

What Makes a Good Team? A Large-scale Study on the Effect of Team Composition in Honor of Kings

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ABSTRACT

Team composition is a central factor in determining the effectiveness of a team. In this paper, we present a large-scale study on the effect of team composition on multiple measures of team effectiveness. We use a dataset from the largest multiplayer online battle arena (MOBA) game, Honor of Kings, with 96 million matches involving 100 million players. We measure team effectiveness based on team performance (whether a team is going to win), team tenacity (whether a team is going to surrender), and team rapport (whether a team uses abusive language). Our results confirm the importance of team diversity with respect to player roles, and show that diversity has varying effects on team effectiveness: although diverse teams perform well and show tenacity in adversity, they are more likely to abuse when losing than less diverse teams. Our study also contributes to the situation vs. personality debate and show that abusive players tend to choose the leading role and players do not become more abusive when taking such roles.

CCS CONCEPTS

• Applied computing → Law, social and behavioral sciences.

KEYWORDS

team composition, team performance, tenacity, toxic behavior, MOBA

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1 INTRODUCTION

The increasing complexity and scale of tasks in modern society require individuals to work together as a team [13, 40]. Crucial to the effectiveness of a team are the individuals in the team, i.e., team composition. Extensive prior research has studied team roles to analyze team composition [6, 7, 30, 31, 36, 38]. The most influential work is Belbin's team role framework, also known as Belbin

Team Inventory. A central hypothesis in Belbin's framework is that balance in team roles is associated with team performance. Belbin [7] defines nine roles¹, and finds that teams with certain role combinations result in poor performance, even if they are formed by members with the sharpest mind and the most experience. However, team roles are usually implicit in real life and it is difficult to identify such nine roles in most contexts.

Another challenge in studying the effect of team composition on team effectiveness arises from the definition of *effectiveness*. Team performance is the most straightforward definition and has been studied in a battery of studies [10, 13, 15, 35]. Example measures of team performance include the impact of published papers from a team [40], winning a sports game [4, 24], etc. However, the effectiveness of a team can also be reflected by the tenacity in face of adversity, and the rapport between team members [9]. The effect of team composition likely depends on the definition of team effectiveness. Therefore, it is important to understand the effect of team composition on the effectiveness of teams in multiple measures.

To address these two challenges, we identify multiplayer online battle arena (MOBA) as an ideal testbed and provide a large-scale study on the effect of team compositions on multiple measures of team effectiveness. We use a dataset from Honor of Kings, the largest MOBA game in the world. This platform is ideal for studying the effect of team composition for three reasons. First, there are defined roles in the game and players choose their roles to form a team. Given that there are five players in each team, we are able to enumerate all possible team compositions. We also have information about the characteristics of each role. Second, the popularity of Honor of Kings leads to digital traces of hundreds of millions of players in hundreds of millions of games. These detailed game records allow us to explore the notion of team "effectiveness" beyond the simple measure of team performance, winning or losing. For instance, we study the effect of team composition on abusive language use, which reflects the rapport in a team. This research question naturally connects to the literature on toxic behavior in online communities and gaming [11, 12, 26]. Finally, we have access to the past history of players for capturing their background and experience. Historical information enables us to investigate questions in the "situation vs. personality" debate [16, 22]: how much of our behavior is determined by fixed personality traits or by the specific situation at hand? We will explore this question in the context of toxic behavior in online gaming.

Organization and paper highlights. In this paper, we conduct a large-scale study on the effect of team composition in the context of online gaming, particularly, in Honor of Kings. Our dataset comes

¹See https://en.wikipedia.org/wiki/Team_Role_Inventories for a quick explanation.

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Statistics	Number(fraction/SEM)
Overall statistics	
#ranked games	54,434,817
#team compositions	126
#surrender games	5,807,005 (10.7%)
#abusing games	30,668,577 (56.3%)
#early games($t \leq 11$ min)	5,049,934 (9.3%)
#middle games($11 < t \leq 16$ min)	23,089,993 (42.4%)
#late games($t > 16$ min)	26,294,890 (48.3%)
Top three frequent combinations	
♂ - ♀ - ♂ - ♀ - ♂	16,186,003 (14.9%)
♀ - ♂ - ♀ - ♂ - ♂	14,516,443 (13.3%)
♂ - ♀ - ♂ - ♂ - ♂	12,630,805 (11.6%)
Personal statistics	
#players	1,306,754
#players who played ranked games	1,173,372
#ranked games each player has	48.4 (0.05)
average winrate	52.4% (1.0×10^{-4})
average abusing probability	9.3% (1.0×10^{-4})
average surrender probability	5.0% (6.9×10^{-5})
#target players who have played at least 20 ranked games	758,494 (58.0%)

Table 1: Statistics of the dataset.

from this popular MOBA game in China, and includes 96 million games and 100 million players in total. We provide details of the dataset and character roles in §2.

We quantitatively study the effect of team composition on three distinct definitions of team effectiveness: (§3) team performance — whether a team is going to win — is directly based on the result/goal in a game and is the most common measure in prior studies; (§4) team tenacity — whether a team is going to surrender — indicates a team’s resilience to adversity and is understudied in existing literature as most studies only look at individual tenacity or perseverance [5, 19]; (§5) toxic behavior, i.e., abusive language use, reflects the rapport in a team and is extracted from the activities during a game.

Our results on team effectiveness confirm the theory that balance in team roles is important for effective teams. We find that diverse teams are more likely to win. Furthermore, diverse teams are less likely to surrender, indicating a higher level of tenacity. Note that the likelihood to surrender does not correlate with winning rate for commonly used team compositions. However, we observe diverging effects on abusive language use: diverse teams are more likely to abuse when losing, but are less likely to abuse when winning.

In addition to exploring the effect of team composition, we investigate individual-level abusive language use to understand how teamwork influences individuals and shed light on the “situation vs. personality” debate [16, 22]. We find that players who choose assassins (the leading role) are more likely to abuse. We further demonstrate that the reason is that abusive players are more likely to choose assassins, instead of the alternative explanation that a player becomes more abusive when playing assassins. Finally, we present related work in §6 and offer our concluding thoughts in §7. A detailed version with additional analysis and prediction experiments can be found on arXiv: <https://arxiv.org/abs/1902.06432>.

Role	Description	Freq.(%)
warrior ♂	Warriors have a large pool of health and considerable damage; they often undertake the stress from enemies in side lanes.	27.1
mage ♀	Mages have heavy spell damage, but a small pool of health; they often take the middle lane and prepare to assist teammates.	25.8
marksman ♂	Marksmen have a small pool of health but can cause heavy damage; they need protection and may need time to grow.	25.7
assassin ♂	Assassins are explosive and control the pace, but the health pool is often small; they are usually the leading role in a team.	11.5
support ♂	Supports always aid teammates; they absorb damage while disrupting opponents by stunning and displacing them.	9.9

Table 2: Description and frequency of each role.

2 DATASET

Our dataset is provided by Tencent² and comes from a multiplayer online battle arena (MOBA) game: Honor of Kings, the most profitable game in the world. Similar to many other MOBA games such as Dota2 and League of Legends, Honor of Kings involves two teams to battle with each other. Each team consists of five players and the success of a team depends on the chemistry and collaboration between the five team members. The main motivation of our study is that players are expected to take certain roles when they select characters. These roles are designed to complement each other and “good” teams usually require particular compositions of roles. In this paper, we aim to explore the effect of team composition on different measures of team effectiveness.

There are multiple types of games in Honor of Kings. *Ranked games* are used to estimate a player’s rank level in the game; while the other games are for practice or for fun. Since players care much less about unranked games than ranked games, all of our analyses are based on ranked games. Unranked games are only used to analyze players’ role preferences.

Dataset description. Our dataset is derived from daily logs spanning three weeks in August, 2017. Specifically, we first randomly sample 20K games in each day of the third week, thereby obtaining 140K games and 1.3M players participating in these games. Among them, there are 78K ranked games. We then retrieve all the games involving any of these 1.3M players in the first two weeks to obtain player information. In total, we obtain 95.6M games and 100.2M players. Among these games, there are 54.4M *ranked games* on which most analyses in §3, §4, and §5 are based. In those analytical settings, we do not need historical information of every player in a team. There are several exceptions where we need historical statistics of every team member, so we use games in the third week in those cases and will point out in the text.

The log of each game includes its start time, end time, result (which team wins), gaming stats recorded when the game ends, and text messages in the chat room with abusive labels. See overall statistics of the dataset in Table 1.

Team roles. There are five roles in Honor of Kings: warrior (♂), mage (♀), marksman (♂), assassin (♂), and support (♂). A team is

²Honor of Kings is developed and published by Tencent, which is one of the largest Internet companies and also the largest game service provider in China.

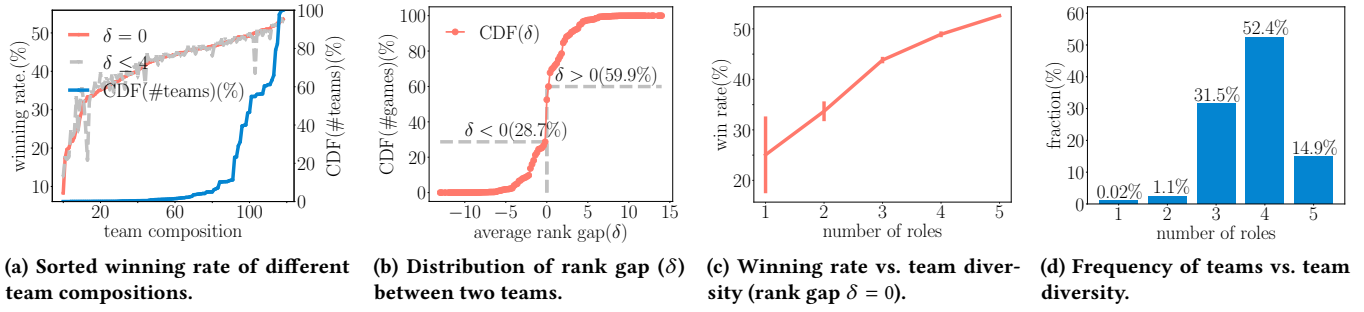


Figure 1: Team composition and winning rates. In Fig. 1a, x -value corresponds to the index of a team composition, and is sorted by winning rate. The CDF of #teams shows the cumulative distribution in #teams according to the order in the x -axis. Fig. 1b shows the distribution of the rank gap between two teams. Fig. 1c shows that a diverse team with more role categories is more likely to win (error bars represent standard errors). Fig. 1d shows that most teams are rationale and cover at least 3 roles.

composed of different roles depending on players' choices. Henceforth, we use five icons to represent a team composition, e.g., (♂ , ♂ , ♂ , ♂ , ♂) stands for a team with one warrior, two mages, two assassins, and no marksman or support. In total, there exist 126 team compositions. Table 2 presents the characteristics and frequency of each role. Table 3 shows several role combinations with its winning rate and frequency. We can clearly see that team compositions are not used equally by players: single roles and role combinations both vary greatly in frequency.

3 TEAM COMPOSITION AND WINNING

We first investigate the effect of team composition on whether a team wins or not, a direct measure of team performance. Although the matching system in Honor of Kings is designed to balance the ability of two teams, we observe that the winning rate of most team compositions is significantly lower than 50%, indicating that some role combinations cannot effectively work with each other.

Although two teams are with similar "skills", there exist winning and losing team compositions (Fig. 1a). Since we have 126 different team compositions in total, it is straightforward to estimate the *winning rate* of each team composition using the fraction of winning games, $\frac{\text{\#winning games}}{\text{\#games}}$. Fig. 1a shows that the winning rate of different team compositions spans a wide range, from 8.3% to 53.6%. It seems that some team compositions are doomed to lose. In addition, the figure also shows the cumulative distribution of #teams for each team composition, suggesting that most losing teams do not occur frequently. Notice that a similar plot will also be made for surrendering and abusing and we will see that the CDFs present very different shapes.

The fluctuation of winning rate between different team compositions among all games may not due to the effect of team compositions; another possible explanation is the ability of individual players: only relatively bad players choose certain bad team compositions. Although a matching system is designed to balance the ability of the players in two teams, it is difficult to always make sure that two teams exactly have the same ability. Fig. 1b shows the distribution of the rank level gap (δ) between two teams³. To calculate δ , we sum up the individual rank level in a team, and subtract the result of losing team from that of winning team. By

³Rank level indicates a player's gaming skill and ranges from 0 to 26.

Team compositions	Win rate	Used frequency(%)
team compositions with the highest winning rate		
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	53.6%	0.3
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	53.2%	2.0
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	52.6%	14.9
team compositions with the lowest winning rate		
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	19.7%	3.1×10^{-3}
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	17.4%	2.2×10^{-2}
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	8.3%	7.0×10^{-4}
team compositions that are most used		
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	52.6%	14.9
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	52.0%	13.3
$\text{♂} - \text{♂} - \text{♂} - \text{♂} - \text{♂}$	48.5%	11.6

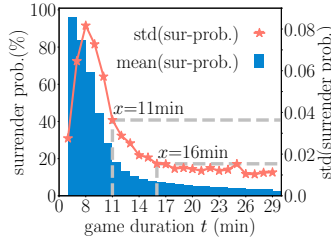
Table 3: Example team compositions and winning rates.

the effect of the matching system, the rank gaps in over 90% games are relatively small (within ± 5). These minor gaps, however, are still associated with a significant difference in winning rate: only 28.7% games end up with the winning of the lower ranked team. Therefore, to demonstrate the influence of team compositions on winning rates and to exclude the ability factor, we control the rank gap between teams in Fig. 1a: we focus on games with $\delta = 0$ (red plots) and $\delta \leq 4$ (gray plots) respectively.

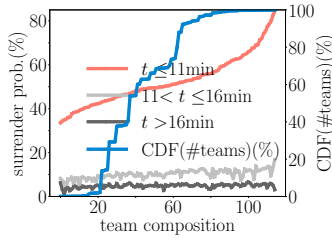
To further illustrate winning and losing team compositions, we present team compositions with the highest (lowest) winning rate in Table 3 (controlling the rank gap $\delta = 0$). Upon a careful examination, these losing teams do not often occur, reflected also by the cumulative distribution curve in Fig. 1a. In total, the bottom 90 losing team compositions only take 11.1% of all teams. This suggests that most players choose a reasonable team composition. However, the last three rows in Table 3 show that the most common team compositions still vary in winning rates, from 48.5% to 52.6%.

Diverse teams tend to perform well (Fig. 1c, 1d). An observation that stands out in Table 3 is that teams with the highest winning rate consist of more role categories than teams with the lowest winning rate. For instance, support (♂) or assassin (♂) dominates the two compositions with the lowest winning rate, while all the top winning teams have at least four roles.

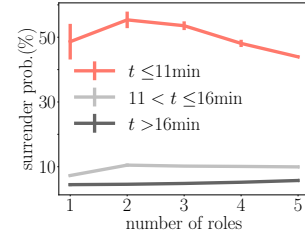
We further explore this observation by examining how winning rate changes as the number of roles in a team grows (Fig. 1c). We



(a) Surrender probability vs. game duration.

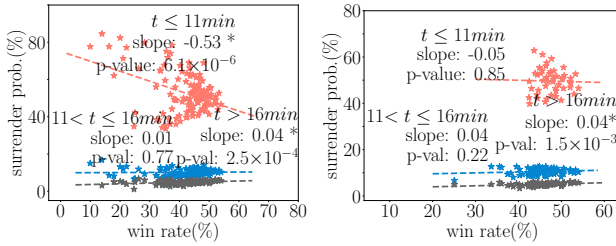


(b) Surrender prob. vs. team composition.



(c) Surrender prob. vs. team diversity.

Figure 2: Team composition and surrender probability. Fig. 2a shows the mean and standard deviation of surrender probability across team compositions conditioned on game duration. Fig. 2b shows that team compositions have varying surrender probabilities in games that end within 11 minutes, but have similar ones in longer games. Fig. 2c shows that diverse teams are less likely to surrender in early games (error bars represent standard errors).



(a) All team compositions. (b) Frequent team compositions.

Figure 3: Surrender probability vs. winning rate. In both figures, each dot denotes a team composition with its x -value for winning rate and y -value for surrender probability. Fig. 3a shows results for all team compositions. Fig. 3b shows the results after removing infrequent compositions, where surrender is not correlated with winning rate.

find that diverse team compositions are much more likely to win. One explanation is that these roles are designed to complement each other and teams with too few roles have weaknesses to be exploited. For instance, a team with no mage (♁) or marksman (♂) cannot cause sufficient damage in a game. Fig. 1d shows that most teams are employing at least three role categories, which is consistent with the observation in Fig. 1a that the losing team compositions on the left are not usually used.

4 TEAM COMPOSITION AND SURRENDER

As nothing worth achieving is going to be easy, tenacity is an important characteristic of an effective team. In the context of Honor of Kings, team tenacity can be reflected by not surrendering easily. The surrendering procedure is as follows: a player can propose to surrender and if at least four of five team members agree, the team will surrender as a whole and lose immediately. In this section, we examine the effect of team composition on team tenacity.

Surrender probability varies across team compositions in early games (Fig. 2a, 2b). Similar to winning, surrender happens at the end of a game. But surrender requires extra careful analysis because surrender may not always reflect team tenacity in Honor of Kings. For example, when the opponents are destroying the team base and all team members are killed, it is time to move on and surrender is simply a sign of “game over”. Therefore, it is necessary to distinguish surrender in different game stages.

We examine the mean and the standard deviation of surrender probability across team compositions conditioned on game duration in Fig. 2a. We make two observations. First, the surrender probability monotonically decreases as game duration increases, partly because a team is only allowed to surrender starting from the 6th minute and games end in 6-8 minutes mostly because a team surrenders. Second, the standard deviation across team compositions first increases and then decreases as game duration increases, indicating that in late games every team surrenders with similar probability to signal game over. Based on Fig. 2a, we define three game stages: *early games* ($t \leq 11$), where the surrender probability has great mean and great std; *late games* ($t > 16$), where the surrender probability has small mean and small std; *middle games* ($11 < t \leq 16$), the middle part.

Having established the three types of games, we hypothesize that surrender in early games is the most indicative of team tenacity and varies across team compositions, while surrender in middle and late games is more of a formality and should not depend on team compositions. To study that, we sort team compositions by surrender probability in early games in Fig. 2b. According to the same order, we show the surrender probability in middle games and late games, as well as the cumulative distribution function of #teams. Consistent with our hypothesis, the surrender probability of different team compositions span a wide range from 33.6% to 84.6% in early games, but is pretty stable in middle games and late games. The CDF of #teams presents a different shape from that in Fig. 1a: commonly used team compositions are neither the most tenacious nor the least tenacious.

Diverse teams tend to be tenacious (Fig. 2c). Role diversity influences surrender probability in early games, especially when the number of roles is large. It seems that diverse teams with five roles are the most tenacious in early games. In comparison, the influence on middle and late games is minimal.

A weak team can still be tenacious (Fig. 3). We have shown that diverse teams tend to both perform well and show tenacity in adversity. One concern is that these two measures are correlated and tenacity is simply a side effect of team strength (winning). This hypothesis suggests that winning team compositions should be less likely to surrender. To further understand this issue, we study the correlation between surrender probability and winning rate for different team compositions. Fig. 3a shows that there is indeed a negative correlation between winning rate and surrender

probability in early games, while little correlation in middle and late games. However, it seems that the correlation between winning rate and surrender probability in early games is dominated by a few outliers with very low winning rates. Given that we know that these teams only take a small fraction of all games in §3, we filter infrequent team compositions that appear less than 10,000 times and find that in the remaining team compositions (98.7% of all teams), surrender probability is not correlated with winning rate in all game stages (Fig. 3b), suggesting that team tenacity is almost independent of team strength/performance.

5 TEAM COMPOSITION AND ABUSIVE LANGUAGE USE

Our final measure of team effectiveness is concerned with the rapport in a team during the game. We use abusive language use to capture the rapport. Toxic behavior in online communities and gaming has received significant interests from our research community recently [11, 12, 26]. Here we provide the first systematic study on the effect of team composition on team-level abusive language use.

5.1 Team-level Abusive Language Use

Team compositions vary in abusing probability (Fig. 4a). In our dataset, we have a label of whether a message uses abusive language for all text messages based on a dictionary-based method officially used by Tencent. A team abuses if any player in that team abuses. For each team composition, we define *abusing probability* as the fraction of games that this team composition abuses.

We find that similar to winning and surrendering, team compositions vary in abusing probability, ranging from 28.7% to 56.2%. The cumulative distribution function of #teams looks much more similar to surrendering in Fig. 2b than winning in Fig. 1a: most commonly used team compositions are neither the most nor the least abusive. We will investigate further the interaction of individual-level abusing and team-level abusing in §5.2.

Losing teams are more likely to abuse. We hypothesize that losing teams are more likely to abuse because winning usually brings positive team morale, while losing leads to frustration and dissatisfaction [26]. This is indeed the case, as we examine the correlation between abusing probability and winning rate by the same way in Fig. 3: the slope of abusing probability with respect to winning rate is -0.41 (p-value is 5.2×10^{-4} , and we omit the figure due to the space limitation). Therefore, it is important to distinguish abusing probability between winning teams and losing teams.

Diverse teams tend to abuse more when losing and abuse less when winning (Fig. 4b). We further explore the effect of role diversity on team-level abusing. We observe different trends in winning teams and losing teams. When a team wins, team diversity is associated with low abusing probability; but it becomes the other way around if a team loses.

5.2 Individual-level Abusive Language Use

Different from winning and surrendering, abusive language use is an individual behavior. It provides a great opportunity to understand the effect of team composition on individual behavior and shed light on the “situation vs. personality” debate [16, 22].

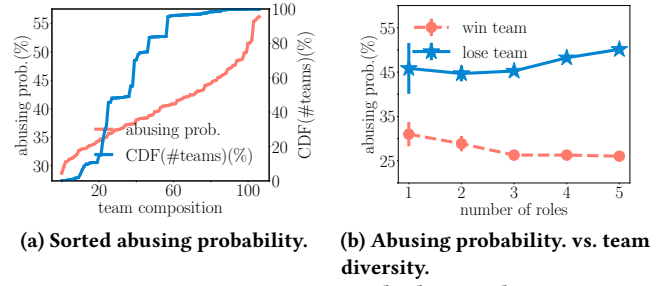


Figure 4: Team composition and abusive language use. Fig. 4a presents sorted abusing probability for different team compositions and its corresponding cumulative distribution function in #teams. In Fig. 4b, x-axis represents #roles in a team, and y-axis represents team-level abusing probability.

Note that we conduct this part of experiments on players who have played at least 20 games to ensure sufficient samples for statistics. **A team does not equal the sum of individuals (Fig. 5a).** We define individual abusing probability based on the fraction of games that a player abuses in. Because of linearity of expectation, the total number of expected abusing players in a team is simply the sum of each player’s abusing probability:

$$\mathbb{E}(\#abusing\ players\ in\ a\ team) = \sum_{v \in team} P_{abuse}(v) \quad (1)$$

where P_{abuse} is estimated separately when a player wins or loses because abusing is associated with losing. This expectation is only valid if all players act independently in a team, but studies on teamwork have shown that a team does not equal the sum of individuals [7]. Therefore, we examine the discrepancy between observed and expected values to understand how team composition influences individual players. This analysis is done on games in the third week since it requires historical information of every team member.

Figure 5a shows the difference between the observed and the expected values for winning and losing teams, where *win/lose diff.* refers to the disparity between the observed and the expected number of abusing players ($\mathbb{O}(\#abusing\ players) - \mathbb{E}(\#abusing\ players)$). For most team compositions, the difference is not zero, indicating that individuals abuse differently depending on team compositions. In particular, in the most commonly used teams (when the CDF grows quickly on the right of the plot), individuals are more likely to abuse than expected when losing.

Players who prefer leading roles are more abusive (Fig. 5b, 5c, 5d). There always exists a leader or a major contributor in a team. In Honor of Kings, assassins usually take this role in a team because of their explosiveness: assassins can carry the team and control game pace. A failed assassin may lead the team to lose.

Fig. 5b shows that assassins are more likely to abuse than other roles. We call this the “abusive assassin” phenomenon. One natural question arises: are assassins more abusive because abusive players tend to choose assassins, or players become more abusive when choosing assassins? To answer this question, we compare the abusing probability of the same roles chosen by different players and the same player choosing different roles. We define the *experienced role* for a player if that player chooses a role frequently, i.e., playing in more than 50% of games. This procedure identifies experienced

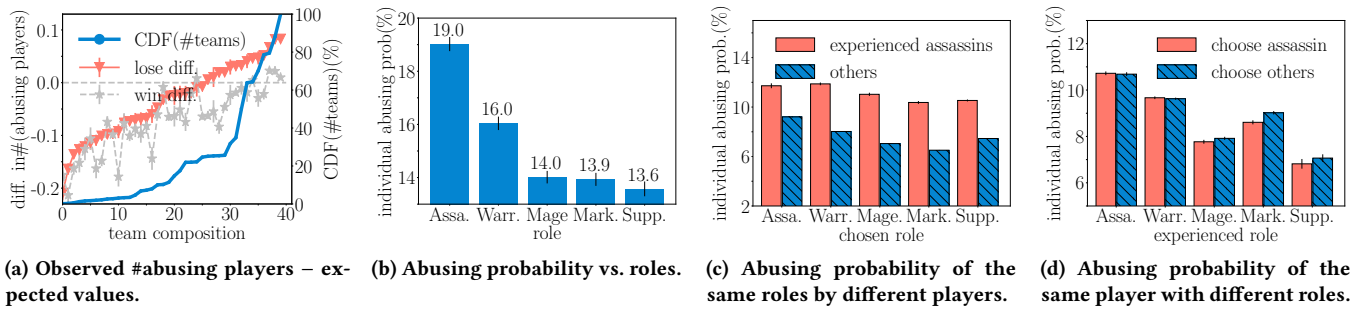


Figure 5: Fig. 5a shows the difference between the observed number of abusing players and the expected value based on individual abusing probability. The right three figures investigate the “abusive” assassin phenomenon. Fig. 5b shows individual abusive probability grouped by roles. Fig. 5c compares the abusing probability of players who usually play assassins with those who usually play other roles, grouped by their chosen role. Fig. 5d compares the abusing probability when a player choose assassin with when the same player chooses other roles, grouped by his experienced role. Error bars represent standard errors.

assassin players, experienced warrior players, etc. Fig. 5c presents the abusing probability of experienced assassin players when they choose each role (the same player choosing different roles). We observe that these experienced assassin players are much more likely to abuse than other players no matter what role they choose.

Fig. 5d examines the alternative hypothesis: players become more abusive when choosing assassins. We compare the same player’s abusing probability when they choose assassins with choosing other roles, grouped by their experienced roles. We find that players do not become more abusive when choosing assassins. If anything, experienced mages and experienced marksmen are actually more abusive when they choose roles other than assassins.

Overall, our results in Honor of Kings support the hypothesis that abusive players tend to choose assassins, the leading role in a team, and players do not become abusive when choosing assassins.

6 RELATED WORK

Team formation. Researchers from the data mining community have formulated the problem of team formulation as a constrained optimization problem based on each individual’s skills and their social networks [2, 3, 27, 28]. For instance, Li et al. [28] study a family of problems in team enhancement including team member replacement, team expansion, and team shrinkage.

Social/team roles. Digitalization of human traces have increasingly made implicit social/team roles explicit and enabled large-scale study on theories of social/team roles [6–8, 14, 41], e.g., Yang et al. [42] study how social roles influence the process of online information diffusion. In the context of gaming, Stetina et al. [37] examined problematic gaming behavior and depressive tendencies among people who play different types of online games.

Online gaming. Many researchers have recognized that online gaming can serve as a platform for studying individual/team behavior and communities [18, 24], where players not only develop individual skills but also coordinate and communicate with others [17, 20, 21, 29, 39]. Among our three measures of effectiveness, team performance is the most heavily studied topic, e.g., Pobiedina et al. [33, 34] explore factors that influence player’s performance in Dota 2. and Agarwala and Pearce [1] demonstrate that different role combinations may affect team performance. Furthermore, gamification can also play an important role in education and scientific discovery

[23, 32]. In addition to these exciting opportunities, online gaming leads to issues such as addiction and depression [25, 37].

7 CONCLUSION

In this paper, we study the effect of team composition in the largest MOBA game: Honor of Kings. We quantitatively show the varying effects of team composition on team performance (winning), tenacity (surrender), and rapport (abusive language use): although diverse teams tend to perform well and show tenacity in adversity, they are more likely to abuse when losing. The double-edged influence of team diversity suggests the importance of balancing team composition. We further examine how team composition influences individual behavior in abusive language use. In addition to showing that a team is not the sum of independent individuals, we contribute to the “situation vs. personality” debate and show that assassins abuse more because abusive players tend to choose assassins instead of players becoming abusive when choosing assassins. Our work suggests that the gaming environment may be improved by adjusting team matching and preventing players from using team compositions that correlate with increased abusive language use.

Limitations. Although we control for roles in our analyses, our study is observational and can be strengthened with experimental studies. However, experimental studies on team compositions are non-trivial because of the great number of possible combinations. Our notion of diversity is limited by our lack of access to users’ demographic information. Despite that Honor of Kings is the largest MOBA game, the selection bias in our data and specifics of the game design may limit the generalizability of our findings.

Future directions. Several promising directions arise from our work. It remains challenging to develop a holistic model that captures the interaction between individual members, learns novel representations for role combinations, and makes accurate predictions for effectiveness metrics to validate and deeply understand our findings in this paper. Furthermore, although MOBA games provide an ideal environment for understanding the effect of team composition, it is important to generalize our findings in other scenarios, e.g., with implicit roles beyond gaming.

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