Over-Lenient and Over-Aggressive Behaviors:

Gender Play in League of Legends

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# ABSTRACT

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Anecdotal intelligence seems to have uncovered unsportsmanlike behaviors directed in particular towards players of League of Legends with ‘feminine’ in-game names (here on called summoners’ names). This paper proposes a data-driven method to investigate behavioral markers that could potentially reveal bad sportsmanship in players of League of Legends and confirm the initial anecdotal insight, producing reflections on how inter-embodied play through movement and gameplay choices adds another layer to bad sportsmanship. Moving beyond toxicity or “bad manners” in chat, or harassment in the early game in lanes, this study looks at players’ actions collected through Riot Games API and investigates whether there are behavioral markers that reveal different, discriminative treatment reserved to players that adopt ‘feminine’ summoner names. Discriminative treatment is here qualified both as over-leniency and over-aggressiveness based on gender perception. With a female player community below 10% in a game with over 27 million unique daily players, the bad sportsmanship highlighted here exposes the subtlety of inter-embodied gender play that players in this community both experience and accept. This research found a few weak signifiers correlating behaviors quantified in the game data with bad sportsmanship, necessitating a more thorough qualitative investigation.

## Author Keywords

Computer Mediated Interaction, Sportsmanship, League of Legends, Gender Representation, In-Game Name.

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K.8.0. [**Personal Computing**]: General – *Games*.

# INTRODUCTION

The basic ideals of ‘sportsmanship’ or being a ‘good sport’ are familiar concepts. Fair play, enjoyment of the game for its own sake, respect, fellowship and a moral minimum attitude towards fellow competitors are historic and regular values espoused around ‘playing well’ [9]. But how is good or bad sportsmanship expressed in modern game spaces that involve networks, algorithms, mediated self-representation, geographically dislocated teams, and in games which are (mostly) achieved in the absence of mature coaches and adjudicators? Who or what feels the impact of the networked bad sport? And how do players and game organizers negotiate what we call here ‘bad manner, leisure lifestyles’? Bad sportsmanship is here intended both as “over-playing” and “under-playing”. Over-playing entails offensive, over-aggressive, vindictive and retaliatory behaviors caused by experiences such as “I will not be defeated by a girl”. Under-playing involves condescending behaviors derived from purposefully playing under one’s skill levels, stemming from experiences such as “she’s a girl, she’s just here for the attention, and she poses no real threat” [34].

This opening study on gender representation, tactics, and expert team-play looks at one of the most popular youth lifestyle computer games of this decade, League of Legends (here-on called *League*). A quantitative study was designed to look for a confirmation on anecdotal knowledge gathered in the field, drawing together a multi-faceted look at one particular practice involving bad sportsmanship in this modern place of play: over-playing and under-playing in League. The initial insight provided researchers with this anecdote: when players encounter another player whom, based on the summoner’s name, they believe is a woman, they adjust their play in one way or the other, over- or under-playing the opponent.

The mid-tier level of League (gold and platinum leagues) is explored as a significant place and practice of play, where ‘open’ or ‘co-ed’ dedicated team-play takes place. The rationale behind the choice of gold and platinum leagues is that lower leagues still find players struggling to learn and assimilate the non-trivial mechanics offered by the game, while higher leagues maybe too routinely instrumental to identify the nuances of non-optimal strategies like over- or under-playing. Traditional sports customarily segregate organized games when it moves into the practiced or expert level of play. In League, highly competitive/collaborative ‘play for all’ is realizable. Most players at this level have used approximately 1.039 hours on the game (based on a survey of 4.674.050 players [29]), which can be situated as their main leisure engagement – in other words, a serious leisure pursuit from which they take significant pleasure [21, 23]. As such, League offers a place to explore how players ‘do’ and experience bad sportsmanship in this particular arrangement of co-ed, dedicated play. Given the impact League has on the practice of e-sports, and potentially sports at large, it is important to unpack the issue of bad sportsmanship. Since League, as a platform, mediates a large amount of players’ interaction, it is essential to understand how perceived gender, represented through summoners’ naming practices, can give rise to unsportsmanlike behaviors. This paper attempts to answer this question through a data-driven analytic method.

# Background

Riot Games, the developer behind League, describes the game as ”a free-to-play, fast-paced, competitive online game that blends the speed and intensity of an RTS with RPG elements. Two teams of five powerful champions, each with a unique design and playstyle, battle head-to-head across multiple battlefields and game modes. With an ever-expanding roster of champions, frequent updates and a thriving tournament scene, League of Legends offers endless replayability for players of every skill level.” [30]

League is the most played PC game in the world, with 90 million summoner names registered, 27 million unique daily players, 7.5 million concurrent users, and 67 million monthly players [20]. There are 10 games being started every second and users are linked in from over 145 countries [13]. What is even more astonishing is the number of spectators attracted to the game: 32 million people watched the Season 3 finals, making it the biggest platform for e-sports worldwide [11]. Despite networked team-play offering players a space to engage in the personal pleasures of competition/collaboration, the socio-technical ‘playing field’ is not the same for all. This is reflected in user statistics: In a game with such a striking reach (since its launch in 2009), fewer than 10% of the 27 million daily users logging in are identified as female players [12]. While arguments have been previously made on essentialised play preferences, ethnographic work with women who play competitive/collaborative networked team games offer some on-the-ground voices which unpack the various pleasures as well as techniques of marginalization that impact on participation in online game cultures [24, 25, 27, 10, 19, 32].

Riot, the developer of League, invests in their notion of a game for all in specific ways. Of particular note is Riot’s early development of the “Summoner’s Code” in 2010 [18]. Essentially, the Code comprises of a list of valued moral behaviors in play, demonstrating an ongoing commitment to the institutionalization of “sportsmanship” in League [36].

Jeffrey Lin, Riot’s lead social systems designer, highlights the socio-cultural gradients which mount an uneven playing field for some players, built on ad-hoc events (such as repetitive teasing received from a stranger) to targeted group ‘harassment’ (sexist/racist trash-talking), both of which reflect bad manners [36]. Riot’s stance is strengthened by the choice of not including an in-game voice-chat function as a reflection of their sportsmanship code.

This research explores the more tacit dimensions of bad sportsmanship, through persistent over- or under-play towards a perceived female-gendered player, by way of performing poor tactics, via embodied choices (poor movement and mechanics choices in terms of strong tactical play), that ‘kill’ or ‘aid’ an enemy player. These unwarranted kills or aids, leave coded (through number of deaths or MMR score) as well as affective marks on the experience of being a ‘marked player’ treated differently. As Lin notes, “Players are 320% times more likely to quit the game entirely the more abuse or toxic behaviour they experience” [36]. However, this refers specifically to language. How do players and developers even start to make sense of embodied toxic behavior in games?

## Qualitative Literature Review

Summoner names are one of the self-selected identity markers embedded into the *League* infrastructure alongside of team-names (e.g. “Rebel Grrls”), presentation of self in chat (pronoun use), embodied communication, and champion (character) selection. Exploring the mid-tier level of *League* play, this research unpacks if and how a player recognizable as female through the summoner’s name, can be understood as a ‘game changer’.

Game-name based discriminative behavior (which under another lens could be called dark play - See [22]) has a long history in online multiplayer game settings. Working through typologies of game-talk, Wright, Boria and Breidenbach [35] highlight how gendered (sexuality and race oriented) insults, as an extension of trash-talking, is a regular occurrence in online competitive play. Referring directly to game-name choice in FPS games, they reflect on identity making in play, noting that “…names communicate symbolically to all players how one prefers to be perceived by another. The symbolic quality of a name leads to its usage in word play. Creative word play was quite common with players making references to the novelty of different names used on their avatars.” [35, para. 5]. This insight leads to a very simple question regarding participation in multiplayer competitive play – under what circumstances is gendered trash-talking received and interpreted as ‘just playful’ during gameplay? Pitching gendered slurs at perceived-as-female players online is ruled as ‘bm’ (bad manners) within Riot’s Summoner’s Code; but it is also recognized as just poor sportsmanship by commonplace standards of amateur to professional competitive sports cultures. Competitive computer game play, such as mid-tier level *League*, sees a spectrum of attitudes towards play, from what can be called ‘process-oriented amateurs’ to ‘hard-core instrumentalists’ [15]. Within that spectrum, trash-talking is reconciled as just a part of the recipe of playing to win, where testing an opponent’s mind and body is ‘fair game’ and anything goes [33, 34]. However, prejudiced ‘play’ clearly moves beyond any given ‘mind-game’ tactics; as it is tacitly acknowledged as unsportsmanlike behaviour through its limited use as a tactic in traditional face-to-face sports or public/visible competitive play [16].

Studies of multiplayer/team games locate gendered trash-talking or gender-based harassment as oriented towards various, often interwoven and assembled, identity presentations [8], which include; in game-names [35], character representation [8], team names and networked identities (such as live-streamers or individuals/teams with other online presence) that are brought into play. In his ethnography in *Second Life*, Tom Boellstorff [1] unpacks the significance of screen names but also highlights how the abovementioned channels participate in the making of online identity, as ongoing configurative practices. Identity configurations in *League* can be quite complex. For example, the following is a multi-layered ‘female’ presentation: a player chooses the game-name ‘Rosalyn’ and plays as the female champion ‘Soraka’. However, in *League*, this player may receive an additional layer of sex-difference depending on the *role* of the champion. In a mixed-methods exploration of gender disparity in *League*, women were regularly found to play support roles, leading to the finding that “female *League* players may face a vicious cycle by believing that they are suitable only for support roles or, more problematically, that they do not belong in the game” [19].[[1]](#footnote-2) Keeping in mind Boellstorff’s observation that virtual practices of ‘the social’ are usually entrenched in a binary of male-female in game worlds, as “heuristically stable referents for online selfhood” [p.144], such embedded experiences are significant. In mid-tier *League*, we would do well to consider how this finding might double-down: where online selfhood enters into a competitive sports scene, local and particular sporting masculinities (sports having a long established tradition of segregating ‘the sexes’ in competitions) are also reified through competitive play [24, 25, 28]. Those performing alternatively to the norms of local gaming/sporting masculinities (which are practiced, multiple and fluid), for example those who identify with another kind of gender, may find themselves in marked territory [33, 34].

The negotiated markers of perceived gender (game-name, team-name, champion representation, character role, networked identities), and the gendering of participation in game cultures, highlight that gender-performance disparities in competitive games are built up through manifold forms of ‘difference making’, which feeds into the textured experience of sportsmanship. These are just some of the coded and cultural traces that *League* players, representing themselves as female, may negotiate in their competitive digital play practices. This research posits, however, that further gender play may be at stake, and challenges to look at an elusive form of ‘bad sportsmanship’ directed towards a (perceived as) female player through their inter-embodied engagements.

Inter-embodied play is an under-researched phenomenon in in particular from the situation of competitive team-play, whether that be traditional or digital [7, 19]. T.L. Taylor offers an early and significant indicator on the embodied playfulness and pleasures of online worlds. In her study of women in *EverQuest* she notes that, “Unlike the 'real world' in which gender often plays a significant role in not only the perception of one's safety, but its actuality, in EverQuest women may travel knowing they are no more threatened by the creatures of the world than their male counterparts are.” [26]. Stressed in this passage is the equal opportunity for freedom of movement in this digital leisure space. Taylor was however looking at situations of PvE play, with neatly programmed non-playing-characters – ‘good sports’ (to an extent). PvP environments bring other sorts of creatures into play; notably, other competitive bodies with particular attitudes towards ‘fair play’, as well as different understandings of sporting masculinity. This space of digital competition sees gender deconstructed, then built right up again [1].

## Evidence of Under- and Over-Playing

Perhaps the best example of how inter-embodied play, gender play and sportmanship matters is an unpacking of an occasion of a high performance player/team being “beaten by a girl”, even if only temporarily, i.e. in a match between all-female promoted Team Siren and team OMGRankedFives, which consisted of two Challenger tier players streamed by the OMG player Hotshotgg, with all teammates voices audible on the stream.Early game tactics and heightened nerves were clearly motivated by OMGRankedFives’ ‘luck’ in drawing the notorious all-female team [14]. The pre-game squeals of excitement from OMGRankedFives, and their displays of nervous tension revealed a deep attention to gender, and in turn the gendering of competitive teamplay (as one OMG player quipped, “I can’t believe how funny this is”). During the opening minutes, practiced OMGRankedFives players had to be reined in by teammates as they started to greedily attack their opponent’s with no attention to usual strategic standards. After the first two kills (one from each team almost simultaneously delivered) OMGRankedFives expressed their ‘embarrassment’:

(dead OMGRankedFives teammate): FUCK

(alive OMGRankedFives teammate): This is bad for our image dude.

(dead OMGRankedFives teammate): I just like embarrassed myself in front of like, how any people?

(alive OMGRankedFives teammate): We’re fucking losing? What’s happening?

While embarrassment in being beaten (just momentarily) by a girl/s was a key theme, many other slices of gender play were alive in this match. These included audible disses on Team Siren ‘trying’ to play well: “Oh my god they have wards over here dude, that's so tryhard, that's so tryhard dude!” (voiced by an OMGRankedFives teammate), in addition to performances of hegemonic masculinity by Siren players in their displays of gendered trash-talking throughout the match (“pussy so big u can join siren” – an all chat message by a Siren player directed at an indecisive OMG play).

While this is an extreme example of a notorious all-female team in addition to a live-streamed performance, it still provokes the question of how ‘expressed femaleness’ can have a different inter-embodied experience of a playing field, which might be considered a subtle form of bad sportsmanship.

Inter-embodied play is a tacit (and often difficult to articulate) pleasure of team-play [7, 32]. It is also an inhabitation of time and space where players’ can embody the idea of the bad sport. Glaring associations can be drawn from the performance and experience of embodied ‘aggression’ and unsportsmanlike behavior in everyday leisure. As specified by Williams et al., “measuring the imbalances that exist on the screen can tell us what imbalances exist in social identity formation, social power and policy formation in daily life” [31]. Gender play, as explored through networked inter-embodied interaction, has subtle and qualitative imbalances within leisure, which are reflective of and on everyday life.

While work on skill-based differences in networked team-play can offer broad strokes or ‘hot’ areas of spatial engagement from a data driven point of view [4], work such as Taylor’s [27] highlights how ‘being there’, or what sports ethnographer de Garis [3] stresses as having a ‘touch’ for play, can open up for richer reflections on the processes, contexts, relationships and values—which can be both personal and present, or social and explicit [17] in this competitive digital leisure experience.

This opening study puts a critical eye on inter-embodied gender play in League, broadening the conversation on toxic behavior from text-based unsportsmanlike behavior to more subtle actions of toxicity within gameplay itself. Further investigation on this particular state of “co-ed” mega-sports activity is essential in rendering visible the subtle layers of gender play in games.

## Quantitative Literature Review

As shown in the previous section there is a wealth of research examining gender-related issues in online games utilizing qualitative methods. Recently, quantitative measures have been extensively used in the evaluation of games [37]. There have also been several studies looking at the relationship between gender or gamer tag (i.e., selected in-game character name) and behavior in games utilizing quantitative methods.

Drachen et al. [38] used an assortment of machine learning techniques to investigate the correlation of gamer tags and in-game performance in four commercial game data sets: World of Warcraft, Battlefield 2 Bad Company 2, Crysis, and Medal of Honor. They first used linear regressions to examine whether name choices in these games follow the same power law that governs real-life name distributions. Next, SIVM, a variant of Archetypal Analysis (AA), is used to obtain archetypes of play style in games. Finally, K-medoid clustering together with Purity measure to validate whether there is any non-random relationship between gamer tags and play style archetypes. Although no significant correlation was found, this establishes a suggestion on how play styles can be retrieved using AA to represent different in-game behaviors, which is adopted in our analysis process.

In another work, Martey et al. [39] examined the relationship between avatar gender and in-game behavior. It turned out that the selection of gender was less of an identity expression and more of a strategic move to gain advantages due to assumed favorable discriminating behavior (e.g., female characters presumably receive more help).

Lou et al. [40] on the other hand examined behavior data from the game Fairyland Online, an MMORPG with turn-based combats and random encounters. As players can possess different avatars to play, they focused on the performance of gender-switched avatars, i.e., female avatars played by male players and vice versa. They adopted aggregated statistics, such as frequency, total session time, chat time, etc., to document and compare the overall behavior of each (player gender, avatar gender) group. When examining the effect of gender choice, hypothesis testing (in this case, Kolmogorov-Smirnov test) is used to verify if the performance discrepancy is significant between avatars of different genders played by the same players.

Huh and Williams [41] matched qualitative survey answers of 6122 EverQuest II players with their logged in-game behaviors, and conducted analyses to validate a set of hypotheses on player behaviors when gender-switched. The main testing method is hypothesis testing, i.e., Chi Square and t-tests, with the test categories being the combinations (player gender, avatar gender). The counts of gender-specific behaviors (such as combating/fighting as male-indicative and sociable actions as female-indicative) are used as the dependent variables.

# METHOD

In order to quantitatively verify whether players modify their behavior by over- or under-playing female-gendered summoners it was necessary to collect game data from a control group and an experimental group. The control group contains 985 summoners whose name is not female-gendered. The experimental group contains 76 summoners with female-gendered name. This process is described in the section “Dataset Identification”. This study intends to examine and compare the performance of the control and the experimental group according to prioritized behavioral features collected from the game data through the Riot Games API. The features selected for the comparison are described in the section “Expert-Defined Prioritized Feature List”. The data collection process is described in the section “Data Collection Through Riot Games API”. In order for the comparison to be possible, it was necessary to control for champions’ base statistics and summoners’ skill level. The champions’ base stats are discussed in the section ”Grouping Champions by Base Stats”. Summoners skill level is discussed in the section “Using MMR to Control for Player Proficiency”. In order to compare features across the bins created it was necessary to normalize the values for each feature as described in the section “Normalizing Features Through Ranking”. Finally we utilized corrected T-tests to compare players’ ranks for all selected features, described in the section “Comparison of Control and Experimental Datasets”.

## Dataset Identification

In order to quantitatively identify unsportsmanlike behaviors directed towards female gendered summoners we needed to isolate two datasets, a control group composed of summoners whose name was not female gendered and an experimental group composed of summoners with female gendered name. Please note that no claim is made on the real gender of members of this group. We initially polled 15000 random summoners’ names by scraping third-party website op.gg's rankings page, which lists every active player by league and also provides a close approximation to the MMR scores. We then enlisted the help of a multicultural pool of League players recruited from the Reddit League page and the official Riot LOL forums. We required all volunteers to be fluent in English, dedicated players, somewhat in contact with League culture and between the ages of 18 and 40; 12 players volunteered from North America, Denmark, Germany, Italy, Korea and Australia. We were unable to enlist the help of players from China, Taiwan and Russia even if some of the top players hail from these countries. Each player had to look through the list of 15000 summoners names and flag what they thought was a female, hyper-feminized or hyper (female) sexualized player names. Only names unanimously flagged were included in the experimental group. Base heuristics were laid out for all the volunteers to follow, for example no names of female champions, celebrities, porn stars or models were included. The rationale is that no player would for a moment think that they were playing against a woman if the summoner’s name is Miley Cyrus, Tyra Banks, Jenna Haze or Taylor Swift. A sample of the gendered names selected is: OpheliaK, Holadie Jaqucline, Ms DandyDaisy LittleLoVelyYing, Tentacle Witch, Famme fatale, Temptress, AgnesA, She is Back, Genius Girl. The control group was also pruned from any female gendered names, but this time no unanimity was necessary. Two additional groups were also identified in terms of a) names that are designed to deflect aggressiveness such as: Stupid Casual, HelplessKitten, Idontplayoften, Novice201, Noobishboy, SuperNoobs, Im Real Lame, noobontheloose; and b) hyper (male) sexualised player names such as: GayTroy, Bruce, King dingdong, ManlyMan, ImakeHerScream. Group a) was also removed from the control group as potentially biasing. In future runs it could be interesting to examine behavioral attitudes towards these groups and additionally also examine religious and political signifiers.

## Expert-Defined Prioritized Feature List

Out of 81 possible features tracked by the API, 3 expert League players (all male and North Americans) identified 29 to be highly relevant to define proficiency of a summoner (see table 1).

|  |  |
| --- | --- |
| doubleKills | inhibitorKills |
| killingSprees | kills |
| largestKillingSpree | minionsKilled |
| largestMultiKill | neutralMinionsKilled |
| pentaKills | neutralMinionsKilledTeamJungle |
| quadraKills | wardsPlaced |
| tripleKills | sightWardsBoughtInGame |
| unrealKills | firstBloodAssist |
| wardsKilled | firstBloodKill |
| assists | firstTowerAssist |
| deaths | firstTowerKill |
| firstInhibitorAssist | totalDamageDealtToChampions |
| firstInhibitorKill | towerKills |
| goldEarned | visionWardsBoughtInGame |
| goldSpent |  |

**Table 1. Game features selected by expert players.**

## Data collection Through Riot Games API

The first step in collecting our data was identifying summoners that met our Gold or Platinum league requirements. This was done by scraping third-party website op.gg's rankings page, which lists every active player by league and also provides a close approximation to the MMR scores. Please note that Riot does not disclose summoners’ MMR score nor explains how it is calculated except mentioning that it is based only on wins and losses. With approximately 2,000 in the control group and 100 in the experimental, we used the Riot API [6] in tandem with the RiotWatcher Python wrapper to get the summoner ID, match history, match data, and most used champion for each summoner for the last 15 games played. All of this data was accessed from several endpoints in the API, however this does not give us the complete picture of information we need. In order to compare players of relatively similar skill levels, we had to approximate their Match Making Rating (MMR), since Riot does not publicly disclose how they compute MMRs in-game. We once again scraped op.gg, but this time used a Selenium driver called Splinter to search by summoner name and get details on their MMR and the average MMR of the league they are in, as approximated by op.gg's algorithm. Once all of this data was collected, we parsed and formatted it into CSV files, ready for slicing into bins and analysis. During the data collection and processing, dozens of summoners had missing or incomplete data and had to be thrown out from the study.

## Grouping Champions by Base Stats

Beside the summoners’ skill level, captured by the MMR score, we also wanted to control for behavioral biases implicitly operated by the base statistics of the champions used. In fact each champion has different starting stats in terms of health, mana, attach damage, attack speed, armor, magic resistance, movement speed or range. Riot already classifies champions in terms of primary and secondary attributes or roles. Attributes roughly communicate the fundamentals of a champion’s playstyle, it sets expectations for what a player's experience will be like and what they can do for their team. Primary attributes are stats agnostic: assassin, fighter, mage, marksman, support, tank. Secondary attributes are based in terms of the role that the champion is best fitted for: jungler, melee, ranged, recommended, stealth.

As we wanted to control for the difference of initial champion stats, and since Riot’s roles are stat agnostic, it was necessary for us to create new champions’ groups based on stats. We opted for archetypal clustering [42], as it aims to uncover the general patterns or trends of a subset of champions collectively. Given a set of data points, clustering algorithms aim to group similar data points together to form several representative groups such that the number of groups is much smaller than that of the data points. Unlike Clustering analysis, whose goal is to find “average” points of a data set, Archetypal Analysis looks for “extreme” points called *archetypes*. As such, any point in the data set can be interpreted as a combination of these archetypes. In practice, cluster analysis tends to yield similar basis vectors for different groups, which renders the champions groups hard to distinguish from one another even for domain knowledge experts. On the contrary, because of the extremeness, archetypes are data points that have the most prominent characteristics and thus easy to interpret by a human. Archetypal Analysis is commonly used to find extreme profiles (outliers), each archetype is a linear mixture of all the data points. Each data point is clustered as a combination of all archetypes.

Our analysis has revealed 5 clusters, identifying 5 champion types that are quite different from the 6 primary attributes defined by Riot.

## Using MMR to Control for Player Proficiency

MMR is a score used for matchmaking purposes based solely on wins and losses, therefore is a good indicator of perceived player proficiency even if it does not account for any game actions. As mentioned earlier, we are examining Gold and Platinum leagues because this is the space where players have the luxury of indulging in under- and over-playing. The gold league collects players with MMR from 1500 to 1900; the platinum league ranges from 1900 to 2400. After consulting with expert players we decided to slice both the control and the experimental datasets in intervals of 100 MMR. At first, each dataset (control and experimental) was divided into 5 bins, one for each champion type based on the groups identified via Archetypal Analysis, as detailed in the previous section. Subsequently, each of the 5 groups was organized into 10 different sub-folders based on their MMR with a tolerance range of 100. This tolerance range was computed based on the highest and lowest MMR as well as the number of summoners in our dataset. The actual tolerance computed was much more precise, but we approximated it to an even 100 based on advice from our expert League of Legends players that any tolerance more precise wouldn't be any more or less meaningful. These 50 bins both for the control and experimental dataset formed the basis of our analysis.

## Normalizing Features through Ranking

The raw values for each of the features selected could not be used for comparison, since many of the features do not have a maximum cap, for example in a game there could be 25 kills while in another only 3. Furthermore match length is very variable. Normalizing the values by reducing them to constant interval between 0 and 1 would not have accounted for team dynamics. We decided to normalize the values by ranking each score in each feature among the 5 team members, so for each feature summoners receive a score between 1 and 5.

## Comparison of Control and Experimental Datasets

For each combination of champion type and MMR range, the 50 bins previously defined, we compare players' ranks in all important features using Welch's T Test to see whether there is any significant difference between control and treatment groups. Welch Test is used to determine if the means of two populations are significantly different. Since we are conducting multi-hypothesis testing, the obtained p-values need to be accordingly adjusted using correction methods so as to avoid false discoveries in which low p-values happen due to chance. The adjusted p-values are called False Discovery Rate. The closer to 1 it is, the worse. Three correction methods are used, namely: Benjamini-Horchberg, Benjamini-Horner-Yekutieli and Bonferroni.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | p.value | p.value. adjusted\_BN | p.value. adjusted\_BY | p.value. adjusted\_BH |
| firstInhibitorAssist,gr2,mmr\_19\_20 | 1.57E-05 | 0.00965 | 0.06758 | 0.00965 |
| wardsPlaced,gr3,mmr\_19\_20 | 0.00040 | 0.25132 | 0.87940 | 0.12566 |
| firstInhibitorAssist,gr3,mmr\_17\_18 | 0.00964 | 1 | 1 | 0.95868 |
| kills,gr5,mmr\_19\_20 | 0.01063 | 1 | 1 | 0.95868 |
| totalDamageDealt,gr1,mmr\_19\_20 | 0.01206 | 1 | 1 | 0.95868 |
| deaths,gr3,mmr\_20\_21 | 0.01208 | 1 | 1 | 0.95868 |
| largestKillingSpre,gr5,mmr\_19\_20 | 0.01530 | 1 | 1 | 0.95868 |
| firstInhibitorAssist,gr5,mmr\_19\_20 | 0.02093 | 1 | 1 | 0.95868 |
| firstInhibitorKill,gr5,mmr\_17\_18 | 0.02154 | 1 | 1 | 0.95868 |

**Table 2. Top 9 results from the Welch t-tests, with three correction methods; gr1 to gr5 are the 5 champion types and mmr\_x\_y are the intervals of 100 MMR.**

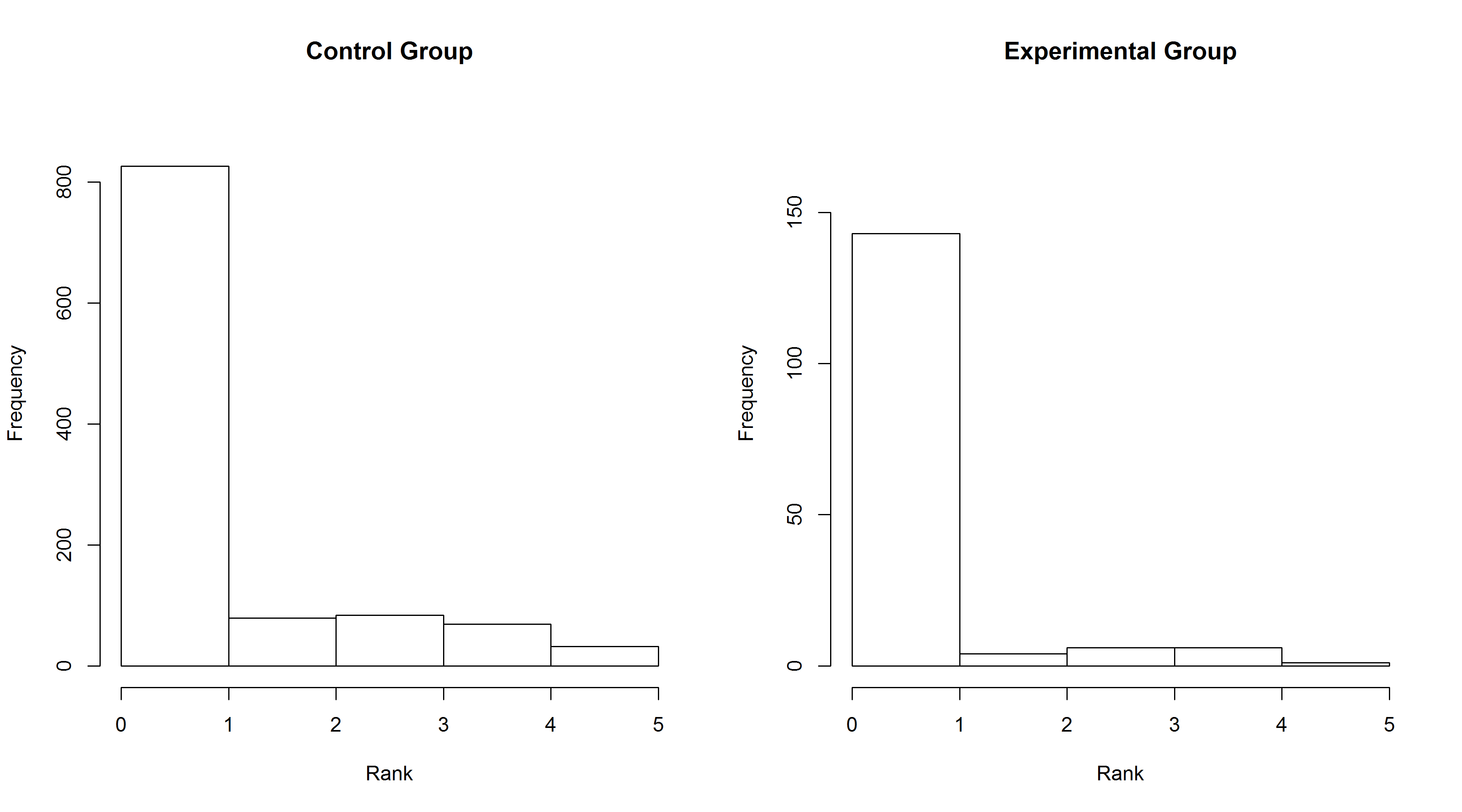
We utilized the 29 features prioritized and identified by the expert players, excluding strings features. The top 9 results are shown in Table 2. The only two features that passed all the corrections are "FirstAssistInhibitor" and "wardsPlaced" and they apply respectively to these bins: champion group 2 with MMR 1900 to 2000 and champion group 3 with MMR 1900 to 2000. Several other features received low p-values within 0.01 but after adjustment through correction methods, it is likely that they are achieved by chance.

# RESULTS & SIGNIFICANCE

First it is interesting to see how both of the features that are significantly different between control and experimental groups concern the bins containing data from champions in groups 2 and 3, which are the most populated groups in terms of number of champions and hence it’s easier to achieve lower p values. It is also interesting to see that in both cases the bins concerned cover the MMR interval between 1900 and 2000, again the most populated interval. Furthermore this seems to further validate the insight that lower MMR scores might be populated by players still trying to fully grasp the complex controls of the game, while in higher MMR scores, players might be too routinely instrumental to identify the nuances of non-optimal strategies like over- or under-playing.

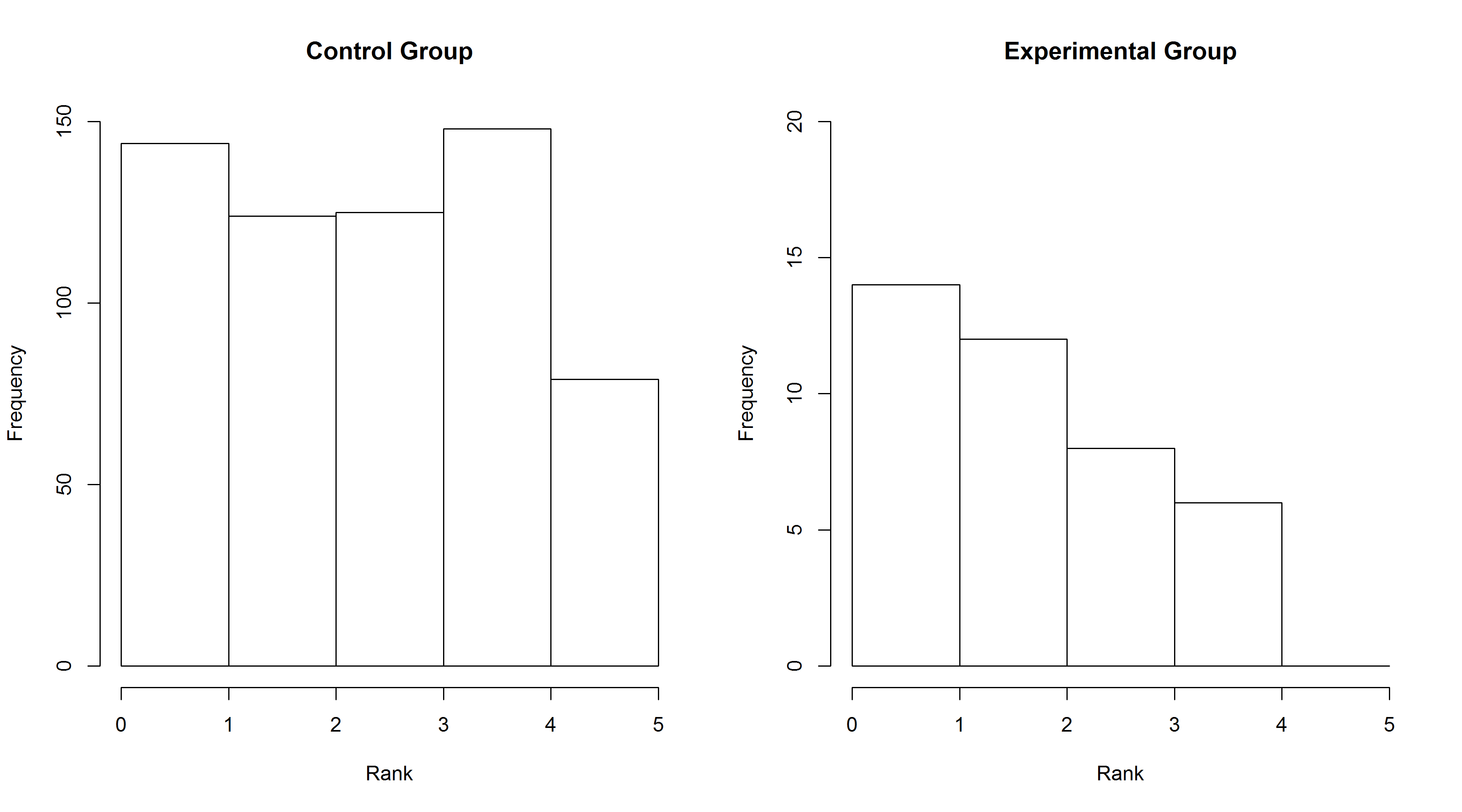
## Discussion

Inhibitors are structures that inhibit the spawning of powerful minions in each lane of a map. When destroyed they allow access to the nexus and its turrets, eventually leading to victory, each team has to destroy at least one in order to win the match. For this feature the control group has a mean rank of 2,16 against the mean of the experimental group of 2,21. This implies that summoners in the control group are more actively participating at assisting the destruction of the first inhibitor. The distribution of ranks among team members for this feature are shown in figure 1, the distribution is very similar for both groups.



**Figure 1. Distribution of ranks for the feature FirstInhibitorAssist, control group on the left, experimental group on the right.**

This insight could appear counterintuitive, as we’d expect to see an apparently supporting feature such as assisting a kill more prevalent in the experimental group rather than in the control group.

Control Wards in League are items that reveal areas of the map previously covered by the Fog of War. They are subtle yet lethal tools used both in defensive and offensive actions. They allow spotting incoming attacks and are helpful for planning informed attacks with higher chance of success. For this feature the control group has a mean rank of 2,82 against the mean of the experimental group of 2,15. This implies that the control groups places significantly more wards than the experimental group. The distribution of ranks among team members for this feature are shown in figure2. 

**Figure 2. Distribution of ranks for the feature WardsPlaced, control group on the left, experimental group on the right.**

The distribution is radically different: while in the control group ranks are almost equally distributed among all players (except that the players that ranks first in terms of number of wards placed are significantly less), in the experimental group there is no player that has attained first rank in terms of wards placed. A superficial reading of this insight could lead to the shallow conclusion that being wards a less direct and more complex mechanic to master, female gendered summoners, with lower perceived skills, might not be concerned with this action.

But both for inhibitor assists and wards placed, these insights become re-contextualized in light of the findings by by Ratan et al. [19]: women tend to play support roles and are often introduced to the game by partners whom they support in game by keeping their champs healthy, there is no time to shift the focus and place wards or even assist with an inhibitor kill as keeping the partner alive is paramount. As we mentioned from the beginning we are not implying that members of the experimental group are women, but independently from the real gender, they are engaged in gender play, hence they may be reproducing to some extent gendered behaviors such as covering support roles.

# conclusions

This study intends to build on existing knowledge of embodied networked team-play and add to it through a lens of ‘sportsmanship’. The players in this study are dedicated competitors, of which *League* can be regarded as a serious and regular leisure activity in their everyday lives.

Over- and under-playing directed towards female-identified game-names but also female characters, textual cues, voice and other signifiers reflects on culture writ large, and in the case of leisure cultures it offers a clear notice on who has the right to play as an unmarked player. Inter-embodied cues might contribute to our understandings if, of and how other kinds of discreet interactions facilitates ‘bad sportsmanship’, where “in-game revenge” for being “beaten by a girl” is a voiced occurrence of play. Here we adopted quantitative methods to investigate whether a control group and an experimental group composed of female-identified summoner names, display different behaviors.

This paper contributes to the largely under-researched phenomenon of inter-embodied gender play and bad sportsmanship in digital games. In exploring how bad sports and gender play intersect, future directions for this research include getting ‘a touch’ for gender play in League through on-going player conversations and observations on inter-embodied play. But also, moving beyond ‘female’ presentations, as a simple receiver of unsportsmanlike behavior, and exploring the active personal actions and tactics involved in doing gender in competitive play. Following the insights from this paper, the tactically sound maneuver of placing wards throughout a match is an area of research to advance. The discrepancy in ward placing signals that mid-tier expertise, roles and ‘good play’ have multiple interpretations which require further exploration. For what is expertise, and for who? In this age of big data and access to immediate and detailed player statistics, what expertise is missed in descriptions of high performance play from the position of the ‘no-stats’ expert? For example the expert players that helped define the features to model skillful play were all males. It is important to include women as expert players to define alternative markers of skillfull play, very different features may emerge, for example the features TotalUnitsHealed or TotalHealed were not included in the analysis, nor was particular attention paid to support roles. This is an introductory study into a broader examination of tactics, expertise and team-play in high performance networked games.

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1. This was a direct result of their pathway into the game (often through a male partner who they ‘supported’ both in game as a support-role character and by supporting their partners preferred leisure choice). [↑](#footnote-ref-2)