# Communication Patterns Predict Team Skill in Multiplayer Online Games

ALEXANDER J. BISBERG, University of Southern California, USA
SONIA JAWAID SHAIKH, University of Melbourne, Australia
YILEI ZENG, University of Southern California, USA
FRED MORSTATTER, Information Sciences Institute, University of Southern California, USA
EMILY CHEN, University of Southern California, USA
EMILIO FERRARA, University of Southern California, USA
DMITRI WILLIAMS, University of Southern California, USA

The present research on team collaboration is typically performed through qualitative interview based studies or social network measurements of connectedness through co-play. In this study, we take the unique approach to build networks from direct messages between players in the massive online game World of Tanks where players self-organize into clans with specific roles assigned from military rankings (from Private to Commander). We explore the relationship between team communication volume and skill level, the impact of communication features on clan rating, and the differences in communication hierarchy between high and low-rated clans. Our findings reveal that higher-rated clans send more pre-battle chat messages, suggesting that effective communication and strategic planning are key to team performance. Evidence shows teams who use voice chat during battle are significantly higher ranked. Finally, we reveal that the highest rated clans have more connected lower-ranked members emphasizing that these teams are "only as strong as their weakest link." This research is guided by the Transactive Memory Systems and Collective Intelligence theories which serve to expand the contribution of this research outside of games to other forms of virtual collaboration.

CCS Concepts: • **Human-centered computing → Social network analysis**; *Empirical studies in collaborative and social computing*.

Additional Key Words and Phrases: teams; networks; machine learning; skill; online games

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## 1 Introduction

Virtual teams are increasingly becoming the norm across industries, including education, marketing, healthcare, and non-profits. Understanding the communication dynamics in these environments is critical for improving team performance and resource allocation. This study examines communication patterns in World of Tanks (WoT), an online multiplayer game where players form "clans" that provide an ideal setting to study virtual team dynamics.

Authors' Contact Information: Alexander J. Bisberg, ajbisberg@gmail.com, University of Southern California, Los Angeles, CA, USA; Sonia Jawaid Shaikh, soniajshaikh@gmail.com, University of Melbourne, Melbourne, VIC, Australia; Yilei Zeng, University of Southern California, Los Angeles, CA, USA; Fred Morstatter, Information Sciences Institute, University of Southern California, Los Angeles, CA, USA; Emily Chen, University of Southern California, Los Angeles, CA, USA; Emilio Ferrara, University of Southern California, Los Angeles, CA, USA; Dmitri Williams, University of Southern California, Los Angeles, CA, USA.


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In WoT, players form clans based on virtual connections or existing relationships. During clan battles, teams of 10 -15 players compete to capture opponents' bases or eliminate all opponents. These battles create resource-limited environments where teams must collaborate to complete concrete tasks, making communication crucial for coordinating actions and achieving victory. Acting alone often proves detrimental to the team's success.

These competitive gaming environments parallel real-world virtual teams working under pressure—whether marketing teams launching multinational campaigns, non-profits distributing aid with international partners, or remote medical teams treating critically ill patients. Both contexts require effective communication, role specialization, and trust. Research has shown that online games reflect core aspects of team collaboration that drive outcomes in both gaming and professional settings [37].

### 1.1 Transactive Memory Systems in Virtual Teams

The collaborative dynamics in WoT clans align particularly well with Transactive Memory System (TMS) theory. TMS describes how groups develop collective knowledge systems where members rely on each other as external memory stores based on recognized domains of expertise[74]. This theory offers a powerful framework for understanding virtual team effectiveness through three core components: specialization (division of cognitive labor), credibility (trust in others' expertise), and coordination (efficient access to distributed knowledge) [39].

In WoT clans, we can observe these TMS components in action: players are assigned and earn specialized roles (e.g., privates, officers, commanders); build credibility through consistent performance in their roles; and coordinate through communication channels to access and leverage distributed knowledge. This specialization allows teams to distribute cognitive load across members, optimizing performance under pressure [6].

The communication networks within these teams are particularly significant for TMS development and maintenance. Palazzolo et al. [53] have shown that communication patterns—who communicates with whom and in what ways—directly impact how effectively teams develop and utilize their collective knowledge. These patterns influence expertise recognition, knowledge exchange efficiency, and ultimately team performance.

The temporal dimension of transactive memory systems is crucial for effective team performance. TMS theory addresses timing through several key mechanisms: developmental phases including encoding, storage, and retrieval of expertise information [47]; communication rhythms that establish expertise recognition patterns [32]; timely expertise retrieval under different task conditions [59]; temporal coordination that enables aligned interdependent activities [20]; and appropriate timing in memory activation [52]. In time-sensitive competitive scenarios like those found in virtual teams, these temporal aspects determine how effectively teams can access and leverage distributed knowledge when under pressure, directly impacting performance outcomes.

Our partnership with Wargaming, the publishers of WoT, provides unique access to anonymized user chat logs alongside gameplay metrics and interaction networks, allowing us to examine how communication structures within these virtual teams reflect TMS development and influence performance outcomes. We discuss user privacy and the ethics of this dataset in Section 5.9.

### 1.2 Research Questions and Contributions

Building on TMS theory, we investigate the following research questions:

(1) **RQ1:** Do elite teams have a higher volume of information exchange within group members compared to low-performance teams?

(2) **RQ2:** What do predictive models for clan performance reveal about TMS activation – the timeliness of communication?
(3) **RQ3:** To what extent does the distribution of communication across expertise levels (as measured by player skill ratings) and clan hierarchy (as measured by assigned roles) reflect effective transactive memory system development and predict team performance?

This study contributes to TMS theory by examining how communication structures -— rather than just communication volume —- facilitate the development and utilization of collective knowledge in virtual teams. Our focus on communication network structures, particularly the patterns of interaction between differently ranked team members, advances understanding of how TMS operates in distributed digital environments where traditional face-to-face cues are absent.

Our findings reveal that high-performing teams demonstrate distinctive communication patterns characterized by greater participation from diverse team members but with more targeted exchanges. Specifically, teams perform better when lower-ranked members are more highly connected through communication, and when more unique members participate in pre-battle planning—even though total message volume is negatively associated with performance. These results suggest that examining communication quantity alone may be a naive approach to analyze effective TMS in virtual teams. Instead, performance depends not on communication quantity but on communication structure that enables efficient expertise recognition and knowledge integration across status boundaries.

Understanding these dynamics has significant implications for virtual team management across domains, offering insights into communication strategies and structures that enhance team performance in distributed digital environments.

## 2 Background and Related Work

### 2.1 Skill Measurement and Rating Systems

How do we know who is better at a game? Arpad Elo, the Hungarian mathematician and amateur chess player, asked this very question to himself in the early 1950s. He wanted a way to rank chess players in tournaments, so they were seeded fairly and the best players would be most likely to move on. This prompted his invention of the Elo algorithm [19]. This model assumes ratings are normally distributed (with constant variance). He used a clever simplification of the normal distribution to make the formula easy to calculate by hand, given it was invented in a time before modern computing. In the 1990s, Mark Glickman enhanced Elo's algorithm with advanced computational and statistical techniques [21]. It accounted for features like time decay in skill, variable variance, back calculation for model hyperparameters and corrections for ratings inflation.

As online competitive games grew, Microsoft Research developed TrueSkill for the popular Halo series [26]. As one of the most successful early online first person shooters it was paramount to scale this model for massive online systems. TruesSkill also accounts for the skill of a team as the sum (or average) of the skill of the constituent team members. After more iterations TrueSkill2 [46] was released, with improved parameter tuning and squad-based modifications. TeamSkill [14] augmented TrueSkill2 by adding more affordances for team modeling – surpassing existing systems in accuracy. Other variations inspired more robust changes to the base Elo model or even other machine learning approaches to adapt skill rating a new sport or game [4, 5, 15, 24].

More recent research also highlights the importance of playing with friends [79] and session length [61] impacting individual and team performance. Overall, there are many complex ways to determine skill rating. WoT has developed their own "personal rating" and "clan rating" formulas.

The goal of the WoT Personal Rating (PR) is to provide players with a numerical representation of their overall performance and skill in the game. The PR serves as a measure of a player's effectiveness in battles, taking into account various factors such as victories, survival in battle, damage dealt to enemies and more. Clan rating is elaborated upon in in Section 3.1.

### 2.2 Social Structure and Teams in Online Games

A rich body of literature has focused on social structure and dynamics within massive online games [2, 16, 17, 62, 67]. These game genres include massive multiplayer online role playing games (MMORGPS) which are similar to WoT. While most of these studies focus on group participation and interactions, they do not specifically explore chat messages and their impact on team skills and performance.

Research on teamwork in online games has highlighted multiple factors influencing team performance, trust, and loyalty. For example, Lee and Chang [38] investigate the role of trust in promoting teamwork in online games. They find that trust only enhances teamwork for players with extensive team experience, with affective commitment acting as a mediator. This suggests that the impact of trust in gaming teams might depend on players' familiarity and comfort with collaborative dynamics. Liao et al. [41] take a social identity theory approach to investigate gamers' commitment to their teams. They find that both participation experience and teamwork knowledge contribute positively to team identification and norm compliance, ultimately fostering commitment to the gaming team. These results suggest that strong identification with a team can motivate players to invest more deeply in collaborative gameplay. Other research has shown the impact of team participation on gamer loyalty. Teng and Chen [68] find that players' adherence to team norms and satisfaction of social needs through team participation enhances loyalty. By introducing social norms as a predictor for gamer loyalty, this work underscores the importance of collaborative engagement for player retention in online games. Huang et al. [28] also examine the relationship between teamwork and social interaction in gaming and note that simply spending more time in teams doesn't necessarily lead to increased social interactions. They identify two distinct types of players: those who prefer solo play and those who favor team environments, each of which can be predicted based on in-game behavior. These findings imply that not all team activities lead to closer social connections in online games, challenging the assumption that teamwork equates to social bonding.

Debkowski et al. [13] present the "Contained" framework, leveraging Minecraft as a testbed for studying collaborative behavior. By modifying Minecraft to create tasks that demand teamwork, the authors demonstrate how online games can be used to collect detailed data on team performance and individual roles. This approach provides a promising model for studying complex team behaviors in controlled virtual environments. In educational contexts, Gorlinsky and Serva [22] suggest that online games offer valuable environments for teaching teamwork and leadership. They outline a conceptual framework for using game-based simulations to foster these skills in students, and propose strategies for transferring these skills to real-world settings, making a case for games as an effective tool in team-building education.

Pobiedina et al. [56] explore team formation in the game Dota 2, using game log data to identify the factors that contribute to team success. Their study reveals that player roles, experience, and friendship ties significantly impact team success and cooperation, illustrating how in-game behavior can be used to predict team dynamics and social patterns. Collective intelligence also plays a key role in gaming team performance. Kim et al. [33] show that collective intelligence can predict performance in competitive games like League of Legends. Interestingly, they find that teams with higher social perceptiveness and female members tend to have higher collective intelligence. The study emphasizes the importance of non-verbal communication, or tacit coordination, over verbal communication in fast-paced gaming contexts.

In a similar context, Eaton et al. [18] highlight the critical role of a "Carry" player in League of Legends, whose survival has a direct impact on team success. Their work demonstrates the value of large datasets from online games to study team dynamics and the specific impact of key players on team outcomes. Pobiedina et al. [57] further investigate team success factors in Dota 2, finding that cooperation, rather than competition, plays a more significant role in achieving success. In the setting of temporary teams, Kou and Gui [36] find that even short-term teams in League of Legends engage in meaningful social interactions, where players develop their own strategies for coordinating with strangers and often try to influence teammates' actions. This finding suggests that even transient teams can develop complex interaction patterns, contributing to both social and gameplay objectives.

Social capital [75] refers to the positive benefits gained from social interactions over time. It can be characterized into "bridging" and "bonding" social capital. The former is more inclusive across networks while the latter can be exclusive within network. One study that underscores the importance of social capital in team networks Benefield et al. [2] finds that a moderate level of network density (or closure) and connections with other groups (high brokerage) maximize team effectiveness in online multiplayer games. Additionally, they note that teams with central leaders tend to be more effective when paired with other central-led teams, suggesting that leadership structures and network connections are key for achieving team goals. Research by Lou et al. [43] on player motivations in team selection shows that social and immersion motivations play a strong role in choosing team members, while achievement motivation influences choices based on individual characteristics rather than social bonds. This study highlights the nuanced ways in which motivation shapes team composition, which can vary depending on the players' social and gameplay objectives. Team Social Capital (TSC) in WoT by measuring bridging (between team) co-play and bonding (within team) co-play and predicts clan rating (what they call effectiveness) as an independent variable [40]. This work gives us confidence that using within-clan communication can be an effective way to predict clan rating, and could strongly corroborate the findings in this work given that text communication is a part of within-group bonding previously unmeasured in WoT [60] .

Sun et al. [65] define groups in WoT using the same clan infrastructure in addition to a co-play network. Co-play is used to analyze which players have entered into a game together, which differs from clan membership alone. Here the emphasis is to understand the differences between membership networks and co-play networks, whereas the aim in *this* work is to analyze the nominal roles defined within a clan and the communication structure surrounding those roles. Results from this previous work [65] are useful for the formation of our hypotheses later on. They convince us that high-rated clans will have strong within-group ties as defined by individual centralization to a clan network.

### 2.3 Virtual Teams in the Workplace

The complexities of managing virtual teams have attracted substantial attention in recent years, particularly as organizations increasingly rely on geographically dispersed team structures. A key contribution to this domain by Nunamaker et al. [49] provides foundational principles to enhance virtual teamwork effectiveness. Their research emphasizes unique challenges faced by virtual teams, such as balancing differing local work processes, adapting to diverse collaboration tools, and managing competing priorities between virtual and local demands. These principles aim to guide virtual team management across sectors and include strategies for overcoming communication barriers and technology adaptation challenges.

The need for specialized management approaches in virtual teams is underscored by Berry [3], who argues that asynchronous communication and computer-mediated interaction fundamentally alter work patterns, decision-making, and relationship dynamics within virtual teams. Effective management, Berry suggests, requires an understanding of these altered dynamics and a departure from traditional team management strategies to accommodate virtual teams' unique time and space constraints. Leadership practices tailored to virtual environments are further explored by Malhotra et al. [45]. They identify trust-building, appreciation of distributed diversity, structured meeting management, and visibility as essential leadership practices for enhancing virtual team performance. Leaders who adopt these practices can foster stronger connections, ensure individual contributions are recognized, and help virtual teams achieve cohesion and sustained engagement despite geographical barriers.

The flexibility and resilience offered by virtual teams are highlighted by Townsend et al. [70], who discuss how advances in telecommunications enable organizations to remain agile in dispersed setups. By leveraging virtual team structures, organizations can tap into a global talent pool and respond to modern workforce demands for remote collaboration and technological integration, creating productive teamwork models that were previously unfeasible. Virtual team literature also identifies specific challenges that must be addressed to facilitate success. For instance, Kirkman et al. [35] delineate five challenges in establishing and supporting virtual teams, including the need to build trust and cohesion, overcome isolation, and select members with the right technical and interpersonal balance. Effective virtual team leaders, therefore, must focus on creating a strong team identity and fostering an inclusive, collaborative environment to mitigate the isolation often experienced by remote team members.

Attaran et al. [44] echo these challenges, highlighting that virtual teams require a distinct approach to communication, particularly with respect to building trust, managing cultural differences, and ensuring clear channels of communication across dispersed members. This "virtual distance" between team members, as Davison [12] proposes, requires teams to develop mechanisms for overcoming time zone barriers and creating structured communication practices that facilitate connection and productivity across locations. Additionally, Jarvenpaa et al. [29] identify key antecedents of trust within global virtual teams, such as perceived integrity, ability, and benevolence among team members, which influence team cohesion and success. They find that trust levels fluctuate over time, with perceptions of integrity proving most critical in the early stages of virtual team development. This underscores the importance of fostering trust early and consistently throughout a virtual team's life cycle.

Collectively, these works provide a foundation for understanding the complexities of virtual teamwork. They underscore the need for tailored management, specialized leadership practices, and trust-building mechanisms to optimize virtual team performance and cohesion. The insights from these studies are critical for further developing frameworks that address the unique challenges and benefits of virtual teams in contemporary, digitally-driven organizations.

### 2.4 Collective Intelligence and Roles in Teams

Collective intelligence involves the idea that groups, as a whole, can exhibit a form of intelligence that exceeds the sum of individual members' contributions [64]. If not a direct counterpart to TMS, it is an intuitive extension. Much like attempting to measure "general intelligence," there has also been shown to be a general collective intelligence that cannot be explained by individual intelligence alone, and in fact it is related more to an individual group's social tendencies than to their skill [76]. Collective intelligence in teams is present in collaborative massive online games, controlling for the amount of time played together as a team [34] .

Longitudinal studies over time explore within-team relationships in both real world sports and a popular Massive Online Battle Arena (MOBA), showing that both qualitative and quantitative interactions significantly improve the odds of winning [48] . Qualitative aspects include "shared prior success" while quantitative measure the number of times two teammates collaborated. Jiang et al. [30] describe roles in the online game League of Legends, similar to the game we address in this work. They show that there are three main player categories that align with their theoretical framework: generalists, specialists and mavericks. This work highlights the fact that roles are an important facet of online games and player have some form of self-selection into these groups.

## 3 Methods

### 3.1 World of Tanks Game and Mechanics

World of Tanks [71] is a MOBA where players engage in team-based battles using mid-20th century tanks from various nations. Developed by Wargaming, the game emphasizes strategic combat and teamwork across diverse battlefields. As of late 2023, WoT is estimated to have over 7 million total players, with approximately 140,000 daily players [58].

In WoT, battles are the core of the gaming experience. Players enter 15 vs. 15 or 10 vs. 10 player matches, where strategic positioning, map awareness, and teamwork are crucial for victory. The game features a wide array of maps with varying terrain, from the jungle to the dessert, providing diverse environments that demand adaptability from players. Tanks are categorized into different classes, such as light, medium, or heavy, each serving specific roles on the battlefield. Successful battles contribute to experience points and in-game currency, allowing players to unlock new tanks and upgrade existing ones.

Clans are player-created groups that provide a platform for social interaction, strategic collaboration, and collective achievements. Players can join existing clans or establish their own, with each clan having its unique identity, tag, and hierarchy. The Clan interface facilitates communication among members, allowing for discussions, coordination of activities, and sharing of resources. One significant aspect of clan mechanics is Clan Wars, a large-scale, global competition where clans vie for control over territories on a world map. Participating clans engage in strategic campaigns to conquer and defend regions, with battles determining territorial ownership. Successful clans gain access to in-game resources and bonuses, enhancing their overall capabilities. Clan Wars thus adds a layer of meta-strategy to the game, requiring clans to plan, coordinate, and execute tactics on a grand scale.

Clan members in WoT typically communicate about battles through in-game messaging systems and external communication platforms. Within the game, clans have access to a dedicated Clan chat channel, providing a real-time communication hub for members. Here, discussions about battle strategies, upcoming Clan Wars, training sessions, and other relevant topics take place. Players communicate before, during and after battles. They can also directly message each other outside of the group communication channels. Additionally, many clans use voice chat through external voice chat or messaging apps. Voice communication, in particular, is commonly used for its efficiency in conveying information during intense gameplay. Although we have access to the text chat data in WoT, the voice chat data is not shared with us. Therefore analyzing any form of voice communication is out of the scope for these studies.

The importance of clan rating varies between different clans in WoT, and it often depends on the goals and priorities of each clan. For some clans, achieving a high clan rating is a primary objective, as it signifies success in competitive aspects of the game, such as Clan Wars. These clans may place a strong emphasis on strategic planning, coordination, and participation in high-stakes battles to improve their rating [50].

In WoT clans, 11 different roles contribute to the overall functioning and success of the clan. The Commander is the leader, making strategic decision and guiding the clan's direction. The Recruitment Officer focuses on expanding the clan by reviewing applications and conducting interviews. The private serves as a front-line participant in battles, following the lead of these aforementioned higher-ranking officers.

The Legionnaire system in WoT allows players who are not members of a particular clan to participate in that clan's battles as temporary members. Invited by individuals within a clan, these temporary members can participate in battles without formally joining a clan. Legionnaires' participation is temporary and ends with the conclusion of the battle, allowing them to explore different clan dynamics without ongoing commitments.

### 3.2 Data Filtering and Handling

The data used in these experiments were collected on a virtual private server (VPS) owned by Wargaming Ltd. We were allowed to request certain datasets, which were then uploaded to the server in the form of *.csv* files. For this analysis, we unified three different datasets: clan ratings, clan chat and clan roles. The clan chat dataset stops in July 2019, whereas the clan ratings data begins in July 2019. This left one month worth of data overlap for the study period (07-2019). In this month there are approximately 1 million chat messages from ~$1,600$ clans. Given this size, we determined the dataset was sufficient to proceed.

The roles dataset is aggregated into monthly increments for approximately $250,000$ players. For an individual, we have the clan they were a member of for the most days in the month, a list of all of the roles they had during that month, and the role that they were in for the most days in the month. About 3.7% of the players played more than one role in July 2019. The role list is ordered, so the first role in the list is the first role the player was assigned, and so on.

This dataset does not consist of the entire population of every server; it is a sample of data from the North American server. The implications of this choice will be discussed in Section 5.8.

### 3.3 In-Game Communications

For the experiments presented here we categorized chat messages into two types: battle chat and non-battle chat. These categories were derived directly from fields in the dataset. Clans with fewer than 10 members were filtered out for all experiments since that is the minimum required to participate in a clan battle. The clans were then stratified into three rating quantiles: the top 10th percentile, middle 10th (45-55 percentile), and bottom 10th percentile.

*3.3.1 Frequency.* We measured the weekly number of chats for each quantile. To assess if there were significant differences in means, non-parametric hypothesis tests, specifically Mann-Whitney U and Kruskal-Wallis, were employed due to the heavily right-skewed distributions of the data.

This experimental procedure involved building an expanded feature set for analysis. Predictors include the age of the clan and the total number of players within each clan. Additionally, average daily battles and lifetime battle count (max at ~$50,000$), are predictors. Communication variables of interest are: counts of chats in various categories (clan, pre-battle, direct messages (DMs), and battle) and the number of individuals engaging in these types of communication. Network-related metrics, calculated from their DMs, such as density, centralized degree centrality, and average clustering, are also included. It is possible that some clans had more Legionnaire participation than others, so two features were added to assess this: the ratio of unique clan members chatting during the battle and the ratio of chats sent by clan members during the battle.

*3.3.2 Sentiment.* In addition, we also had access to the message text sent by the teams. Therefore, we decided to implement chat processing features. At first, we considered using a lexicon-based approach to analyze the sentiment of game chat. Thompson et al. [69] generated a complete lexicon for StarCraft 2 (a similar game) using human annotators to modify the existing SO-CAL model; however, the lexicon was not released, so we were unable to test this method. Alternatively, we

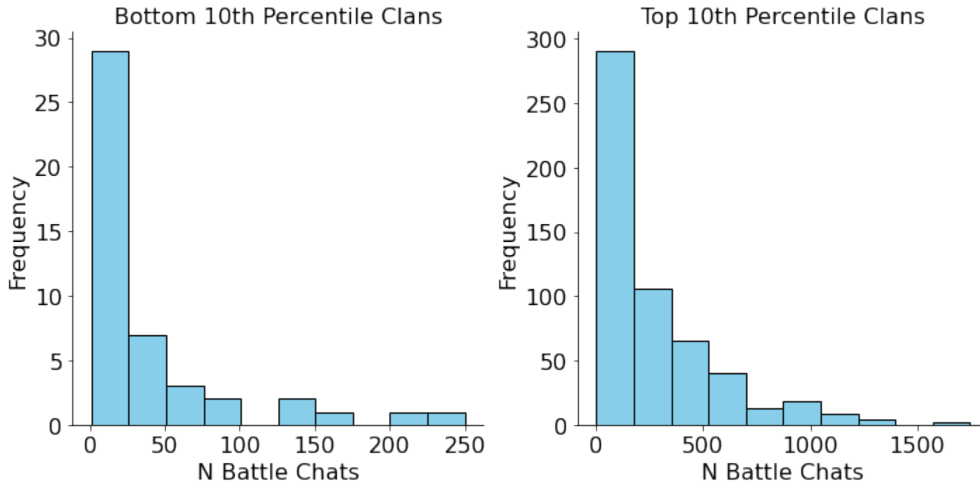



Fig. 1. Count of each of the number of battle chats per week for each clan divided by rating threshold.

note that game communication consists of short snippets of text, slang, and language patterns similar to social media communication. Therefore, we used the Twitter XLM Roberta [1] for classifying the sentiment of multilingual chat data, enhancing the study's ability to capture nuances in communication within the gaming context. This models output scores for positive, neutral and negative sentiment that are run through a softmax function and scaled to 0-1.

BERT-based sentiment analysis involves adapting a pre-trained transformer-architected language model for sentiment prediction. After preprocessing the text and representing it numerically through BERT embeddings, a classification layer is added for sentiment labels (positive or negative). The model is fine-tuned on a sentiment-labeled dataset (in this case from social media) using supervised learning, optimizing its weights to minimize classification error. The bidirectional context understanding of BERT and its deep architecture contribute to its effectiveness in capturing nuanced relationships in language, making it suitable for sentiment analysis tasks.

The target variable in this study is the clan rating. By incorporating these diverse features, we aimed to comprehensively examine the factors influencing clan ratings within the multiplayer online gaming context, considering both communication dynamics and structural network characteristics.

*3.3.3 Chat Networks.* In the investigation of direct communication patterns within clans in WoT, this study focused on examining interactions among clan members. The dataset contains records of direct messages exchanged between members. Clan members assign each other positions, falling into three main categories: Authoritative (including commanders and executives), Job-specific (such as quartermasters and officers), and Participants (encompassing private and reservist roles). To ensure enough members and messages for network analysis, we filtered out clans that had fewer than four members actively engaged in chatting. Networks were generated based on a complete month of chat data for each clan, allowing for a comprehensive understanding of communication dynamics. The analysis specifically compared communication networks between the top 50 rated clans and the bottom 50 rated clans, as the previously used quartile divisions left too few clans per category for analysis.

# 4 Results

## 4.1 RQ1: Chat frequency

| Chat type | Bot 10 | Mid 10 | Top 10 |
|---|---|---|---|
| N weekly battle chats | 36* | 45* | 257 |
| N weekly non-battle chats | 27 | 66 | 883 |

Table 1. Number of chat messages sent in each category for different percentiles of clan ratings (with more than 10 clan members) * = these two are not significantly different from each other, all others in each row are. (Mann-Whitney U, $p < 0.01$)

The interpretation of Table 1 is that all pairwise comparisons in a row are significant, **except** for the two that are noted with an asterisk. We find that the number of battle chats from the top 10th percentile is significantly greater than the bottom 10th percentile, and the top 10th percentile is greater than the middle 10th percentile. The middle 10th percentile is not significantly greater than the bottom 10th percentile of battle chats.

Overall, we found that higher skill teams have significantly more battle chats and non-battle chats than lower skill teams. It is somewhat interesting that there is not a significant difference in battle chats as opposed to non-battle chats. The count of battle chats is much lower than the count of non-battle chats. Although non-battle chat is comprised of clan chat, direct messages and pre-battle chat, there may be another reason for the small number of battle chats, namely, external voice chat platforms.

In WoT, players often utilize external voice chat platforms like Discord or Teamspeak for communication during battles. These platforms offer several advantages over in-game text chat, primarily providing real-time and seamless communication. Voice chat allows for quicker and more efficient coordination among team members, enabling instant sharing of strategies, warnings, and tactical information. In the fast-paced environment of WoT battles, where split-second decisions can determine the outcome, voice chat enhances teamwork and responsiveness, fostering a more dynamic and coordinated gameplay experience compared to the slower-paced nature of in-game text communication.

| Chat type | N | Mean Clan Rating |
|---|---|---|
| Server invite | 29 | $6,547^{\dagger}$ |
| No server invite | 5,061 | $2,763^{\dagger}$ |

Table 2. Number of chat messages sent containing an external voice service invite link. † = significantly different (Mann-Whitney U, $p < 0.01$)

To detect if invites were sent, we searched the chat messages for strings specifically containing "discord.gg" or "teamspeak3.com." The fact that the result is significant with such a small sample of invite links is somewhat surprising. The clans that sent links were much higher rated, on average, than clans who didn't send a chat server link as seen in Table 2. This is a strong indicator that communication and clan skill are closely intertwined.

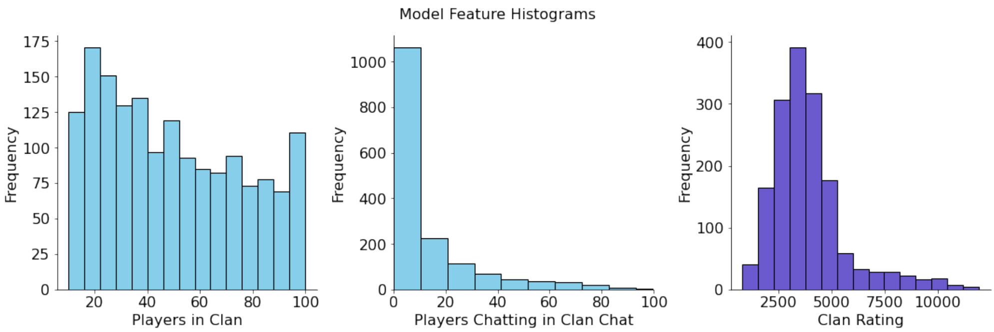



Fig. 2. Distributions of some features (left and center plots) and the study target variable – clan rating (right-most plot). After performing the Shaprio-Wilk normality test, no variables were distributed normally. Therefore, we chose to use the Spearman correlation to calculate the R value as opposed to Pearson.

### 4.2 RQ2: Predicting clan and individual rating

*4.2.1 Clan Rating Prediction.* The analysis involved assembling a comprehensive feature set for predicting the clan rating to ensure that we would not only be using chat features but also other features that controlled for things like longevity, experience and success. The rating data was only available at a monthly granularity, so we could not summarize weekly for this analysis (as we did for the previous one). Figure 2 portrays distributions of few different dependent variables analyzed in this study including the total number of players in a clan and the total number of unique players who sent a message in clan chat. For this experiment, we broke down non-battle chat into it's constituent components – pre-battle chat, clan chat and direct messages. A benefit of aggregating monthly is that breaking out each of these categories is easier since there were more chats for each clan in these categories. We explain clan chat in Section 3.1, while the other two non-battle chat types are self-explanatory.

Another notable aspect of Figure 2 is that these variables are not normally distributed, and neither is our target variable, clan rating. We performed a Shapiro-Wilk test on all 20 features and none of them were normal. Therefore, we made the decision to use Spearman correlation as opposed to Pearson, so all correlations and R values in this analysis are Spearman coefficients.

Predictors related to historical and team stats included the age of the clan, the total number of players within it, average number of daily battles and the total battles. The total battle count represents the clan's lifetime battles as opposed to the total within a month. These features had a maximum around 50,000 and was significantly ($p < 0.01$) correlated (R = 0.75) with Clan Rating. Notably, the average battles daily exhibited a high maximum of approximately 16, showing a strong correlation (R = 0.67) with Clan Rating. Variables of interest included counts of chats (clan, pre-battle, direct messages, and battle) and counts of individuals participating in these communications. Finally, we derived more statistics related to the direct message communications of these clans. Based on the results of previous work [23, 63], we created various network metrics like density, centralized degree centrality, and average clustering from the direct message network of clans. These DMs comprised about 37% of all messages in the study. The target variable for analysis was the Clan Rating, forming the basis for assessing the impact of these factors on clan performance.

To make the predictions we chose two different regression models, one linear and one non-linear. Normalized regression (Lasso, L1-regularization) was chosen for the linear model to prevent over-fitting and provide a more generalized predictive model.

Since some model features are correlated it is important to use the L1 norm, which introduces sparsity [7]. This method is used to implicitly perform feature selection [80] without explicit transformations like Principal Component Analysis or Linear Discriminant Analysis [31]. For this analysis we used built-in functions from the popular Python machine learning library scikit-learn [55]. We performed 5-fold cross validation to select the best alpha from $\{10^{-4}, 10^{-2}, 1\}$. Data normalization was performed to be able to compare the model coefficients. Given that the data is not normally distributed we proceeded to use min-max scaling as opposed to standard scaling (which uses Z-score normalization). The best model Spearman R was 0.958 ($\alpha = 1$), meaning this model captured a significant amount of the features' contribution to Clan Rating.

| 3 Highest Lasso model $\beta$s | $\beta$ | Re-scaled $\beta$ | 3 Lowest Lasso model $\beta$s | $\beta$ | Re-scaled $\beta$ |
|---|---|---|---|---|---|
| N unique pre-battle chatters | 5570 | 64.03 | N pre-battle chats | −1019 | −0.2117 |
| Avg battles daily | 4516 | 293.8 | N clan chats | −930.4 | −0.1885 |
| Players in clan | 2925 | 29.25 | N unique battle chatters | −578.1 | −8.758 |

Table 3. Lasso model coefficient values for the clan rating model (and their re-scaled counterparts based on the min-max scaling method).

| 3 Highest Lasso model $\beta$s | $\beta$ | 3 Lowest Lasso model $\beta$s | $\beta$ |
|---|---|---|---|
| N battles | 8405 | N active days | −438.0 |
| N pre-battle chats | 5310 | DM network centrality | −364.3 |
| Total XP spent | 5181 | Role most days | −26.50 |

Table 4. Lasso model coefficient values for the individual rating model

In Table 3 the features with the three highest and lowest $\beta$s are displayed. The highest values show a positive relationship between the feature and clan rating, while low values show a negative relationship. For the Lasso model the target variable **clan rating** was left un-scaled, so to calculate the re-scaled $\beta$ we divide the model $\beta$ by the feature maximum value. Since the original features were min-max scaled, this achieves the appropriate scale to analyze the magnitude of the original feature on the prediction. In this case, the number of unique individuals who chatted during pre-battle chat has the highest magnitude of influence over the prediction (largest $\beta$). It was interesting to see that a the derived chat feature **number of unique pre-battle chatters** has more influence over a prediction than the clan summary variables **average battles daily** and the **total players** in the clan. After re-scaling, a one unit change in a team's average daily battles corresponds to a 293-point increase in clan rating with all other variables held constant while a a one unit change the number of unique battle chatters corresponds to a 64-point increase in clan rating with all other variables held constant. Increasing participation in pre-battle chat only takes convincing one person to contribute to the conversation, whereas convincing 10-15 clan members to participate in another battle during the day is harder. This fact also highlights why it's important for clans to have more players in their clan, to allow for higher number of battles when members may not be available.

The magnitude of normalized pre-battle chats has a negative model coefficient meaning that a one unit change in this variable is associated with a 1019-point decrease in clan rating holding all other variables constant. However, when we re-scale the variables to the original range of pre-battle chatters, a one person increase in pre-battle chat only leads to a decrease in clan rating of 0.2117. Clan ratings are on a scale in the thousands, so this number is practically insignificant. It would take approximately 5 more pre-battle chats sent to reduce a clan's rating by 1 point. An explanation for this could be that clans who spam *too much* information before the battle may just lead to at best, unrelated noise, and at worst, confusion about plans for the battle. This aligns with the information saturation theory proposed earlier.

Random Forest Regression is valuable for predicting a variable due to its capability to model complex relationships within the data. Unlike linear models, Random Forest can capture non-linear patterns and interactions among predictors, making it particularly effective when the true underlying relationship is intricate and involves multiple variables. The method constructs an ensemble of decision trees and leverages their collective predictive power to provide robust predictions. This ensemble approach enhances generalization performance by reducing overfitting, accommodating noisy data and handling outliers. The Random Forest's ability to handle both numerical and categorical features without extensive pre-processing is another reason why we chose to use this model.

| Parameter | Values | | |
|---|---|---|---|
| Splitting Criterion | squared error | absolute error | Friedman MSE |
| N Estimators | 50 | 150 | 300 |
| Max depth | 5 | 10 | 20 |

Table 5. Model hyperparameters for random forest regression

In this model we decided to test three different hyperparameters: (1) the max depth of the tree (2) the number of estimators in the ensemble and (3) the splitting criterion. The max depth parameter determines the maximum depth of individual decision trees, impacting the model's complexity and susceptibility to overfitting. Higher values may result in more intricate models that fit the training data closely but risk poor generalization to new data. Conversely, lower values may yield simpler models that generalize better. The number of estimators parameter represents the number of decision trees in the ensemble, with an increase generally enhancing predictive performance by averaging out individual tree predictions. However, this improvement comes with increased computational cost. The choice of splitting criterion, whether based on absolute or squared error, affects how the algorithm measures the quality of splits. The absolute error criterion (MSE) is more sensitive to outliers, potentially influencing the model's robustness. In contrast, the squared error criterion is less sensitive to outliers but may lead to biased predictions. We tuned the model using grid search with 5-fold cross validation. The range of parameters tested can be found in Table 5

Feature importance refers to the measure of the impact each input variable has on the predictive accuracy of the model. Random Forest calculates feature importance based on how often a feature is used to split the data across all the decision trees in the ensemble and how much it improves the model's performance. The more a feature is used to make significant splits and contributes to reducing prediction errors, the higher its importance. Random Forest assigns a score to each feature, and these scores are normalized to represent the relative importance of each feature.

There weren't significant differences in model performance based on hyperparameter tuning. Most models were identical in Spearman R, Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE). The best model demonstrated a Spearman R of 0.963, indicating it very strongly captures the relationship between then model variables and Clan rating. Given this is a complex, multivariate model observing other facets of the model will help us understand the

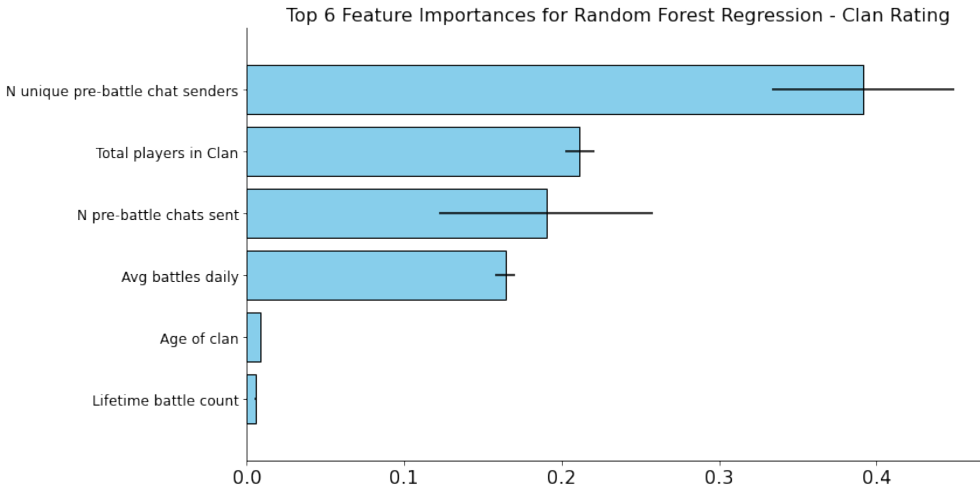



Fig. 3. Mean feature importance for the Random Forest Regression model. The black line represents the 1 std deviation between the 5 iterations of cross-validation.

underlying relationships in the variables. As seen in Figure 3, the feature importances generally lined up with the model coefficients seen above in the Lasso regression analysis. The number of battle chatters was the most important feature, nearly double the next most important feature, the number of players in the clan. The average battles daily and the number of pre-battle chats sent were similar, although pre-battle chat sent has much higher variance. This may be explained by what was happening in the Lasso model where the number of chatters increasing negatively impacted Clan Rating. The legionnaire, DM network and chat sentiment features were not within the top five most significant features in either model. Legionnaires, or substitutes for clan members, were very sparse so they likely do not have much predictive power in this analysis.

*4.2.2 Individual Rating Prediction.* Predicting personal rating including covariates along with communication factors will help us derive whether communication is as important to quantify individual skill, or if it is specifically useful for quantifying skill in groups of individuals. We have separated the features into four groups for this analysis. Battle features, experience features, clan chat and clan role features. The battle features include the total number of battles played. Experience features include the amount of in-game currency or experience spent to unlock tanks and other upgrades and the total active days. For clan chat we measured the number of chats sent in each context (battle, pre-battle, DM, clan) and measured their centrality in the direct message network. It is possible that individuals who were in positions of connectivity in the clan were also highly rated individually and skilled at the game. Finally, we ranked their assigned role in the clan, starting with commander (1) down to reservist (11). The goal is to discover whether players are typically promoted based on whether they themselves were good at the game or for a different reason, like communication skills or charisma.

The graph in Figure 4 displays the feature importance for the variables in the individual ratings prediction model. The results of this model show that far and away battle count is the most important feature in the model, outpacing communication features like number of pre-battle chats and clan chats sent. The network measures were not in the top 5 most important features in this model. Individual rating isn't a function of clan performance so the clan network features likely

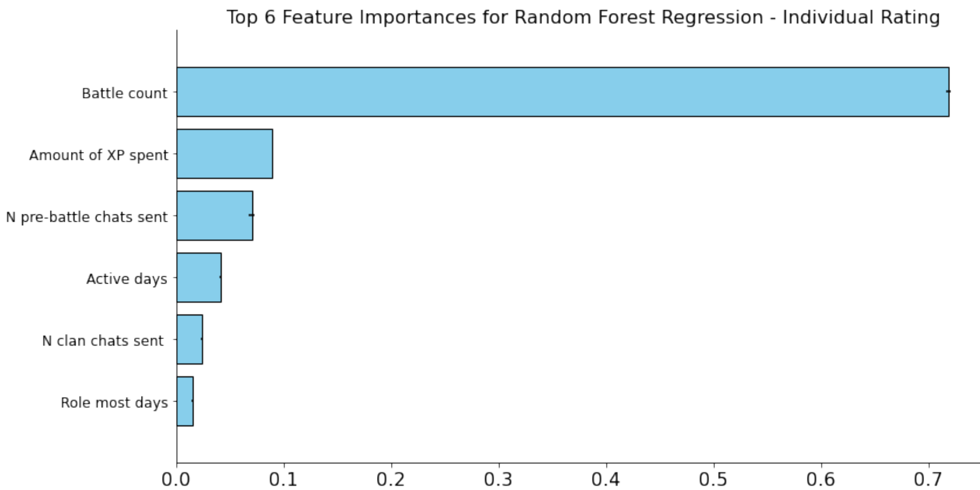



Fig. 4. Mean feature importance for the Random Forest Regression model. The black line represents the 1 std deviation between the 5 iterations of cross-validation.

don't play a significant role in this model's predictive power. Overall this model had a much lower mean Spearman R at 0.640, capturing less of the variance in individual rating than the clan rating model counterpart. The linear model results were nearly identical to the random forest and their highest coefficient values lined up with the highest 3 random forest model features.

*4.2.3 Text analysis.* Not only do we have access to the message frequency and classification, but also we have access to the message text. This experiment aimed to investigate the potential of chat sentiment in predicting clan ratings and explore the correlation between sentiment and the perceived friendliness of higher-rated clans. Initially we considered a lexicon-based approach for text sentiment classification but settled on a Bidirectional Encoder Representations from Transformers (BERT) model for simplicity.

| | Negative | Neutral | Positive |
|---|---|---|---|
| Mean | 0.36 | 0.41 | 0.23 |
| Std. Dev. | 0.25 | 0.18 | 0.16 |

Table 6. XLM Roberta Model Sentiment Analysis Scores

The sentiment analysis task involved classifying chats into negative, neutral, and positive categories, assigning scores ranging from 0 to 1. Potential shortcomings were identified, particularly in the interpretation of sentiment due to context differences between in-game communication and other platforms like Twitter. For instance, expressions such as "nice shot" received a positive score of 0.66, while "great damage" was assigned a negative score of 0.74. Overall, the analysis indicated that, while chats tended to be predominantly neutral, there was a slightly higher prevalence of negative sentiments compared to positive ones.

Adding the average sentiment per clan divided by chat type did not contribute much to the clan rating prediction results. This could be explained by the fact that as the quantity of messages a clan sends increases, the sentiment approaches the population mean sentiment, so no information is gained from this information. In the future we plan to swap the averaging approached to a label discretization, where each chat takes the category assigned to it with the highest rating. Also, it would be possible to divide the chats on a per-battle level. Some battles maybe someone lost their cool, or there was a particularly angry player. Chat sentiment on the enemy team would affect the outcome of an individual battle as opposed to clan rating.

### 4.3 RQ3: Roles and clan messaging structure

The goal of this analysis is to understand the relationships between hierarchies in clans. From the previous dataset of clan chat and clan rating, we now joined on a third dataset of clan roles. This dataset was described above in Section 3.1. After filtering the roles dataset to July 2019 and joining on the clan chat/ratings dataset, the total number of clans decreases to 1, 213. In addition, since we are now measuring direct message networks directly and attempting to extract network information from these chats, we also set the minimum number of clan members chatting to five. This way centrality would represent something meaningful in the network as opposed to a nearly trivial very small DM network. Adding this filter left 684 clans remaining. Given the diminished dataset size, the 3 quantile division did not provide enough clans per division. So instead, the 50 highest rated and the 50 lowest rated clans were selected for this study.

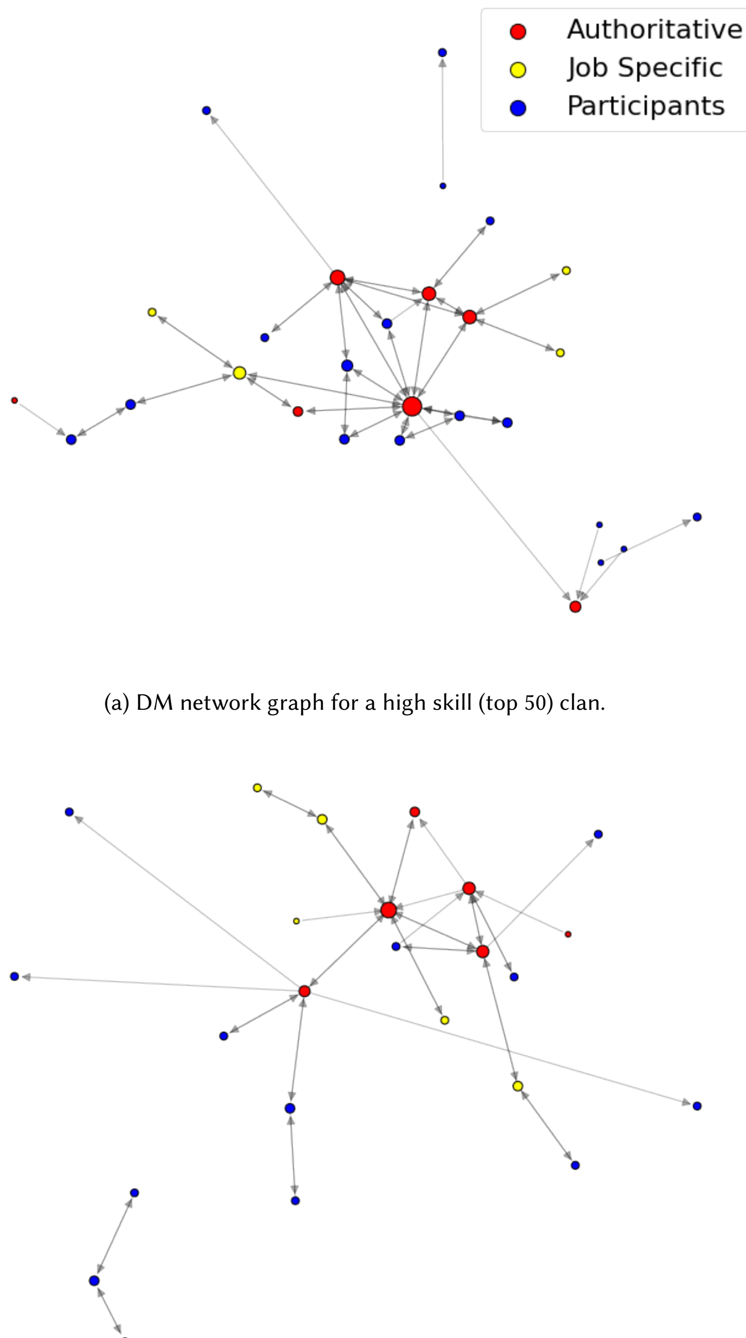
| Category | Roles |
|---|---|
| Authoritative | Commander, Officers: Executive, Personnel, Combat, Intelligence |
| Operations | Quartermaster, Officers: Junior, Recruitment |
| Participant | Private, Recruit, Reservist |

Table 7. Roles grouped by category

To classify the roles into different groups, we read through the online documentation and grouped the roles into different functions based on their definitions [51]. For each clan a bi-directional chat network was assembled from the direct messages within a clan. We classified all individuals into their role group, then measured in-degree and out-degree centrality, otherwise known and *group in-degree centrality.*

In-degree centrality quantifies the number of incoming edges to a node, reflecting the level of attention or connections directed towards that node. Nodes with high in-degree centrality are often perceived as influential or popular within the network. On the other hand, out-degree centrality measures the number of outgoing edges from a node, indicating the extent to which the node initiates connections with others. Nodes with high out-degree centrality are considered active or influential in terms of reaching out to other nodes. Together, these centrality measures provide valuable insights into the structural importance of nodes in a network, helping to identify key players and nodes with significant influence or communication roles.

Table 8 highlights the results of these group centrality measures. There were no significant differences in either in or out-degree centrality of the authoritative group or the operations groups between high and low rated clans. There was a significant difference in both in and out degree centrality for the participant group between high and low rated clans. So in the top clans, participants had many more outgoing messages and more incoming messages. This suggests that in higher rated clans participants are likely in the fold of daily operations, battle planning and less socially isolated than in lower ranked clans. This embodies the idiom that a team is “only as strong as its weakest link.” Increasing clan rank is a grind, and it requires both skill and consistency. It’s not possible for a clan to be carried just by its commanding officers. The participants must step up and play their part in order to ensure the success of a clan.




(a) DM network graph for a high skill (top 50) clan.

(b) DM network graph for a low skill (bottom 50) clan.

Fig. 5. Direct Message (DM) network graphs

| | Mean degree centrality | Top 50 | Bot 50 |
|---|---|---|---|
| Authoritative | Out | 0.618 | 0.681 |
| | In | 0.618 | 0.595 |
| Operations | Out | 0.258 | 0.265 |
| | In | 0.261 | 0.264 |
| Participant | Out | 0.804* | 0.478* |
| | In | 0.781* | 0.457* |

Table 8. Centrality Measures for Different Roles in Top 50 and Bottom 50 Rated Clans. * = row is significant at $p < 0.01$, Mann-Whitney U

Figure 5 serves as a case study to visualize these connections in graph form. The higher rated clan has a flatter organizational structure than the lower rated clan. Many of the authoritative group nodes are connected equally to each other along with other job specific and participant nodes. There appears to be a more even distribution of connections among all levels of hierarchy in the higher rated clan. The overall connectedness, especially among participants, seems to be higher. This could lead to greater accountability and a more stable group over time [54].

In the lower rated clan there is one authoritative node with many incoming messages. This authoritative node also has many connections with participant nodes. However, the participant nodes are not well connected. They tend to remain on the periphery of the network without much connection to other participants. It's possible that this creates information bottlenecks and silos within the network. This further emphasizes that successful clans have clear communication channels between all roles and disseminate information more equally among all members.

## 5 Discussion

Our study reveals several important patterns in the communication behaviors of virtual teams that directly impact team performance. Here, we present an in-depth analysis of our findings and their broader implications for teamwork in digital environments.

### 5.1 Communication Frequency and Team Performance

Our findings support the hypothesis that higher-rated teams communicate more frequently. The quantitative analysis in Table 1 provides compelling evidence of this relationship, with top-performing clans (90th percentile) generating significantly more messages in both battle (257 weekly messages) and non-battle contexts (883 weekly messages) compared to bottom-performing clans (10th percentile, 36 and 27 messages respectively). This represents an approximately 7-fold increase in battle communication and a 32-fold increase in non-battle communication. The magnitude of this difference is statistically significant ($p < 0.01$), indicating a robust relationship between communication volume and team performance.

Notably, our regression analysis in Table 3 further substantiates this finding, with the number of unique pre-battle chatters emerging as a powerful predictor ($\beta = 5570$, re-scaled $\beta = 64.03$) of clan rating. This aligns with theoretical perspectives on team cognition and coordination from both gaming [42] and organizational contexts [9], where pre-task communication facilitates shared mental models and strategic alignment.

However, our data also suggest potential diminishing returns and even negative effects from excessive communication. The negative coefficient for the raw number of pre-battle chats ($\beta = -1019$) in our Lasso model indicates that while having diverse participation in pre-battle communication is beneficial, message overload may become counterproductive. This nuanced finding supports cognitive load theories in team communication [66], suggesting an optimal balance between sufficient information exchange and cognitive overload.

### 5.2 Communication Network Structure and Team Performance

Beyond raw communication volume, our network analysis reveals critical differences in communication patterns between high and low-performing teams. The centrality measures in Table 8 demonstrate that higher-performing clans exhibit significantly greater connectivity among non-administrative participants (participant out-degree centrality of 0.804 vs. 0.478, in-degree centrality of 0.781 vs. 0.457, $p < 0.01$). This quantitative difference represents a fundamental distinction in information flow within these teams.

The visualized network structures in Figure 5 further illustrate this distinction, with high-performing clans demonstrating more distributed communication patterns compared to the hierarchical, centralized structure of lower-performing teams. This distributed pattern potentially facilitates rapid information sharing, reduces bottlenecks, and enhances collective problem-solving capabilities—all critical factors in fast-paced, complex coordination tasks [23].

This finding extends previous research by [63] on network centrality and team performance by demonstrating that in virtual gaming teams, the connectivity of rank-and-file members (not just leaders) is crucial for team success. The statistical significance of these differences ($p < 0.01$) underscores the importance of inclusive communication structures that engage all team members, regardless of formal role or status.

### 5.3 Multi-channel Communication and Performance

Our analysis of external voice chat platform usage provides particularly compelling evidence of the relationship between advanced communication strategies and team performance. As shown in Table 2, clans that shared voice chat server links demonstrated markedly higher ratings (mean of $6,547$) compared to those that did not (mean of $2,763$, $p < 0.01$). This substantial performance gap of nearly $4,000$ rating points suggests that leveraging multiple communication modalities represents a sophisticated communication strategy employed by high-performing teams.

The strong statistical significance despite the small sample size of voice chat invitations (n = 29) highlights the robust nature of this relationship. This finding extends research by [11] on communication channel selection in virtual teams by demonstrating that the strategic use of synchronous voice communication alongside asynchronous text channels may be particularly advantageous in time-sensitive coordination tasks. The real-time nature of voice communication likely facilitates more rapid information exchange and coordination, particularly during intense battle scenarios where text communication might prove too slow or disruptive.

### 5.4 Communication Content and Performance

Our sentiment analysis results in Table 6 provide additional context to the structural communication patterns observed. While sentiment scores alone did not significantly enhance predictive models of clan rating, they reveal important characteristics of communication content in this context. The relatively balanced distribution of sentiment (0.36 negative, 0.41 neutral, 0.23 positive) suggests that effective team communication in this environment is not exclusively positive or encouraging in nature.

This finding challenges simplified assumptions that "positive" communication necessarily correlates with better team outcomes. Instead, it suggests that in skill-based, competitive environments, critical feedback and task-focused communication (which may register as neutral or even negative in sentiment analysis) play important roles in team development and performance [77]. The slight prevalence of negative over positive sentiment may reflect the demanding, critical nature of high-level competitive gaming, where identifying errors and areas for improvement takes precedence over positive reinforcement.

### 5.5 Cultural Context and Communication Patterns

Our dataset's limitation to North American servers could be interpreted in light of established cultural differences in communication patterns. As previous studies demonstrate [25, 27], the direct, explicit communication style typical of North American cultures differs from the implicit, contextual communication prevalent in many Asian cultures. These differences may influence communication volume, network structures and sentiment patterns.

For instance, the higher participation centrality we observed in successful North American teams aligns with the findings from Yamada et al. [77], demonstrating that American teams typically engage in more confrontational and direct problem-solving discussions with broader participation. In contrast, teams from collectivist cultures might demonstrate different patterns of success, potentially favoring hierarchical communication structures that emphasize harmony and consensus [8]. These cultural variations underscore the importance of cultural context when interpreting our findings and suggest caution in generalizing these results to global gaming communities.

### 5.6 Theoretical Implications

*5.6.1 Transactive Memory Systems in Virtual Teams.* Our findings significantly advance the understanding of TMS in virtual environments. The strong correlation between pre-battle communication participation and team performance supports the theory that effective TMS development requires active engagement from diverse team members. Specifically, the high coefficient for unique pre-battle chatters in our regression model ($\beta = 5570$) suggests that distributed knowledge sharing from multiple team members contributes more to performance than message volume alone.

This distinction between participation diversity and raw communication volume offers an important refinement to TMS theory. While traditional TMS research has emphasized the importance of communication frequency for developing shared mental models [9], our findings suggest that in virtual contexts, the diversity of voices may be even more crucial than the absolute amount of communication. This insight extends TMS theory by highlighting the specific mechanisms through which virtual teams develop effective shared memory systems.

*5.6.2 Network Theory and Team Performance.* Our network analysis results challenge conventional wisdom about optimal network structures for high-performing teams. While much organizational literature has emphasized the importance of centralized coordination and clear hierarchies [63], our finding that participant-level connectivity strongly differentiates high and low-performing teams suggests that distributed network structures may be particularly advantageous in complex, fast-paced virtual environments.

The significant difference in participant centrality measures between high and low-rated clans (0.804/0.781 vs. 0.478/0.457, $p < 0.01$) provides empirical support for theories of collective intelligence that emphasize the importance of distributed cognition and information processing [78]. These findings suggest that theories of team performance may need refinement to account for the unique dynamics of virtual collaboration, where rapid information sharing across all team members may outweigh the benefits of hierarchical coordination.

### 5.7 Practical Implications

*5.7.1 Design of Communication Systems.* Our findings have direct implications for the design of communication systems in virtual teams. The strong relationship between communication network structure and team performance suggests that communication platforms should facilitate broad participation rather than centralizing communication through designated leaders. Features that encourage peripheral members to engage in pre-task planning and strategy discussions may be particularly valuable, given our finding that diverse participation in pre-battle chat strongly predicts team success.

Additionally, the significant performance advantage associated with external voice chat platforms (mean rating $6,547$ vs. $2,763$) suggests that effective communication systems should integrate multiple modalities, allowing teams to select appropriate channels based on task demands. This aligns with media richness theory [10] and suggests that communication system designers should focus on seamless integration of synchronous and asynchronous channels rather than optimizing a single communication method.

*5.7.2 Training and Development for Virtual Teams.* Our results offer practical guidance for training and developing high-performing virtual teams. The finding that participant-level connectivity significantly differentiates high and low-performing teams suggests that team building exercises should focus on establishing communication connections between all team members, not just strengthening leader-member relationships. Training programs might specifically target increasing comfort with direct peer-to-peer communication, particularly among non-leadership team members.

Furthermore, the significant advantage associated with multi-channel communication strategies suggests that teams should be trained in effective channel selection and integration. Our studies indicate that high-performing teams leverage different communication modalities for different purposes, with voice chat likely reserved for time-sensitive coordination and text chat used for more deliberative planning. Training programs should help team members develop nuanced understanding of which communication channels best serve different collaborative needs.

### 5.8 Limitations

While our study provides robust evidence of the relationship between structural communication features and team performance, several limitations suggest directions for future research. Notably, although we incorporated sentiment analysis and examined specific message types (e.g., voice chat invitations), we did not conduct an in-depth thematic analysis of communication content—such as tactical discussions, coordination strategies, or social interaction topics within teams. This omission limits our ability to fully characterize the substance and agendas underlying collaborative interactions, constrains the depth of our conclusions, and reduces the specificity of our practical recommendations for designing systems that support distinct communication content themes.

Detailed thematic or agenda-level analyses are important for uncovering the nuanced mechanisms by which teams coordinate and collaborate. Our decision to focus on structural indicators was driven by the scale and heterogeneity of our dataset as well as by the need to establish a broad empirical foundation before pursuing fine-grained coding. To that end, we performed extensive sentiment classification across over 250,000 chat messages and systematically categorized invitation and response patterns in voice chat metadata. This level of content-related analysis—while not substituting for full thematic coding—provided sufficient depth to justify our structural emphasis and to inform the design of subsequent, more targeted thematic studies.

The regional limitation of our dataset to North American servers may constrain the generalizability of our findings. Future studies should explicitly compare communication patterns across different cultural and regional contexts to identify both universal principles and context-specific adaptations in successful virtual team communication.

Additionally, our analysis of voice communication was limited to metadata (e.g., invitation links) rather than direct analysis of synchronous voice chat. Future research incorporating transcription and thematic coding of voice communication -— or multimodal analysis combining text, audio, and video—- may reveal additional dimensions of communication effectiveness not captured by text-based analysis alone.

Finally, while our predictive models achieved high accuracy (Spearman's R > 0.8) in forecasting performance outcomes from structural features, they do not account for potential interactions among covariates such as team size, prior experience, and task complexity. Future work should explore these interactions in greater depth to uncover how specific communication behaviors and contextual factors jointly influence team success.

### 5.9 Ethical Considerations

For this study Wargaming shared anonymized user data collected through their platforms in accordance with their Terms of Service and their Privacy Policy [72, 73]. Wargaming outlines that aggregated data shared with third parties remains protected by confidentiality and data protection agreements, and users can manage their data-sharing preferences through account settings. Additionally, the data collection process received approval from the Institutional Review Board (IRB) [University of Southern California, UP-19-00138]. These practices include housing all player data on a remote server that is managed by Wargaming and access controlled.

We have never had access to any identifying information in this dataset such as user location, name, email, etc. All of this content was removed before our receipt. Identifiers are present for chat senders, receivers and clans. These identifiers are anonymized so it would be nearly impossible to reconstitute the original identity of the chatters and clans.

## 6 Conclusions and Future Work

The investigation centers on fundamental research questions that aim to uncover whether higher-rated teams in WoT exhibit distinct communication patterns compared to lower-rated teams. Additionally, the study explores the specific communication features that contribute to clan rating and investigates potential differences in communication based on team hierarchy within clans of varying skill levels. The insights gained from these questions have broader implications for understanding communication dynamics in virtual teams, providing valuable knowledge for the development of strategies and tools that can enhance performance in remote work environments. By drawing parallels between the virtual battlefield of WoT clans and real-world remote teams, this research contributes to the ongoing discourse on effective communication practices in diverse collaborative settings.

Moving forward, future research could explore more sophisticated methods for analyzing the sentiment of in-game chat messages. While our initial exploration considered lexicon-based approaches and BERT-based sentiment analysis, there is room for refining these methods or exploring alternative techniques. One avenue for improvement could involve a more nuanced lexicon tailored to the specific jargon and slang used in WoT, addressing the contextual challenges present in gaming communication. Additionally, examining the distributional aspects of sentiment scores and exploring the impact of specific phrases or expressions unique to the gaming community could enhance the accuracy of sentiment analysis. Integrating advanced natural language processing techniques and considering the cultural and contextual nuances of gaming communication would contribute to a more nuanced understanding of sentiment within WoT clans.

This study's implications suggest avenues for future research into developing collaborative tools that enhance team cognition, facilitate role-based communication, and support non-verbal coordination—tools that could extend beyond gaming to a wide array of virtual and remote work environments.

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## References

[1] Francesco Barbieri, Luis Espinosa Anke, and Jose Camacho-Collados. 2022. XLM-T: Multilingual Language Models in Twitter for Sentiment Analysis and Beyond. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*. European Language Resources Association, Marseille, France, 258–266. https://aclanthology.org/2022.lrec-1.27

[2] Grace A. Benefield, Cuihua Shen, and Alex Leavitt. 2016. Virtual Team Networks: How Group Social Capital Affects Team Success in a Massively Multiplayer Online Game. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (San Francisco, California, USA) *(CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 679–690. doi:10.1145/2818048.2819935

[3] G. R. Berry. 2011. Enhancing Effectiveness on Virtual Teams: Understanding Why Traditional Team Skills Are Insufficient. *Journal of Business Communication* 48, 2 (feb 23 2011), 186–206.

[4] Alexander J Bisberg and Rogelio E Cardona-Rivera. 2019. Scope: Selective cross-validation over parameters for elo. In *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, Vol. 15. 116–122.

[5] Alexander J Bisberg and Emilio Ferrara. 2022. GCN-WP–Semi-Supervised Graph Convolutional Networks for Win Prediction in Esports. In *2022 IEEE Conference on Games (CoG)*. IEEE, 449–456.

[6] David P Brandon and Andrea B Hollingshead. 2004. Transactive memory systems in organizations: Matching tasks, expertise, and people. *Organization Science* 15, 6 (2004), 633–644.

[7] Emmanuel J Candes, Michael B Wakin, and Stephen P Boyd. 2008. Enhancing sparsity by reweighted L1 minimization. *Journal of Fourier analysis and applications* 14 (2008), 877–905.

[8] Guo-Ming Chen and William J Starosta. 1998. Foundations of intercultural communication. *Boston, MA: Allyn & Bacon* (1998).

[9] Laura Dabbish, Robert Kraut, and Jordan Patton. 2012. Communication and commitment in an online game team. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM.

[10] Richard L Daft and Robert H Lengel. 1986. Organizational information requirements, media richness and structural design. *Management Science* 32, 5 (1986), 554–571.

[11] Tugrul U Daim, Annette Ha, Shawn Reutiman, Brennan Hughes, Ujjal Pathak, Wayne Bynum, and Ashok Bhatla. 2012. Exploring the communication breakdown in global virtual teams. *International Journal of Project Management* 30, 2 (2012), 199–212.

[12] Robert Davison. 2006. Virtual work, teams and organisations. *Information Technology & People* 19, 4 (oct 1 2006).

[13] Damian Debkowski, Andrew Marrero, Nicole Yson, Li Yin, Yichen Yue, Seth Frey, and Mubbasir Kapadia. 2021. Contained: Using Multiplayer Online Games to Quantify Success of Collaborative Group Behavior. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment* 12, 1 (jun 25 2021), 149–154.

[14] Colin DeLong, Nishith Pathak, Kendrick Erickson, Eric Perrino, Kyong Shim, and Jaideep Srivastava. 2011. TeamSkill: Modeling Team Chemistry in Online Multi-player Games. In *Advances in Knowledge Discovery and Data Mining*, Joshua Zhexue Huang, Longbing Cao, and Jaideep Srivastava (Eds.). Vol. 6635. Springer Berlin Heidelberg, Berlin, Heidelberg, 519–531. doi:10.1007/978-3-642-20847-8_43 Series Title: Lecture Notes in Computer Science.

[15] Qilin Deng, Hao Li, Kai Wang, Zhipeng Hu, Runze Wu, Linxia Gong, Jianrong Tao, Changjie Fan, and Peng Cui. 2021. Globally Optimized Matchmaking in Online Games. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 2753–2763.

[16] Nicolas Ducheneaut and Robert J. Moore. 2004. The Social Side of Gaming: A Study of Interaction Patterns in a Massively Multiplayer Online Game. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work* (Chicago, Illinois, USA) *(CSCW '04)*. Association for Computing Machinery, New York, NY, USA, 360–369. doi:10.1145/1031607.1031667

[17] Nicolas Ducheneaut, Nicholas Yee, Eric Nickell, and Robert J Moore. 2006. " Alone together?" Exploring the social dynamics of massively multiplayer online games. In *Proceedings of the SIGCHI conference on Human Factors in computing systems*. 407–416.

[18] Joshua A. Eaton, Matthew-Donald D. Sangster, Molly Renaud, David J. Mendonca, and Wayne D. Gray. 2017. Carrying the Team: The Importance of One Player's Survival for Team Success in League of Legends. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 61, 1 (9 2017), 272–276.

[19] Arpad Elo. 1978. *The Rating of Chessplayers, Past and Present.* Ishi Press International.

[20] J Alberto Espinosa, Sandra A Slaughter, Robert E Kraut, and James D Herbsleb. 2007. Team knowledge and coordination in geographically distributed software development. *Journal of Management Information Systems* 24, 1 (2007), 135–169.

[21] Mark E. Glickman. 1995. A Comprehensive Guide to Chess Ratings. *American Chess Journal* 3, 1 (1995), 59–102.

[22] Cathryn Gorlinsky and Mark A. Serva. 2009. Leveraging online gaming for teaching student leadership and teamwork. In *Proceedings of the special interest group on management information system's 47th annual conference on Computer personnel research*. ACM, 73–76.

[23] Thomas U. Grund. 2012. Network structure and team performance: The case of English Premier League soccer teams. *Social Networks* 34, 4 (2012), 682–690. doi:10.1016/j.socnet.2012.08.004

[24] Yin Gu, Qi Liu, Kai Zhang, Zhenya Huang, Runze Wu, and Jianrong Tao. 2021. Neuralac: Learning cooperation and competition effects for match outcome prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 4072–4080.

[25] Edward T. Hall. 1976. *Beyond Culture*. Anchor Books, New York.

[26] Ralf Herbrich, Tom Minka, and Thore Graepel. 2007. TrueSkill™: a Bayesian skill rating system. In *Advances in Neural Information Processing Systems*. 569–576.

[27] Geert Hofstede, Gert Jan Hofstede, and Michael Minkov. 2010. *Cultures and organizations: Software of the mind*. McGraw-Hill.

[28] Yun Huang, Wenyue Ye, Nicholas Bennett, and Noshir Contractor. 2013. Functional or social?: exploring teams in online games. In *Proceedings of the 2013 conference on Computer supported cooperative work*. ACM.

[29] Sirkka L. Jarvenpaa, Kathleen Knoll, and Dorothy E. Leidner. 1998. Is Anybody out There? Antecedents of Trust in Global Virtual Teams. *Journal of Management Information Systems* 14, 4 (3 1998), 29–64.

[30] Julie Jiang, Danaja Maldeniya, Kristina Lerman, and Emilio Ferrara. 2021. The Wide, the Deep, and the Maverick: Types of Players in Team-based Online Games. *Proc. ACM Hum. Comput. Interact.* (2021). doi:10.1145/3449290

[31] A. Jović, K. Brkić, and N. Bogunović. 2015. A review of feature selection methods with applications. In *2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*. 1200–1205. doi:10.1109/MIPRO.2015.7160458

[32] Prasert Kanawattanachai and Youngjin Yoo. 2007. The impact of knowledge coordination on virtual team performance over time. *MIS Quarterly* 31, 4 (2007), 783–808.

[33] Young Ji Kim, David Engel, Anita Williams Woolley, Jeffrey Yu-Ting Lin, Naomi McArthur, and Thomas W. Malone. 2017. What Makes a Strong Team?. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. ACM.

[34] Young Ji Kim, David Engel, Anita Williams Woolley, Jeffrey Yu-Ting Lin, Naomi McArthur, and Thomas W. Malone. 2017. What Makes a Strong Team?: Using Collective Intelligence to Predict Team Performance in League of Legends. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. ACM, Portland Oregon USA, 2316–2329. doi:10.1145/2998181.2998185

[35] Bradley L. Kirkman, Benson Rosen, Cristina B. Gibson, Paul E. Tesluk, and Simon O. McPherson. 2002. Five challenges to virtual team success: Lessons from Sabre, Inc. *Academy of Management Perspectives* 16, 3 (8 2002), 67–79.

[36] Yubo Kou and Xinning Gui. 2014. Playing with strangers. In *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play*. ACM.

[37] Alex Leavitt, Brian C. Keegan, and Joshua Clark. 2016. Ping to Win?. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM.

[38] Chun-Chia Lee and Jen-Wei Chang. 2013. Does Trust Promote More Teamwork? Modeling Online Game Players' Teamwork Using Team Experience as a Moderator. *Cyberpsychology, Behavior, and Social Networking* 16, 11 (11 2013), 813–819.

[39] Kyle Lewis. 2003. Measuring transactive memory systems in the field: Scale development and validation. *Journal of Applied Psychology* 88, 4 (2003), 587–604.

[40] Yiqi Li, Nathan Bartley, Jingyi Sun, and Dmitri Williams. 2023. The larger, the fitter, the better: clans' evolution, social capital and effectiveness. *Internet Research* 33, 3 (2023), 1053–1078.

[41] Gen-Yih Liao, Thi Tuan Linh Pham, T.C.E. Cheng, and Ching-I Teng. 2020. How online gamers' participation fosters their team commitment: Perspective of social identity theory. *International Journal of Information Management* 52 (6 2020), 102095.

[42] Viktoriya Lipovaya, Yuri Lima, Pedro Grillo, Carlos Eduardo Barbosa, Jano Moreira de Souza, and Francisco José de Castro Moura Duarte. 2018. Coordination, Communication, and Competition in eSports: A Comparative Analysis of Teams in Two Action Games. *ECSCW Exploratory Papers* (2018).

[43] Tianyang Lou, Yuning Zu, and Ling Zhu. 2019. A study of motivation and team member selection in online games. *Asia Pacific Journal of Marketing and Logistics* 32, 6 (nov 12 2019), 1286–1304.

[44] Attaran M. and Attaran Sharmin. 2003. The Coming Age of Virtual Teaming: Guidelines for Managers. (2003).

[45] Arvind Malhotra, Ann Majchrzak, and Benson Rosen. 2007. Leading Virtual Teams. *Academy of Management Perspectives* 21, 1 (2 2007), 60–70.

[46] Tom Minka, Ryan Cleven, and Yordan Zaykov. 2018. *TrueSkill 2: An improved Bayesian skill rating system.* Technical Report MSR-TR-2018-8. Microsoft.

[47] Richard L Moreland and Linda Argote. 2003. Transactive memory: Knowledge and coordination in groups. In *Shared cognition in organizations: The management of knowledge*, Leigh L Thompson, John M Levine, and David M Messick (Eds.). Lawrence Erlbaum Associates, 3–31.

[48] Satyam Mukherjee, Yun Huang, Yun Huang, Julia Neidhardt, Brian Uzzi, and Noshir Contractor. 2019. Prior shared success predicts victory in team competitions. *Nature Human Behaviour* (2019). doi:10.1038/s41562-018-0460-y

[49] Jay F. Nunamaker, Jr., Bruce A. Reinig, and Robert O. Briggs. 2009. Principles for effective virtual teamwork. *Commun. ACM* 52, 4 (4 2009), 113–117.

[50] World of Tanks. 2023. Clan Rating FAQ. https://na.wargaming.net/clans/wot/#features&guide-slug=ratings. Accessed: 2023-12-05.

[51] World of Tanks. 2023. Update 9.3: Changes in Clan Structures. https://worldoftanks.eu/en/news/general-news/update93-changes-clan-structures/. Accessed: 2023-12-14.

[52] Yohsuke Ohtsubo. 2005. The function of group heuristics in the reduction of confirmation bias. *Asian Journal of Social Psychology* 8, 2 (2005), 182–199.

[53] Edward T Palazzolo, Damon Serb, Yuwen She, Chunke Su, and Noshir S Contractor. 2006. Individual memory and communication effects on knowledge network behaviors. *Social Networks* 28, 3 (2006), 177–191.

[54] Akshay Patil, Juan Liu, and Jie Gao. 2013. Predicting group stability in online social networks. In *Proceedings of the 22nd international conference on World Wide Web*. 1021–1030.

[55] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* 12 (2011), 2825–2830.

[56] Nataliia Pobiedina, Julia Neidhardt, Maria del Carmen Calatrava Moreno, Laszlo Grad-Gyenge, and Hannes Werthner. 2013. On Successful Team Formation: Statistical Analysis of a Multiplayer Online Game. In *2013 IEEE 15th Conference on Business Informatics*. IEEE, 55–62.

[57] Nataliia Pobiedina, Julia Neidhardt, Maria del Carmen Calatrava Moreno, and Hannes Werthner. 2013. Ranking factors of team success. In *Proceedings of the 22nd International Conference on World Wide Web*, Vol. 45. ACM, 1185–1194.

[58] MMO Populations. 2023. World of Tanks Player Count. https://mmo-population.com/r/worldoftanks/. Accessed: 2023-12-05.

[59] Yuqing Ren, Kathleen M Carley, and Linda Argote. 2006. Transactive memory and knowledge transfer in organizations. *Academy of Management Proceedings* 2006, 1 (2006), B1–B6.

[60] Yuqing Ren, F Maxwell Harper, Sara Drenner, Loren Terveen, Sara Kiesler, John Riedl, and Robert E Kraut. 2012. Building member attachment in online communities: Applying theories of group identity and interpersonal bonds. *MIS quarterly* (2012), 841–864.

[61] Anna Sapienza, Yilei Zeng, Alessandro Bessi, Kristina Lerman, and Emilio Ferrara. 2018. Individual performance in team-based online games. *Royal Socienty Open Science* (2018).

[62] Cuihua Shen. 2014. Network patterns and social architecture in Massively Multiplayer Online Games: Mapping the social world of EverQuest II. *New Media & Society* 16, 4 (2014), 672–691.

[63] Raymond T. Sparrowe, Robert C. Liden, Sandy J. Wayne, and Maria L. Kraimer. 2001. Social networks and the performance of individuals and groups. *Academy of Management Journal* 44, 2 (2001), 316–325. doi:10.2307/3069458

[64] Erika Suarez Valencia, Víctor Bucheli, Roberto Zarama, and Ángel Garcia. 2015. Collective intelligence: analysis and modelling. *Kybernetes* 44, 6/7 (2015), 1122–1133.

[65] Jingyi Sun, Dmitri Williams, and Yiqi Li. 2021. Let's bail!: the evolution of individual-group affiliation in an online gaming community. *Computers in Human Behavior* 121 (2021), 106818.

[66] John Sweller. 2011. CHAPTER TWO - Cognitive Load Theory. Psychology of Learning and Motivation, Vol. 55. Academic Press, 37–76. doi:10.1016/B978-0-12-387691-1.00002-8

[67] Michael Szell and Stefan Thurner. 2010. Measuring social dynamics in a massive multiplayer online game. *Social networks* 32, 4 (2010), 313–329.

[68] Ching-I Teng and Wei-Wen Chen. 2014. Team participation and online gamer loyalty. *Electronic Commerce Research and Applications* 13, 1 (1 2014), 24–31.

[69] Joseph J Thompson, Betty HM Leung, Mark R Blair, and Maite Taboada. 2017. Sentiment analysis of player chat messaging in the video game StarCraft 2: Extending a lexicon-based model. *Knowledge-Based Systems* 137 (2017), 149–162. doi:10.1016/j.knosys.2017.09.022

[70] Anthony M. Townsend, Samuel M. DeMarie, and Anthony R. Hendrickson. 1998. Virtual teams: Technology and the workplace of the future. *Academy of Management Perspectives* 12, 3 (8 1998), 17–29.

[71] Wargaming. 2010. *World of Tanks.* Wargaming.

[72] Wargaming.net. 2024. Terms of Service and Privacy Policy. https://legal.na.wargaming.net/terms-of-service/ Accessed: 2024-10-29.

[73] Wargaming.net. 2024. Terms of Service and Privacy Policy (EU). https://legal.eu.wargaming.net/en/terms-of-service/ Accessed: 2024-10-29.

[74] Daniel M Wegner. 1987. Transactive memory: A contemporary analysis of the group mind. *Theories of group behavior* (1987), 185–208.

[75] Dmitri Williams. 2006. On and off the'Net: Scales for social capital in an online era. *Journal of computer-mediated communication* 11, 2 (2006), 593–628.

[76] Anita Williams Woolley, Christopher F. Chabris, Alex Pentland, Nada Hashmi, and Thomas W. Malone. 2010. Evidence for a Collective Intelligence Factor in the Performance of Human Groups. *Science* 330, 6004 (2010), 686–688. arXiv:https://www.science.org/doi/pdf/10.1126/science.1193147 doi:10.1126/science.1193147

[77] Haru Yamada. 1997. Different games, different rules: Why Americans and Japanese misunderstand each other. *Journal of Cross-Cultural Psychology* 28, 5 (1997), 629–631.

[78] Norhayati Zakaria, Andrea Amelinckx, and David Wilemon. 2004. Working together apart? Building a knowledge-sharing culture for global virtual teams. *Creativity and Innovation Management* 13, 1 (2004), 15–29.

[79] Yilei Zeng, Anna Sapienza, and Emilio Ferrara. 2019. The Influence of Social Ties on Performance in Team-based Online Games. *IEEE Transactions on Games* 1502, c (2019). doi:10.1109/TG.2019.2923223

[80] Zhihong Zhang, Yiyang Tian, Lu Bai, Jianbing Xiahou, and Edwin Hancock. 2017. High-order covariate interacted Lasso for feature selection. *Pattern Recognition Letters* 87 (2017), 139–146.

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