	6	7	8
1. Team closure								
2. Team-bridging social capital	−0.437*							
3. Team size	−0.515*	0.663*						
4. Evolutionary fitness	0.214*	−0.006*	−0.138*					
5. Team effectiveness	0.001*	0.126*	0.288*	−0.032*				
6. Clan age	−0.120*	−0.105*	0.042*	−0.146*	0.285*			
7. Diversity (Maximum tier)	−0.084*	−0.004*	−0.149*	0.045*	−0.699*	−0.301*		
8. Diversity (XP gained)	−0.463*	0.101*	0.004*	−0.116*	−0.263*	0.070*	0.288*	

Note(s): * $p < 0.001$

Table 2. Correlation table for all variables in the first month ($N = 1{,}267$)

Variable	Model 1 (random linear model + AR (1)) Model for team closure	Model 2 (random linear Model + AR(1)) Model for bridging social capital	Note
Fixed effects			
Intercept	0.063*** (0.002)	0.009*** (0.0002)	
Team size	0.0001*** (0.00003)	0.0002*** (0.000002)	H1a not supported and H1b supported
Evolutionary fitness	−0.00004 (0.0002)	0.0005*** (0.00003)	H3a not supported and H3b supported
Clan age	−0.0003 (0.0005)	−0.00013*** (0.00002)	
Rate of change			
Intercept	0.063*** (0.0023)	0.004*** (0.000008)	
AR(1)	0.446*** (0.006)	0.526*** (0.006)	
Goodness of fit			
−2 Residual log likelihood	−152,695	−328,211	
AIC	−152,685	−328,201	
BIC	−152,660	−328,175	
Degree of freedom	4	4	
Chi-Square	35969.83***	21784.61***	

Note(s): Cell entries represent parameters, and values in the parentheses are standard deviations
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3. Results of the MLM analysis for team closure and team-bridging social capital

Table 4. Results of the MLM analyses for team effectiveness

Variable	Model 3 (random linear 2model)	Model 4 (random linear Model)	Model 5 (random linear model)	Model 6 (random linear model)	Note
Fixed effects					
Intercept	3.817*** (0.036)	3.812*** (0.036)	3.885*** (0.036)	3.832*** (0.036)	
Team size	0.003*** (0.0002)				H2 supported
Categorized team size (small/large)				0.061*** (0.006)	
Team closure		1.181*** (0.090)			H5 supported
Team closure^2		−4.855*** (0.546)			H5 supported
Team-bridging social capital		1.787*** (0.242)		3.030*** (0.381)	H6 supported
Team-bridging social capital × Categorized team size (small/large)				−2.010*** (0.433)	H7 supported
Evolutionary fitness			−0.003 (0.002)		H4 not supported
Control variables					
Diversity (Maximum tier)	−1.032*** (0.057)	−0.989*** (0.056)	−1.103*** (0.048)	−1.153*** (0.048)	
Diversity (XP gained)	0.026** (0.010)	0.041*** (0.010)	0.018 (0.010)	0.021* (0.010)	
Clan age	−0.039*** (0.006)	−0.034*** (0.006)	−0.040*** (0.005)	−0.040*** (0.006)	
Rate of change					
Intercept	0.008*** (0.0007)	0.008*** (0.0007)	0.007*** (0.0007)	0.008*** (0.0007)	
Goodness of fit					
−2 Residual log likelihood	−4198.0	−4561.0	−3862.3	−4042.5	
AIC	−4190.0	−4553.0	−3854.3	−4034.5	
BIC	−4169.4	−4532.4	−3833.8	−4013.9	
Degree of freedom	3	3	3	3	
Chi-Square	107475.76***	113489.76***	112874.66***	109156.44***	

Note(s): Cell entries represent parameters, and values in the parentheses are standard deviations
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

H3b. H4 hypothesizes that clans' fitness is positively associated with team effectiveness, and it was not supported ($b = -0.003$, $p > 0.05$).

H5 posits that there exists a curvilinear relationship between clans' evolutionary fitness and effectiveness. Model 5 indicated that the effects of team closure ($b = 1.181$, $p < 0.001$) and squared team closure were significant ($b = -4.855$, $p < 0.001$), thus supporting this hypothesis (see Figure 2 for visualization). H6 hypothesizes that bridging social capital is positively associated with team effectiveness, and it was supported in Model 4 ($b = 1.787$, $p < 0.001$). H7 hypothesizes that the effect of bridging social capital on team effectiveness is higher for smaller teams. In our data, small teams were coded as 0, and large ones as 1. Therefore, small teams were treated as the reference. As seen in the interaction effect ($b = -2.010$, $p < 0.001$), the relationship between bridging social capital and team effectiveness was smaller for larger teams than for smaller ones. Robustness of the MLMs can be found in Appendix 2.

6. Discussion

6.1 Mechanisms of TSC building

As discussed, contributing to TSC theory (e.g. Bao *et al.*, 2013; Gu *et al.*, 2013; Oh *et al.*, 2004), this research identifies the understudied mechanisms behind TSC building. Membership is a

Figure 2.
The curvilinear relationship between clan network density and effectiveness

key resource that contributes to the maintenance and development of virtual teams (Wang *et al.*, 2013), and TSC takes membership resource to construct and in turn contributes to the recruitment and maintenance of members. Based on this premise, this study contributes to understanding the roles of two variables related to membership resource—team size and team fitness—in the mechanisms of TSC building.

6.1.1 Large clans are more cohesive. Specifically, our findings suggest that size is positively related to team closure in the context of competitive self-organized teams. As suggested in Williams *et al.* (2006), larger clans are more competitive than smaller ones. They tend to attract more competitive players who are more active in co-play networks. Moreover, larger teams have more in-clan activities because they are more able to field a full team than smaller clans, many of which do not have enough members. In this specific game, clans have an upper limit of 100 members. As large clans approach 100, individual members may have less incentive to seek growth, considering that the team's number could top out at any time. Without the motivation to grow their membership, these teams may have more time and energy to bond. In summary, because of the unique affordances of competitive and self-organized clans, the finding in previous research that large formally organized work groups tend to be less cohesive (e.g. Wincent *et al.*, 2010; Wheelan, 2009) is not applied in this setting.

6.1.2 Fit clans bridge better. This study also found connection between TSC theory and evolutionary theory, and especially the important role of fitness in TSC building. Teams with higher evolutionary fitness tend to have higher bridging social capital, indicating that teams with higher fitness status may have a more outward orientation to establish boundary-crossing ties and attract more members onto their teams. However, evolutionary fitness is not associated with team closure, indicating that teams' momentum of growth is not related to teams' orientation in within-team bonding.

6.2 Building an effective team

Consistent with previous TSC literature, our results support the hypothesis that team closure has an inverted curvilinear relationship with clan performance. Bridging social capital is also positively associated with team effectiveness. These results align with previous research (e.g. Benefield *et al.*, 2016; Oh *et al.*, 2004; Wise, 2014). Contributing to existing TSC literature, this study took a step further and found that team size moderates the relationship between bridging social capital and team effectiveness. Specifically, the relationship between bridging social capital and effectiveness is more substantial for smaller teams than larger ones.

Moreover, this research also highlights that membership is a valuable resource for virtual teams (Wang *et al.*, 2013), contributing to our understanding of the relationship between team size and effectiveness. Larger clans also tend to be more effective as the larger the team, the more people contribute to its construction. Lee and Littles (2020) also found that in comparison to small teams, large teams have the "initial critical mass of people with the motivation and resources to act" (p. 193). Unlike teams with formal organization that find size to be a liability (Wincent *et al.*, 2010), size is advantageous for clans to achieve good performance. Fitness, however, was not significantly related to team effectiveness, indicating that although the scope of evolutionary fitness covers reproduction success and the potential for survival in natural selection (Nowak, 2006), it cannot be extended to performance.

6.3 Clan evolution

This research also contributes to a longitudinal view of TSC, adding to the cross-sectional analysis of most previous TSC studies (e.g. Gu *et al.*, 2013; Han *et al.*, 2014; Wei *et al.*, 2011). First, our findings suggest that the age of the clan matters for TSC building. Older clans tend to have lower inter-clan bridging social capital. There are two possible explanations. One is that older clans are losing vitality, and they no longer play as much as younger clans. Another explanation is that as older clans grow more stable in membership, and as members within the clans grow closer, they are increasingly self-sustainable, and they increasingly shut out exterior connections.

By tracking clans' evolution, our analyses also reveal that, overall, clans tend to experience growth in team closure, team-bridging social capital, and team effectiveness. This indicates the general evolutionary patterns of clans: They seek a more cohesive within-team structure, more out-team networking activities, and improved effectiveness as time changes, providing in-depth insights on evolutionary patterns of self-organized and competitive teams.

By observing clans' evolutionary patterns at the population level, the findings suggest, in general, that clans tend to experience membership churn as time goes by, which is consistent with Ducheneaut *et al.*'s (2007) findings. Expanding younger teams is challenging, and older teams are often more likely to maintain a large size. Age dependence theory can help explain this. It states that young clans often have less experience and face more challenges establishing legitimacy, so they are more likely to decline than older clans (Freeman *et al.*, 1983). Future studies can focus on young clans and study strategies to overcome their growth challenges.

6.4 Practical implications

This study also offers practical implications for successful clan organizing. First, clans should maintain an optimal team closure to achieve best effectiveness. Second, our finding recommends that teams recognize the importance of building bridging social capital, and this strategy is especially beneficial for small teams' effectiveness. Finally, membership is a central resource for teams to build social capital and maintain effective performance, but expanding membership is especially challenging for younger teams and may call for more active participation, commitment, and management from the members. Game operators should also design programs to help young clans to achieve sustainability if they hope to maintain in-game team vitality and diversity. This would likely aid in their own goals of retention and stability.

6.5 Generalizability

This research also broadens the scope of current TSC research (e.g. Bao *et al.*, 2013; Chau *et al.*, 2017; Lee *et al.*, 2015) and provides insights on gaming clans, which leads to focused generalizability toward settings of shared affordances (Gibson, 1979) that allow similar "opportunities for action" (Cardona-Rivera and Young, 2013, p. 1). Game settings "map" "real-life" settings surprisingly well because of the roles and motivations of the people involved (Williams, 2010, p. 451; see also Huynh *et al.*, 2013; Trepte *et al.*, 2012). Given the affordances of clans in our research site, our findings can be generalized to similar virtual and offline teams that are self-organized, competitive, and engaged in frequent sessions or tasks. For example, gaming clans resemble competitive virtual teams self-formed for sessions of contests (e.g. crowdsourcing contest teams). Our findings can also be applied to other types of offline clan-like social teams such as self-organized sports teams or even street gangs (Ahmad *et al.*, 2011). Gaming clans are also like self-organized teams in business contexts that are zero-sum, competing with other teams to win and achieve higher ranks.

7. Conclusion

This study makes several contributions. First, this study expands current TSC research by studying competitive and self-organized clans. Our findings suggest that for clan-like teams that are largely self-organized, contrary to formal teams, the larger the team's size, the more effective it is. In addition, this study provides insights on the mechanisms of TSC building. Our results indicate that larger teams have higher closure and team-bridging social capital. Moreover, this research views TSC in a dynamic manner. Methodologically, this research applies a longitudinal model to capture teams' evolution, and theoretically, this study bridges TSC and evolutionary theory, suggesting that evolution of membership provides an important explanation in TSC building. Evolutionary fitness is also found to be a significant factor influencing TSC strategies. Fit clans have high bridging social capital.

8. Limitation and future research

The measurement of team effectiveness in this study was team performance, but there are more dimensions to team effectiveness. For instance, for certain types of virtual teams, the level of in-game satisfaction or emotional support (Reer and Krämer, 2018, 2019) may better predict outcomes like attracting more members, achieving more success, or winning higher rankings. Future studies should also take other dimensions beyond competitive standards like supportiveness, equality, and open communication into consideration.

This also brings up the point that the measurements of team closure can be alternative network metrics such as within-team triadic closure, strong, reciprocated, and even multiplex network ties (Oh *et al.*, 2006). Bridging social capital can also be measured by metrics such as connecting members' leadership roles and diversity of connections (Oh *et al.*, 2006). Future empirical efforts should adopt and compare these metrics to understand the multidimensionality of TSC. Moreover, aside from being examined structurally (e.g. Bainbridge, 2007; Chung *et al.*, 2011; Shen *et al.*, 2014), social capital can be studied as an outcome (e.g. Coleman, 1988; Putnam, 2001; Williams, 2006). Research in this vein measures emotional support, information access, and exposure to diverse opinions and often uses survey scales (e.g. Williams, 2006; see also Reer and Krämer, 2014). Future research might extend the current scope to consider more dimensions of TSC by examining the roles of team size and evolutionary fitness in TSC building defined by cognitive outcomes, such as team support; whether team members share a similar language, vision, and goals in their knowledge sharing (Bao *et al.*, 2013; Lee *et al.*, 2015); the nature of team relationships such as trust, shared values, responsibilities, and identities (Lee *et al.*, 2015); or cross-level social capital such as linking social capital that examines the power structure and hierarchy individuals face in the teams (Clausen *et al.*, 2020; Meng *et al.*, 2018).

Another limitation is that team transformation is more complicated than the measurement of evolutionary fitness. Previous team change studies have proposed to also study team splitting and merging (e.g. Bródka *et al.*, 2013; Gliwa *et al.*, 2012). Additionally, the definition of fitness in this research only covers one dimension of the core capacities that are relevant to the survival and development of team membership. Because the evolution of social entities is complicated (Malik, 2008), future research should identify other core capacities of teams to draw up a more comprehensive fitness landscape of teams in TSC building.

It is also important to note that, since the gaming platform places upper limits on clans, a fitness score for larger teams may not accurately describe their capacity in environment adaptation or ability to attract new members. For larger clans approaching the upper membership limit, fitness reflects their discretion or powerlessness in further expansion because of the upper limit. The limitation on fitness in this study does not prevent us from studying its relationship with TSC. Fitness still accurately captures clans' growing momentum. However, the upper limit may make it more difficult to find the relationship between teams' momentum of growth and effectiveness, because fitness for larger clans may not reflect their true growth potential or capacity to attract and absorb new members. Future research should explore teams without membership limits and see whether their fitness score has a different relationship with team effectiveness. Moreover, this research drew data solely from WoT's North America server. Future research can compare how clan-like team activities differ in different cultural backgrounds. Finally, future research should delve deeper on the organizing and evolution of self-organized and competitive virtual teams via qualitative methods such as interview and ethnography.

Based on the Pearson's correlation table (Table 2), among the independent variables, team size and team closure were highly correlated ($r = -0.515$, $p < 0.001$). Team size and team-bridging capital were also highly correlated ($r = -0.663$, $p < 0.001$). To ensure model does not have multicollinearity issue, these highly correlated variables were not fit simultaneously in the same models. *Fitness* was not significant across models and adding this variable reduced Goodness of fit. Therefore, it was fit in a separate model (Model 5).

Notes

1. Data for May 2019 were also available, but data in this month were only used to calculate the fitness score for April 2019.
2. The Pearson's correlation score between team size and team fitness is small ($r = -0.138$, $p < 0.001$; see Table 2). This indicates that although large clans tend to grow slower, which is likely caused by this constraint, they share a very small correlation.

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Appendix 1

A Detailed Account of Diversity Measures

Two types of diversity were included. In the game, each player has a garage of many tanks, with each having a "tier" from one to ten, with ten being the most powerful and most costly to acquire. The maximum tier score is calculated by the highest tier tank a player owns. It reflects the players' long-term level of experience and expertise in the game, and sometimes their willingness to spend money.

The second type of diversity measurement is based on the experience points (XP) gained over the month. Players gain XP by investing time in the game, learning how to improve their skills, and contributing to the combat. XP gained over the month reflects players' short-term skill as well as their investment of time that month. In each clan, this diversity score measures the distribution of all clan members' XP points gained over the month.

These two types of diversity represent both long-term and short-term skills. For each clan, at each time, both diversity scores were calculated using a Gini coefficient (Cowell, 2008; Dixon *et al.*, 1987), which corresponds to the dispersion of a given score (i.e. maximum tier and XP gained) of all clan members, ranging from zero to one. If a clan's diversity score is zero, it means all members in that clan share the same score, and there is no variance. In comparison, if a clan has a diversity of one, it indicates an extremely uneven distribution with one person having the highest score, and the rest the lowest. Previous research shows that teams with members of diverse experience and skill levels face challenges collaborate, increased costs for management, and lowered performance (Ancona and Caldwell, 1992).

For games, short-term experience and skills may also be relevant because games are constantly update the game to keep players engaged, and recent practice helps prevent skills from getting rusty.

Appendix 2
Robustness Check for MLM Models

To check the robustness of the tests, 600 clans without missing attributes were randomly sampled out of all 11,404 clans. All models were fit on these 600 clans. Results remained overall consistent with previously reported models on 1,267 clans.

Variable	Model 1 (random linear model + AR (1)) Model for Team Closure	Model 2 (random linear Model + AR(1)) Model for Bridging Social Capital	Note
Fixed effects			
Intercept	0.064^{***} (0.003)	0.009^{***} (0.0002)	
Team size	0.00009^{*} (0.00004)	0.0002^{***} (0.000002)	H1a was not supported and H1b was supported
Evolutionary fitness	−0.0003 (0.0003)	0.0005^{***} (0.00003)	H3a was not supported and H3b was supported
Clan age	−0.0006 (0.0007)	-0.00014^{***} (0.00003)	
Rate of change			
Intercept	0.001^{***} (0.00008)	0.0004^{***} (0.00001)	
AR(1)	0.445^{***} (0.007)	0.526^{***} (0.006)	
Goodness of fit			
−2 Residual log likelihood	−96318.6	−207979	
AIC	−96308.6	−207969	
BIC	−96285.2	−207946	
Degree of freedom	4	4	
Chi-Square	22778.33^{***}	14218.03^{***}	

Variable	Model 3 (random linear model)	Model 4 (random linear Model)	Model 5 (random linear model)	Model 6 (random linear model)	Note
Fixed effects					
Intercept	3.646^{***} (0.046)	3.655^{***} (0.047)	3.726^{***} (0.047)	3.611^{***} (0.048)	
Team size	0.003^{***} (0.0002)				H2 was validated to be supported
Categorized team size (small/large)				0.058^{***} (0.007)	
Team closure		1.013^{***} (0.109)			H5 was validated to be supported
Team closure^2		-4.274^{***} (0.667)			H5 was validated to be supported

(*continued*)

Variable	Model 3 (random linear model)	Model 4 (random linear Model)	Model 5 (random linear model)	Model 6 (random linear model)	Note
Team-bridging social capital		2.026*** (0.301)		4.340*** (0.933)	H6 was validated to be supported
Team-bridging social capital × Categorized team size (small/large)				−1.466** (0.531)	H7 was validated to be supported
Evolutionary fitness			−0.005* (0.002)		H4 was validated to be not supported
Control variables					
Diversity (Maximum tier)	−1.101*** (0.058)	−1.059*** (0.057)	−1.014*** (0.058)	−1.055*** (0.057)	
Diversity (XP gained)	0.007 (0.012)	0.019 (0.012)	0.010 (0.012)	0.015 (0.012)	
Clan age	−0.015 (0.008)	0.015 (0.008)	−0.014 (0.008)	−0.015 (0.008)	
Rate of change					
Intercept	0.003*** (0.0009)	0.003*** (0.0009)	0.002* (0.0009)	0.003*** (0.0009)	
Goodness of fit					
−2 Residual log likelihood	−4387.3	−4394.4	−4193.0	−4317.6	
AIC	4379.3	−4386.4	−4185.0	−4309.6	
BIC	4360.5	−4367.7	−4166.3	−4290.8	
Degree of freedom	3	3	3	3	
Chi-Square	70437.63***	71656.94***	73692.27***	71145.27***	

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