Toxicity in Valorant: a general panorama and analysis of a female player experience

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Coimbra, October of 2023

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Project work submitted to the Institute of Accounting and Administration of Coimbra in partial fulfill of the requirements for the Master's Degree in Data Analysis and Decision Supporting Systems held under the supervision of Professor Antônio Trigo Ph.D. and the guidance of the Professor Clara Viseu Ph.D.

Coimbra, October of 2023

STATEMENT OF RESPONSIBILITY

I declare that I am the author of this project, which is an original and unpublished work, that has never been submitted to another Higher Education Institution for obtaining an academic degree or other qualification. I also attest that all citations are properly identified and that I am aware that plagiarism is a serious lack of ethics, which may result in the cancellation of this project.

"We educate women because it is smart. We educate women because it changes the world"

- *Drew Faust*

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DEDICATORY

I dedicate this work for my family,

Who gave me in the journey of life and education, your unwavering support and love. This thesis is a testament to the sacrifices you've made and the encouragement you've given me throughout life.

You all made this all possible, since the moving to a whole new country and start of a new life to the realization of this master studies which has enrichment my knowledge in so much.

This work is not just a culmination of my efforts but a reflection of the love, support, and faith you have shown me. You are and will always be my greatest motivators. This thesis is dedicated to you, with profound gratitude and love.

With all my love

Jessica Amorim.

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Jessica Amorim.

RESUMO

Os videogames se tornaram uma das indústrias mais lucrativas do mundo, com um crescimento substancial, especialmente após a pandemia de COVID-19 em 2020. Com sua crescente importância, as pesquisas sobre a indústria de jogos e seus problemas também cresceram. Muitos desses trabalhos abordam a toxicidade dentro desta comunidade de jogos como tema principal e as causas e consequências que a cercam, e algumas abordam como o machismo e o preconceito de gênero podem afetar a experiência do jogador, tanto como jogador casual quanto profissional. Valorant, um jogo do gênero *First-Person-Shooter (FPS)* multijogador colaborativo da empresa Riot Gmaes, foi lançado em 2020 e por isso é um jogo relativamente novo, mas com uma taxa de toxicidade já bastate elevada, tornou-se então relevante focar uma investigação com o propósito de estudar comportamentos tóxicos e disruptivos dentro do jogo e perceber se e como a toxicidade e o sexismo pode afetar a experiência de um jogador dentro dele. Dados tanto de partidas reais de Valorant, disputadas pelo autor da presente pesquisa, quanto de um questionário disponibilizado para outros jogadores nas redes sociais, foram coletados e analisados por meio de análises qualitativas e quantitativas para traçar um panorama de toxicidade neste jogo. A abordagem da metodologia foi principalmente exploratória, encontrando corroboração em pesquisas anteriores. Os resultados indicaram que a toxicidade ainda é um grande problema dentro da comunidade de Valorant, independentemente da classificação, servidor ou sexo do jogador. No entanto, constatou-se que a toxicidade relacionada com o género, embora menos frequente, também continua a ser um problema e acontece de forma mais incisiva e agressiva quando se trata de ofender ou prejudicar jogadoras, tornando-se uma tarefa mais difícil de enfrentar quando comparada com toxicidade mais gerais, como quando relacionada, por exemplo, ao desempenho do jogador. Os dados também indicaram que embora a detecção de toxicidade no chat de texto está a melhorar no Valorant, ainda há um ponto fraco na detecção e combate de toxicidade da Riot Games quando se trata do chat de voz e comportamentos não-verbais tóxicos, como *trolling*, especialmente quando os dados indicam que essas são as formas de exibição de toxicidade mais comuns em partidas.

Palavras-chave: toxicidade, seximo, jogos, comportamento tóxico

ABSTRACT

Video games have become one of the most lucrative industries in the world with a substantial growth specially after the COVID-19 pandemic in 2020. With its raising importance, research about the gaming industry and its issues had also come to a growth. A lot of these works approach the toxicity inside this gaming community as main Thema and the causes and consequences surrounding it, as well as how machismo and gender bias can affect a player experience both as casual player and professional ones.

Valoran, a game from the First-Person-Shooter (FPS) gender, collaborative multiplayer from Riot Games Company, was released in 2020, being a relatively new game that contains a high toxicity rate, it became, then, relevant to focus research on the purpose of studying toxic and disruptive behavior inside the game and understand if and how toxicity and sexism can affect a player experience inside it.

Data from both real Valorant matches, played by the author of this present research, and from a questionnaire available for other players through social media, was collected and analyzed through both qualitative and quantitative analyses to trace a panorama of toxicity in this game. The approach of the methodology was mainly exploratory, encountering corroboration in previous research.

The results indicated toxicity still as a big issue inside the Valorant Community independently of a player's rank, server or gender. However, it was found that gender related toxicity, albeit less frequent, is also still a problem and happens in a way more incisive and aggressive manner when it comes to offend or harm female players, becoming a harder task to cope with when compared to general toxicity related, for an example, to player performance. It also indicated that although toxicity detection in text chat is improving in Valorant, there is still a weak point in toxicity detection and combat from Riot Games when it comes to the voice chat and toxic non-verbal behaviors such as trolling, especially when data indicated that these are the most common toxicity forms of display in game matches.

Keywords: toxicity, sexism, Valorant, gaming, toxic behavior

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LIST OF ABBREVIATIONS AND ACRONYMS

ADL	Anti-Defamation League
AFK	Away From the Keyboard
ANOVA	Analysis of Variance
CONDA	Contextual Dual-Annotated
CS:GO	Counter Strike: Global Offensive
DN	Direct Negative
DOTA	Defense Of The Ancient
DP	Direct Positive
FPS	First-Person-Shooter
KDA	Kill, Deaths, Assists
LGBTQ+	Lesbian, Gay, Bisexual, Transgender, Questioning, plus
LOL	League of Legends
MOBA	Multiplayer Online Battle Arena
NLP	Natural Language Processing
ODE	Online Disinhibition Effect
SCT	Social Cognitive Theory
TPB	Theory of Planned Behavior
USA	United States of America

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INTRODUCTION

Digital games industry had a significant growth in 2020 resulted from the COVID-19 pandemic and it was expected to show a little decline in 2021 with the different circumstances, but against those expectations, that industry had a 1,4% growth when compared to 2020 with a total revenue of $180,3 billion dollars and 3 billion active players around the world, 5,3% more than the year before (Wijman, 2021).

Considering the growth of this segment, as well as its economic importance, it is not surprising that research has been developed related to the area and the community created by these games. A topic present in several of these studies, and that is quite worthy of attention, is the toxicity in digital games. Research shows that the anonymity behind the voice and text chats of these games contributes to the development of toxic behaviors, especially in competitive scenarios (Kordyaka et al., 2020).

Bonny & Castaneda (2019) talks about the reasons that leads each person to play certain type of video games and motivation to continue in specific game genres comparing six possible reasons: arousal, challenge, competition, diversion, fantasy and social interaction. In a study conducted by Sherry et al. (2006) the results show, for example, that first-person-shooter games are highly related to social interactions and competitiveness.

However, despite the positive interaction presented by online games, players are also often exposed to toxic and disruptive behavior that can severely affect a player’s experience, decreasing players retention, being harmful for both the company and users. In this present work, as well as in previous research, toxicity is addressed as any type of negative behavior that involves abusive communication with the aim to disturb or harm another person and disruptive gameplays that goes against the game rules and policies, including harassment, spams, cheating and flaming, for an example (Beres et al., 2021, Reid et al., 2022).

In a game, it is very common for a player's value to be related to the role played in it, and in the vast majority of them, women are portrayed in support positions, with healing and control functions, without real combat power. Stereotypes like these make people expect real gamers to play these roles too, making it difficult for the general public to accept when minorities

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gain prominent positions, whether through an important role in a big game story, or in the competitive digital game landscape, this difference automatically creates an environment that is much more attractive to some than to others.

Although at the beginning of the digital gaming industry in the 1980s, it was estimated that only 5% of the audience was female, a recent survey from 2020 show that in the US and some European countries, almost half of the players are female (Bryter., 2020). Analysis made to games, considering their structure, story, characters and the community itself, demonstrate that certain misogynic stereotypes that contribute to the propagation of some prejudices are reaffirmed by the game itself, and considering that the female players population grows by each year and our society changes to include this new game community is important to address these stereotypes and the toxicity experienced in the digital games scenario so we can improve the general game experience and maintain games as a playful light activity and not a stressful toxic one.

Although recent research has addressed both the toxicity issue and the gender-specific topic in many ways, none of them used the game Valorant as a base to the research, taking it as a new game, released in 2020 and being sometimes addressed as a "girlish" version of Counter Strike: Global Offensive (CS:GO), and also considering the recent polemic about gender bias on the work environment that Riot Games was involved into, it is important to see if/how general toxicity and gender prejudice had developed in this game and how Riot copes with the problem (Shepherd, 2023).

This research will present an overview of toxicity in Valorant, how it develops in different circumstances and what it may be related to, analyzing variables such as the server, rank, solo and group queues and what the most common form of toxicity is, and trying to better understand toxic phenomena within this specific game. At the same time, to analyze the data collected by a female player and understand if and/or how sexism can affect a person's gaming experience, through the analysis of qualitative and quantitative data and statistical resources, using Excel and Microsoft Power BI as analysis tools.

The work is structured with an introduction on the gaming scenario and toxicity, a theoretical framework that contextualizes the current scenario, as well as presenting previous research relevant to the topic, then there is a presentation of the methodology used for data collection and analysis, followed by the results obtained and their discussion. The results of the research are summarized in the conclusion, followed by the bibliographical references and appendices.

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1 TOXICITY OF ONLINE MULTIPLAYER GAMES AND GENDER DIFFERENCES

This chapter provides a framework for the theoretical concepts needed to carry out the work, which goal is to build a general panorama of toxicity in Valorant and acknowledge the different experiences of men and women in the game. To this end, we present the toxicity of online games, the difference between genders in the toxicity shown in online games and, finally, a review of the literature in which eight articles on this subject were selected.

Although games were always seen as an anti-social activity played by those with no social skills, technology and internet connection made digital games a place where people from all around the world can interact, collaborate, and communicate turning online games into a new way to make friends. The problem of this online connection comes when players use this same possibility of voice and text interactions to offend and attack other players, sometimes, even committing hate crimes (Euteneuer, 2018; Silva Bartolomeu & Passos Canteri, 2021)

The definition of what is toxicity usually takes into consideration the rules gaming companies establish for in game behavior and the actions which you can report a player for. Players, however, define toxicity more as an intention than certain specific actions, stating that an apparently flaming behavior can be considered as non-toxic considering a whole context and intentions and vice-versa (Türkay et al., 2020).

1.1 Valorant: the game

Information contained in this section was found in the Beginner's Guide in Valorant official website Valorant (2023).

Valorant is a free to play online game from the company Riot Games released in 2020. It is available to download in the official website and has now, in 2023, 17 million of active players (Ferreira, 2023). It consists of a five versus five first-person shooter game with original characters. Each character has its own abilities and one of the four basic roles that can be played in a team, that being, duelist, sentinel, initiator, and controller. There are some game modes that can be chosen inside Valorant, but the main ones are Unranked and

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Competitive, the basic rules between them are the same, but in the Competitive mode the matches are created based on your game rank and you gain or lose points for each victory or defeat, and also based in your performance in that match.

The game has, in the present moment 7 available maps in the competitive mode being: Ascent; Haven; Split; Bind; Lotus; Breeze; Sunset.

Each map has two spawns areas, one for the defender team and one for the attacker. The Spike is what the bomb is called inside the game, and the main goal of each round is to either plant it and ensure it explodes, in case of attacking, or defusing and prevent if from exploding or even not letting it be planted at all, if defending. The map also has what is called Bomb Sites, signaled in the pictured below as the sand-colored area marked as A and B, that are the specific areas where is possible to plant the Spike.

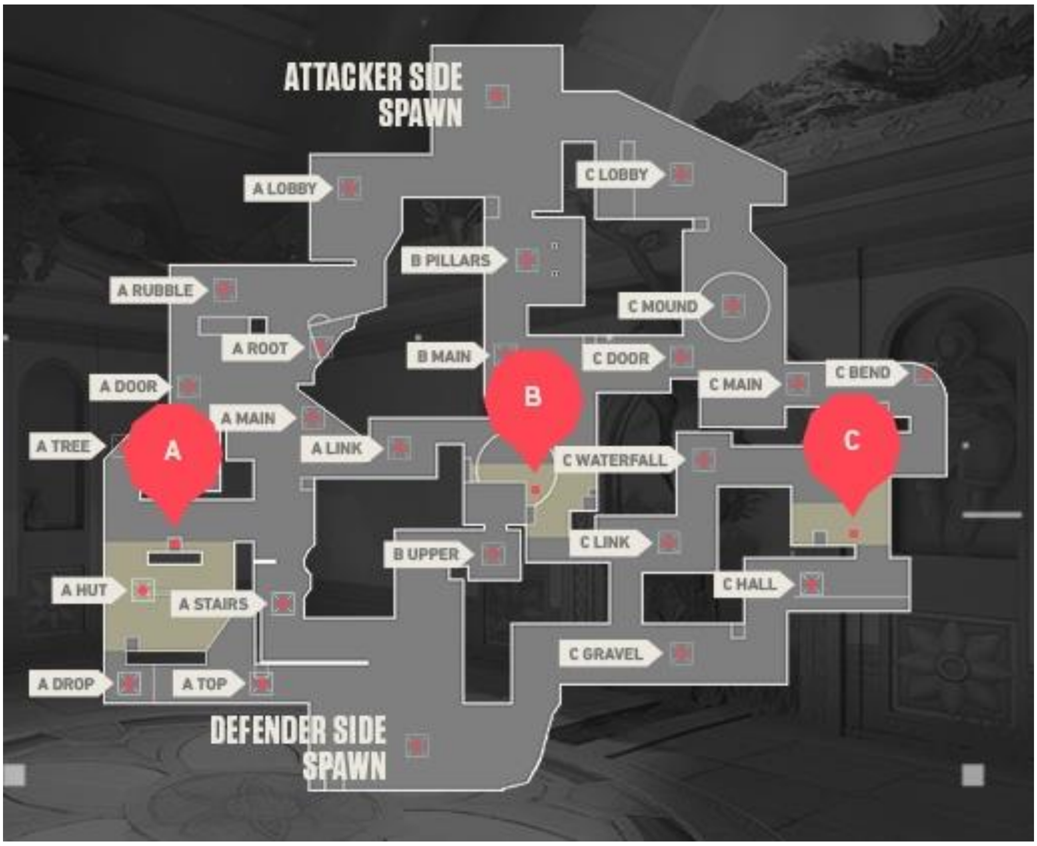

Figure 1-1. Lotus Valorant game map

Source: Image obtained from Valorant official website (https://playvalorant.com/pt-br/maps/)

In both Competitive and Unraked modes, ten players divided in two teams face each other in a 13 rounds match, the team who wins 13 rounds first wins the match, in one of the maps of the game. Between rounds each team plays the role of attacking or defending a bomb site, or simply taking down the entire enemy team. In competitive there is a specific game feature where, if the two teams tie in a 12 x 12 score, the game enters in "overtime" mode, that is a best of three mode where a team has to win two rounds in a row in order to win the match, and the teams has also the option to draw the game and no one loses points.

1.2 Toxicity in Digital Games

Abusive behavior can be performed by many means and to many kinds of people, though frequently directed to younger players, beginners, women, and the LGBTQ+ community. This kind of harassment is also much more likely to happen between teammates than between opponents, much because a team victory in these kinds of games requires collaboration. This behavior and toxic culture installed in digital games severely affects a player's experience and can lead people to abandoning a game because of the harassment suffered in it. This effect is particularly bad for beginners who are usually still learning games features and are normally not attached enough to the game to be willing to endure this kind of toxic behavior to continue playing (Zhu et al., 2022).

Some games present a higher level of toxicity than others, sometimes getting to the point where threats and sexual harassment become banal things. Players reported being told things like "I'll find your address", "I will rape you and your mom" and "I'll come rape you." This kind of behavior is more often reported in Multiplayer Online Battle Arena (MOBA) games. Although being a serious matter, many situations, and actions that, in a different environment, would not be tolerated, when performed in digital games, are considered acceptable, ordinary or simply unavoidable (Zhu et al., 2022, Darvin et al., 2021).

Over 70% of the total participants of a research from 2021 declared that they "strongly agree" that toxic behavior is an issue in online games and only 17% reported not to be affected by toxicity in any way. The research also shows that, in general, women feel more affected by toxic behavior than male players. Most female players reported having experienced gender

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related toxicity "always" and "often". The participants were also questioned on how they deal with these behaviors, most of them responding that they try to stay calm, report and block toxic players and assist the victims (Souza et al., 2021; Türkay et al., 2020).

In 2021 Anti-Defamation League (ADL) conducted a survey in the United States with nearly 100 million adult gamers about players' gaming experience where 83% of the participants reported having experienced some form of harassment during the game, a significant rise from the 74% reported in the same survey in 2019, and 71% of them reported cases of severe toxic behaviors including, even, physical threats. The games in which the players reported having suffered more with harassment situations were Valorant and Defense Of The Ancient 2 (DOTA 2) for two years in a row. Considering that Valorant was only released in 2020, developing such a high level of toxicity in such a short period is alarming (ADL, 2021).

Trying to face this problem, in 2017, big game companies and professional players got together to find a global coalition called Fair Play Alliance to fight toxicity and help to create a healthy environment and community in online games. It works with the principle that "*all players should be safe to enjoy and engage with others in the games of their choosing*" Although a very noble initiative, toxicity remains as a big issue in the digital environment (Members – Fair Play Alliance, 2022).

1.3 Why are players toxic?

With all data showing that toxicity is indeed a problem in this constantly growing industry that is online gaming, research has been made in order to better understand and explain this phenomenon. There are some theories that try to explain toxic behavior in this digital context, one of them being the *Online Disinhibition Efffect* (ODE) that is when an individual feels more likely to share raw thoughts and feelings in an online environment than they would in a real-life situation. This happens because of the Internet's possibility of anonymity and, specifically in games, because of the very low probability of encountering the same player again due to the huge number of users, people tend to be way more aggressive and disrespectful online (Kordyaka et al., 2020).

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Another approach is the *Social Cognitive Theory* (SCT) that shows how our behavior is influenced and learned by the environment around us. So, basically, being inserted in a toxic environment for a certain situation will lead us to also becoming toxic, spreading this behavior. The article also talks about the *Theory of Planned Behavior* (TPB) which argues that people engage in certain behaviors as a consequence of three past factors: the behavior itself, the influence of other people of significance also engaging in the behavior and the difficulty to cope with this behavior itself (Kordyaka et al., 2020).

Another possible explanation was approached in a research led by Santos et al. (2022) who analyzed the Proteus effect in the MOBA game League of Legends (LOL). This theory analyzes how people behavior is influenced by their users, nicknames, avatars in games or, in this specific research, the champion that they choose in a game match. The champions were classified by body type, gender, visual-based aggressiveness, cultural origin, difficulty and role. The results showed that male champions seem to be associated with a higher toxicity level when compared to female champions in what the author described as an "*unsurprising result"*.

Research from Mattinen and Macey (2018) also found a correlation between age and toxicity in the MOBA game, DOTA 2, it says that newer players are, the more likely to engage in disruptive behavior and that older players take in game verbal abuse, as a problem. The author takes that correlation also as a consequence of the normalization effect being perpetuated by time and affecting players' generations.

When talking through the reason why toxicity found such a solid ground in digital games specifically, a possible explanation is the common concept that this disruptive behavior is an essential characteristic of how the gaming community communicates in such a competitive scenario, leading to an acceptance state and normalization of such harmful actions creating an endless toxicity cycle (Beres et al., 2021).

1.4 Women in Games

Research conducted by Bryter (2020) shows that most women usually play alone, are less likely to have online friends and also normally play less with random opponents than men.

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Data showed that 84% of women prefer to play offline single player games and 32% of them, only play these kinds of games, also, female players are reluctant to declare themselves as a gamer even when playing the same average hours per week as men.

The motivation to play and the chosen gender also vary from men to women. According to the results, women are much more inclined to play puzzle, resource management and trivia games, being motivated by mastering and creativity, while men choose by action potential and social aspects. While men are very likely to have friends to play a game with, is harder for females to find a welcoming environment to insert themselves into and to find another female player, with no friends to play with is very hard to remain playing these competitive games. Also, having to deal way more often with toxicity, is common for female players to hide their gender or simply to give up on some games (Balakina et al., 2022).

Obstacles for women in games starts way earlier that most people usually think. The lack of support from families when it comes to gaming, especially comparing to men, that usually have access to video games and are able to play in dedicated consoles and hardware since an early age, affects not only professional players but also casual gamers seeing that, when not presented to this industry when young a lot of women discover their fond to gaming way later in life, which takes them to begin with very little ability, or, in some cases, none at all, being constantly discouraged and led to believe that they will never be as good as men, ending up with a lot of them being terrified to even start to play a new game (Darvin et al., 2021; Poeller et al., 2023).

A study made by Souza et al. (2021) traced the profile of gamer participants categorizing their gender in male, female, transgender, and non-binary, gathering information about their age, place where they are located, which games they usually play and for how long they have been playing it. The results show that while most of male players have 10 years or more of experience, most females have only started playing games in the last 5 years. Most female player use unisex avatars and names in game while most male players use characteristics that are commonly seen as exclusively male, this is probably due to the constant fear of harassment and retaliation towards women and some of them feels the need to hide their gender when playing.

1.5 Sexism in Digital Games

To try and understand how sexism can be inserted and affects the gaming community is important to first understand how it is inserted in the society in general and in which ways it maintains itself into it.

Connell (2005), in his research about gender and society, defines the concept of hegemonic masculinity as a gather of social practices that aims to guarantee the superiority of men in detriment of women in society and defines, then, five key characteristics for it: *"(1) physical force and control, (2) occupational achievement, (3) patriarchy, (4) frontiersmanship, and (5) heterosexuality"*

According to Darvin et al. (2021), three of this five points are explicitly found in video games: patriarchy is included with the oversexualization of women, presenting clearly which public it aims to reach, physical force and control is shown in the categorization of games where video games involving violence, cars and action are supposed to be for men and, when developed for women, are related to shopping, taking care of babies or animals, going to beauty salons, *etc.* It is also very clear with how different genders are portrayed in games, where women are more likely to be in support roles and men more as fighter and warriors. Then we have frontiersmanship with a strong community, mostly consisted by men, that makes it hard for women to be included in.

The latest years brought awareness to gender disparity and actions were taken to try and mitigate the sexism effect in this scenario and support and encourage female players. Despite the best efforts, the first person-shooter game field remains dominated by men. A big example of this genre is CS:GO, a competitive multiplayer game that despite its low appeal for women has a considerable female player base that, according to studies, have very similar ability levels when compared to men considering the same practice time (Balakina et al., 2022).

However, female players report that the prejudice inside games is not always related to the ability level or performance, a lot of them saying that they already feel an extra pressure simply for being a woman. The sureness that any mistake that they do will be directly connected with the fact that they are "a girl" and not to bad luck, day or lack of practice.

Women are also more afraid of making mistakes, being bottom frag or having a bad gameplay because they sense that, even a small slip, will contribute to the prejudice that women are worse players than men (Balakina et al., 2022; Madden, et al., 2021; Poeller et al., 2023).

Is important to address that gender bias goes both ways as men report themselves as more competitive and aggressive than woman, that being the reason why they are more “attracted” to games like CS:GO and, therefore, they are better than women in it, despite previous researches having already proven the ability potential of both genders being equal. Also, some women appear to have the same biased thought, especially women that are somewhat involved to gaming events or media but are not gamers (Madden, et al., 2021).

The gender difference persists in the gaming design and production industry as shown in employment data collected from big companies, like the fact that, in Rockstar games, women earns only 36% of the average men salaries, and Riot Games, in 2018, had only 20% of women as employees and 21 of their 23 management roles were occupied by men. In 2021, Riot games was ordered to pay $100 million dollars in a lawsuit for gender-bias discrimination and harassment in workplace, where female employees reported unwanted advances and hiring and promotion process that passed over female candidates for being insufficiently into gaming (Poeller et al., 2023; Shepherd, 2023).

1.6 Gender Bias in the competitive gaming scenario

Studies from 2021 shows that while the player’s community in the United States of America (USA) is divided in 45% women and 55% men, in championships and in the competitive scenario in general the proportion is of three women for each thirteen men. The study approaches how the problem of misrepresentation, and the way men perceive women participation in this scenario leads to a culture of constant harassment. A culture that was stablished a long time ago by content created specifically from men to men and is still fed by the perception of women roles in games and in the gaming community, where even if a female player is on the same level, when it comes to abilities, as a male player, they are still perceived as less and reduced, in many cases, to their appearance. This culture also englobes the sexualization of female streamers in Twitch as a result of practices already sealed in other previous social media platforms (Sørensen, 2022).

When analyzing the competitive scenario, both the game competitive mode and professional championships are supposed to be a space where people with similar performance levels can face each other in a fair competition and win or lose depending only on who played better in that match. However, authors such as Euteneuer (2018) and Paul (2018) relate the competitive scenario of digital games to the concept of meritocracy, stating that it creates a false feeling that your success or failure in a certain area depends solely on your effort when, in fact, there are several factors that influence this result. In gaming, for an example, a person's hardware, location and even having or not a constant team to play with, can interfere in a match despite player's performance. And even if a person manages to reach, by themselves, a certain level of success in some segment, this successful position is automatically aggregated with benefits that are no longer dependent on their effort or personal capabilities.

When digging further into this false sense of fairness, we can find inequalities that affects specifics groups of people, such as, women. Even when inserted in the competitive scenario, women are less inclined to join esports tournaments and some declared that would feel uncomfortable in these type of events (Balakina et al., 2022).

Loat (2021) describes esports as a field with real potential of being a common ground for all people to compete, with no biological characteristics in the way and a big transformative power, but such potential goes to waste with the lack of equal opportunities in a huge gap of employment ratio and wage differences.

A big part of the problem resides in how the organization of tournaments and championships is conducted. Organizers usually thinks that gender separated events are an action to create a safe place to women. The gamers, however, say to seek mixed championships and think that separated tournaments only make it harder for women to mature they professionalism and make the gender gap even wider. They support the idea that: "the best should be able to play against the best, despite their gender" (Madden, et al., 2021).

Coming back to the cultural aspect of this matter, the common sense that video games is a manly activity also plays a big part in gender segregation inside the competitive world. Study conducted by Balakina et al. (2022) and Madden et al. (2021) showed that female players are often referred to as "tomboys", implying that the women who enjoy gaming are more masculine. Male interviewed also reported that they think it is natural to have more men as professional players since women are not as competitive and do not have the "necessary" aggressiveness to enter and succeed in gaming championships.

One men reported that in the common sense of society, women are naturally just not interested in computing and gaming:

> *"Men are interested in things, women are interested in people. And a computer is a thing. That's why there are a lot more male ITs and more female nurses."* (Madden, Liu, et al., 2021, p.7)

A lot of male players find it harder to accept defeat for a woman. Female players said that they are usually more accepted when they are "less skilled" than men. It is common to find male teams that are on the same level but refuses to play against a female team or that play less seriously when facing women, what makes it hard for female teams to find good opportunities to practice seriously (Balakina et al., 2022).

The players interviewed reported cases where, when considered by someone building up a team, they would be neglected just for "being a girl" even when playing in the same level as the other male players. Also constantly receiving comments about their appearance in a context that would make them uncomfortable and self-conscious about being a woman in an environment that is dominated by men (Balakina et al., 2022).

Female pro-players also referred to Bootcamps, periods where the team would live together and do intensive play practice to championships and to improve their gameplay, as, usually, not being a comfortable experience when you are in a mixed team and often being the only woman in among a lot of men, having to divide the space, bathroom and get involved in their conversation because you are always the minority (Balakina et al., 2022; Darvin et al., 2021).

Balakina et al. (2022) interviewed 15 women that played, had played or are willing to play CS:GO in a professional manner. Some of them reported that their gaming career was usually

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taken as a hobby and not considered "a serious job" even when making her own money. Others said that the parents did not believe it could be a job, not letting them travel for championships claiming that it was a trap. This can be also blamed to the lack of awareness of competitive esports as a profession.

A lot of male players find it harder to accept defeat for a woman. Female players said that they are usually more accepted when they are "less skilled" than men, that being said, it is common to find male teams that are on the same level, but refuses to play against a female team or to play less seriously when facing women, that being said, is hard to female teams to find to good opportunities to practice seriously (Balakina et al., 2022).

In conclusion, the lack of women in the competitive scenario is not for inabilities or inferiority, but for an ideology already enhanced in video games brought by many other places in society, one of them being the traditional sports, in which, women are also frequently misrepresented (Sørensen, 2022).

1.7 Literature review on the toxicity of online multiplayer games and gender differences

This review aims to search for the already existent literature in the toxicity and sexism in video games area for information and evidence enough to contextualize this research and reaffirm its relevance to the gaming field. To reach this goal a Research String, shown below, was created in Scopus database and used to guide this research and also, to increase its reproducibility.

" ALL (toxicity AND (sexism OR gender) AND (esports)) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019)) "

From the initial list of 40 articles obtained with the above search string, 8 articles were selected, listed in Table 1-1 and their content is summarized below.

Table 1-1. Results of the Research String obtained in Elsevier

Author and year	Title
(Kordyaka et al., 2020)	Towards a unified theory of toxic behavior in video games. Internet Research
(Bonny & Castaneda, 2022)	To Triumph or to Socialize? The Role of Gaming Motivations in Multiplayer Online Battle Arena Gameplay Preferences
(Beres et al., 2021)	Don't you know that you're toxic: Normalization of toxicity in online gaming
(Şengün et al., 2022)	Do players communicate differently depending on the champion played? Exploring the Proteus effect in League of Legends
(Balakina et al., 2022)	From the Cradle to Battle: What Shapes the Careers of Female CS:GO Esports Players
(Madden, Liu, et al., 2021)	``Why Are You Playing Games? You Are a Girl!'': Exploring Gender Biases in Esports
(Türkay et al., 2020)	See No Evil, Hear No Evil, Speak No Evil: How Collegiate Esports Players Define, Experience and Cope with Toxicity
(Poeller et al., 2023)	Not Tekken Seriously? How Observers Respond to Masculine and Feminine Voices in Videogame Streamers

Source: Table constructed by the author

Esports have become so big and gain such importance that certain universities already consider it as a regular sport considerable for scholarships. Türkay et al. (2020), in their study, try to better understand how these collegiate players experience, define and cope with toxic behaviors in esports. The findings were diverse, since some participants defined toxicity as more of a concept like "anything that meant bad intentions" and other cited some specific actions. When it comes to experiencing and coping with it, most of the participants showed a lot of signs of normalization of said toxicity by perceiving it as something intrinsic to the gaming community.

Beres et al. (2021) also talk about how toxicity has been normalized over the years in online games creating a never-ending cycle from not reporting this behavior to reproducing it due to its trivialization. In the research they gather situations that would lead a player to report and others that, is spite of being against the game conducts, they tend to consider so normal that they would not raise a flag for it.

With such grow in the importance of gaming industry, people tried to find an explanation for said phenomena. In Kordyaka et al. (2020) research, they approach the three following existing theories to why players start and keep toxic behaviors in order to create a unified one focusing in addressing specifically MOBA games. It was found that the most significant theory was the Online Disinhibition Effect (ODE) that works alone but also as a mediator for the Social Cognitive Theory (SCT), while the Theory of Planed Behavior (TPB) one was a negative predictor of toxicity.

In that same line, Şengün et al. (2022) verified the existence of a correlation between the character chosen by a player and some aspects of their behavior inside a game match. The authors did not find a significant relation between the champion and player vocality. The most significant connection was stablished between a player toxicity level and valence, being the negative scores vs the positive ones in language usage, and the champion they play in a match. The characters were separated by types and some of them were related to higher toxicity levels and lower valence.

Bonny & Castaneda (2022) went a little further and researched the reason why players play games at all. The authors recruited professional players attending international tournaments of DOTA 2 to analyze their motivation to play online team-base games as well as they preferences when playing those games, for an example, if they prefer solo or party matches, measuring they motivation scores when it comes to the reason why they play games. The results showed greater motivation for social interaction reasons from the participants, although participants who prefer solo queues showed higher scores for competitiveness reasons.

Some authors aborded the issue of specific toxicity directed to a selected group of people, especially women, who seem to have more difficulties and obstacles when trying to insert themselves in the gaming community when compared to men.

Balakina et al. (2022) interviewed female CS:GO players that plays professionally, had played professionally before or are aiming a professional career. The article describes their experience and obstacles as women in the professional competitive scenario and the results show that the simple fact of being a girl in such a male-dominated world is already a challenge and stereotypes and the lack of acceptance from the community makes it even harder to persist in this path. Reports from the participants reaffirm the difference existent

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between men and women according to their starting point in the careers, the difficulties in competing against men when they are usually trained in different circumstances, the obstacles in finding professional teams to play in and the lack of visibility of the female segment of tournaments.

Madden, et al. (2021) approach the gender bias in esports very directly, seeing if and how it persists in the scenario and affects representativeness in the competitive gaming. The research was conducted through interviews with people involved with professional gaming in some way and once again there is the reaffirmation of how stereotypes such as women preferences for “housing” games and support roles persists and that men are biologically capable of performing better than women in esports. It also approaches the problem of underrepresentation of women in games and how it affects the public and sells games as a “manly” activity.

Poeller et al. (2023) analyzed how people perceive and react differently to the same speech, in the same tone, when spoken by a man and by a woman, women being related to characteristics such as “annoying” and “less calm” especially when in a winning match. The speeches were played together with video records from 2 game matches, both in losing and winning situations and the answers from the participants showed that, no matter the outcome of the match, the idea that women perform worse than men in video games persists and is not necessarily actually related to the game performance.

1.8 Toxicity in communication

1.8.1 Voice chat communication

As technology advances, more games started to introduce voice interaction features to enhance and improve in-game communication. Then, the first studies approaching specifically voice chats toxicity started to appear. Research conducted by Kuznekoff and Rose (2013) about the difference in situations experienced by different genders when communicating in game chats attested that the same message, portrayed by a female and a male voice, has different responses and that female voices receive three times more negative comments than the male ones even when the game performances were nearly equal.

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Similar research was conducted in 2023 but, instead of analyzing the players reactions to the different voices, impartial people not involved in the game were recorded when watching videos from women and men playing Tekken both in winning and losing situations speaking the same word at the same speed. The results show that the feminine voice was more "disliked", especially when winning a game, the same voice being perceived as more annoying when winning. Also, only a minority of the participants thought men and women to be able to achieve the same level of performance in online games, the majority still assuming that men are better at gaming. It is important to remark that this assumption was made both by male and female participants, proving it to be known as common sense in the society as a whole and not just among men, even if already proved as a myth (Poeller et al., 2023).

Other authors address the lack of an efficient, in real-time method to recognize toxic behaviors, seeing that only the player report system is not enough. Also, considering previous works that aimed to address text toxicity, it is clear that although they seem efficient to their purpose, they are still limited when it comes to voice communication. The research proposes a model that can measure the level of toxicity (between low and high) and aims to prevent toxicity by acting proactively when something happens, contrary to the present strategy used by companies, that only act when "the damage is done". The results show that higher ranks have a higher level of toxicity in game communication, the players feeling more pressured in higher levels, and also that toxicity levels have a positive association with the game word count, probably because toxic players tend to speak more and this behavior opens space for long arguments during the game, also, when the word count is higher, the probability of having a toxic spot in it is also bigger. Contrary, toxicity was negatively associated with character's names and "call-to-action" words and expressions, usually used in strategic conversations, these ones being much less present in matches with toxic behavior (Reid et al., 2022).

Due to this inefficiency of the big companies to deal and to contain this behavior, the community itself came up with some strategies to cope with toxicity, such as *Black Girl Gamers* and *Transmission Gaming*, both being communities created by players to encourage

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diversity and inclusion and also to bring awareness of the minorities in the digital games' scenario (Brewer et al., 2020).

1.8.2 Toxicity detection in in-game voice communication

When researching for studies of toxicity detection or prediction in online game communication is visible that the majority of it uses text chat messages as raw data to work, which is expected seeing that it is easier to collect, to analyze and also because some games do not even offer voice chat features. However, considering the goal of this research to approach the different response behavior to a voice interaction based on a player's gender, the voice chat communication becomes way more relevant since it is possible to identify a player's gender by it.

Considering then, voice chat analysis, two main approaches were found, them being Machine Learn and non-Machine Learn methods.

When it comes to non-Machine Learning methods the studies usually use regular statistics analysis and data mining technics to classify words into categories where, between them, is possible to address toxic behavior.

The first approach to gender differences in in-game voice chat was made from Kuznekoff and Rose (2013). In this study three XBOX accounts were used to access the multiplayer mode of Halo 3 and analyze the players interaction considering a male voice, a female voice and no voice. Standard phrases that could be used in different points of a match were created and recorded with the same intonation with both a male and female voice.

The study proposed two hypotheses and dialog analysis was used to support or deny them, being H1: the female voice situation would receive more negative comments and H2: the female voice situation would receive fewer positive comments. To analyze the in-game dialogs independent coders were recruited and trained to identify when a certain speech was directed to a player and how to categorize it between Direct Positive (DP) and Direct Negative (DN) and queries. 245 game matches were recorded, 82 with the female voice, 81 with male and 82 with no voice communication. An ANOVA test was used to attest mean difference for the DN, DP and queries values between the three conditions.

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One of these articles is the one conducted by Poeller et al. (2023) in which participants were exposed to videos containing two of the four possible situations: a male voice player in a winning match, a male voice player in a losing match, a female voice player in a winning match and a female voice player in a losing match. In both winning and both losing situations the female and the male voices were recorded saying the exact same words with the same intonation to them.

Informative data about the participants was recorded and they were then enquired about who they thought were better at video games, men, or women. The participants rated the player on a 0 to 4 Likert scale about how much they perceived the player to be competent, confident, experienced, competitive, aggressive, calm, emotional, likeable, friendly, and annoying. Considering single relatable variables, the authors used 3-way MANCOVAs to see how players were categorized depending on the presented situation and Chi Square test was used to perceive if the perception of gender performance differed by gender.

2 METHODOLOGY

For this present research, namely for the data collection phase, two different methodologies were used. In a first stage the method of individual participant observation was used to collect data from real Valorant matches. In this methodology the data collector chooses a community to study, immerse themselves into it and collect the data while actively participating into that community. Since these matches were only played by a single player, the author of the present research, it was decided to add a further step to data collection, a survey made through a questionnaire with similar variables observed in the matches, but available to a wider range of players, so the data could complement each other in the analysis.

For the analysis phase, a mostly exploratory approach was used to try and trace a general panorama of toxicity inside the game Valorant as well as to follow and understand the experience of a female player within the matches observed.

Here we aim to trace a general panorama for toxicity and sexism in Valorant by answering these questions:

RQ1: Is toxicity still an issue in Valorant?

RQ2: What are the variables that interfere in toxicity?

RQ3: Is sexism an issue in Valorant?

2.1 Data Collection

2.1.1 Practical data collected from real matches

Data from 64 Valorant ranked matches played in a row by the author, who identify herself as a cisgender woman was collected in a sheet containing the game server, if the player who collected the data was on a solo queue, their rank, if the match contained toxicity (based on the definition of toxicity referred above), if yes, how was it displayed and the number of deaths, kills and assists that player achieved in that match. The set also contained a column named "Phrase" where, if the offense displayed in that match contained some specific form of discrimination against a player characteristic such as gender, ethnicity or/and sexuality,

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for an example the phrase used by the offender should be recorded. The data can be seen in Table 2-1.

Table 2-1. Valorant game matches data

Rank	Server	Solo queue	Toxicity	Sexism	Text	Voice	Behavior	Phrase	Win/Loss	KDA
Bronze 2	Frankfurt	True	False	False	False	False	False		win	1,29
Bronze 2	London	True	False	False	False	False	False		loss	1,00
Bronze 2	London	True	False	False	False	False	False		win	1,50
Bronze 2	London	True	False	False	False	False	False		win	1,53
Bronze 2	London	True	False	False	False	False	False		win	1,91
Bronze 2	London	True	False	False	False	False	False		win	3,10
Bronze 2	London	True	True	False	False	True	False		loss	0,54
Bronze 2	London	True	True	False	False	True	True		loss	1,10
Bronze 2	Madrid	True	False	False	False	False	False		win	1,06
Bronze 2	Madrid	True	False	False	False	False	False		win	1,60
Bronze 2	Madrid	True	False	False	False	False	False		win	3,83
Bronze 2	Paris	True	False	False	False	False	False		win	1,71
Bronze 3	Frankfurt	True	False	False	False	False	False		loss	0,82
Bronze 3	Frankfurt	True	False	False	False	False	False		loss	1,11
Bronze 3	Frankfurt	True	False	False	False	False	False		win	0,50
Bronze 3	Frankfurt	True	False	False	False	False	False		win	1,13
Bronze 3	Frankfurt	True	False	False	False	False	False		win	1,50
Bronze 3	Frankfurt	True	False	False	False	False	False		win	1,75
Bronze 3	Frankfurt	True	False	False	False	False	False		win	1,86
Bronze 3	Frankfurt	True	False	False	False	False	False		win	2,10
Bronze 3	Frankfurt	True	False	False	False	False	False		win	2,40
Bronze 3	Frankfurt	True	False	False	False	False	False		win	2,55
Bronze 3	Frankfurt	True	True	False	False	False	True		loss	1,33
Bronze 3	Frankfurt	True	True	False	False	True	False		loss	1,35
Bronze 3	Frankfurt	True	True	False	True	True	False		win	1,85

Source: N = 64. Data collected by author in September of 2023.

The KDA column was obtained from data about the player's kills, deaths, and assists, suppressed in the table above but shown in Table 2-2 below.

Table 2-2. Number of kills, deaths and assists of the player in each match

kill	death	assist
17	10	4
9	19	11
9	16	2
15	16	4
23	15	8
17	18	6
10	16	2
7	20	20
14	15	6
14	14	0
19	14	5
19	17	7
2	13	0
19	8	5
12	14	9
14	14	6
8	14	2
12	18	3
9	14	1
22	15	6
5	13	2
20	17	2
20	10	11

Source: N = 64. Data collected by author in September of 2023.

This measure is called KDA ratio. Is used to measure player's performance in a game match, and was obtained using the formula below:

$$KDA = \frac{(k + a)}{d}$$

Where k is the number of kills the player achieves, a is the number of assists and d is the number of times the player died in that match.

The number of data obtained for each of the most relevant variables is displayed in the table 2-3 below.

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Table 2-3. Number of data obtained for each variable

Win/Loss		Server		Rank	
Win	30	Frankfurt	16	Bronze 2	14
Loss	34	London	16	Bronze 3	42
		Paris	16	Silver 1	8
		Madrid	16		

Source: N = 64. Data collected by author in September of 2023.

For the purpose of this present research, only toxicity displayed between allies on the player's team was considered since it is the most common form of toxicity and it is the one that usually has an effective impact in the match (McLean et al., 2020; Neto et al., 2017).

It is important to attest that, here, in this research, the toxicity column as marked as true anytime a toxic behavior occurred, being not necessarily directed to the player filling in the data, also, only toxicity occurring inside the ally team (from ally to ally) was considered.

The number of matches in each server was equal (sixteen in each) although not necessarily played in a row.

2.1.2 Questionnaire

Considering that the data collected from the game matches could be biased and only represented the experience of one player, the author deemed that a second data collection method was necessary, so more players could report their experience and the results could be compared further into the research.

The second way chosen to collect data was through a questionary available for gamers playing in Brazil and European servers containing questions about how they identify themselves (gender), since when they play Valorant, in which server(s) they usually play, they current rank and if they have ever experienced toxicity and sexism in the game. All questions were marked as mandatory.

The questionnaire was available for one week in September of 2023 in Facebook groups from Brazil and Europe related to Valorant. and answers were obtained from 120 random participants. All answers were considerable appropriate for the research and none of them was discarded.

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2.2 Data Analysis

2.2.1 Practical Data from real matches

The first analyzed parameter was the toxicity one. A pie chart was constructed to better visualize the number and frequency of toxicity occurrence in the analyzed matches. Then, the occurrences were divided into three different toxicity forms: voice chat, text chat and behavioral toxicity. A bar chart was constructed to indicate the number of occurrences of each one knowing that a same match can contain more than one type of hostile display.

Then, also through graphic visualization, the toxicity display was analyzed per rank, server, and in the won and lost matches to check for indications of an association between these variables. In the rank and win/loss analysis the KDA ratio was used as a significant measure to determine the existence of a correlation. This analysis, however, are more detailed in topic 2.2.1.1.

The graphics were created in the Microsoft Power BI tool. Pie and bars charts were the most used in this work because of the nature of data, mostly qualitative data. These graphics were useful for better visualization and understanding of the key points in this research.

As for the text data, it was only collected from 5 of the 64 matches here considered, all with sexism related occurrences, and the phrases collected were qualitatively analyzed and contextualized with the theoretical framework presented above seeing how sexism occurs in the Valorant community.

As to trace the toxicity panorama with the variables collected in the study, chi-square test was used to verify the existence of a significant association between solo queue, rank and win/loss with toxicity. Chi-square test is a statistical test that is used to determine whether there is any statistically significant association or dependence between two categorical variables. It is a non-parametric test, so it does not take into consideration the data distribution (Illowsky & Dean, 2013).

The test was conducted using Python in the Google colaboratory tool. The libraries used were pandas and numpy and the base code for this analysis is in the image 2-1.

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```
from numpy import longdouble


# For categorical variables (Rank and Solo Queue)
crosstab_rank = pd.crosstab(data['Rank'], data['Toxicity'])
chi2_rank, p_rank, _, _ = chi2_contingency(crosstab_rank)

crosstab_solo = pd.crosstab(data['Solo queue'], data['Toxicity'])
chi2_solo, p_solo, _, _ = chi2_contingency(crosstab_solo)

# For binary variables (Win/Loss)
crosstab_winloss = pd.crosstab(data['Win/Loss'], data['Toxicity'])
chi2_winloss, p_winloss, _, _ = chi2_contingency(crosstab_winloss)


# Print the results
print(f"Chi-Square for Rank vs. Toxicity: p-value = {p_rank}")
print(f"Chi-Square for Solo Queue vs. Toxicity: p-value = {p_solo}")
print(f"Chi-Square for Win/Loss vs. Toxicity: p-value = {p_winloss}")
```

Figure 2-1 Python code used for the chi-square test calculation

Source: Analysis made by the author using the google collaboratory tool.

2.2.1.1 KDA

The KDA, as introduced above, is used to measure player's performance and, is this research in some situations, to verify the existence of significant difference between the KDA values in different groups, statistics tests were applied.

The first was a t-test to determine if there is a significant difference between the means of KDA in two situations, in a win and in a loss case. The t-test is one of the most used to compare the means of two groups of data and attest if there is any statistical relevant difference between them (Kim, 2015). The test was conducted using an Excel sheet. But first, the normality of the data was verified to see if the assumptions for the realization of a t-test were fulfilled.

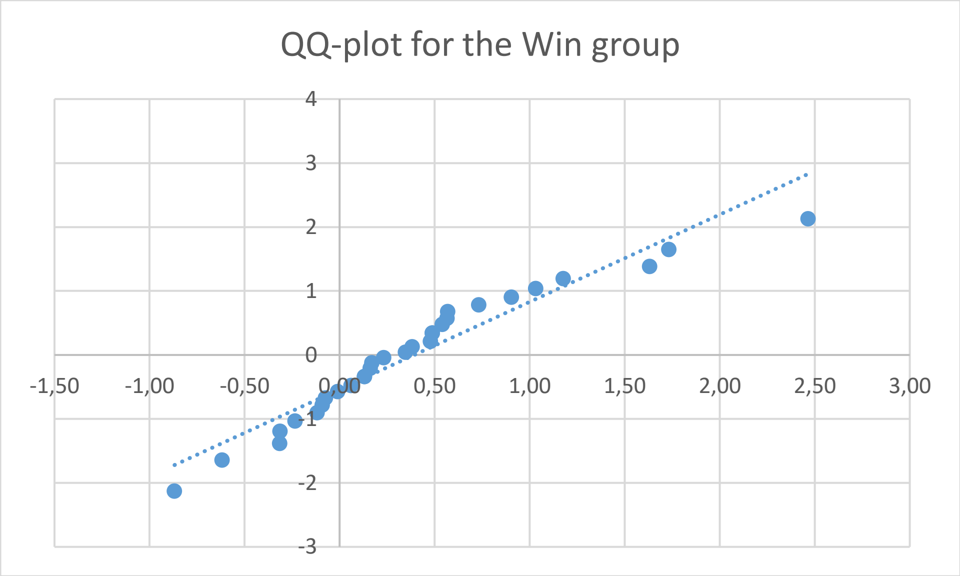

Figure 2-2. QQ-plot for normality check of the KDA value for the Win variable

Source: Scatter chart obtained by the author using the Microsoft tool.

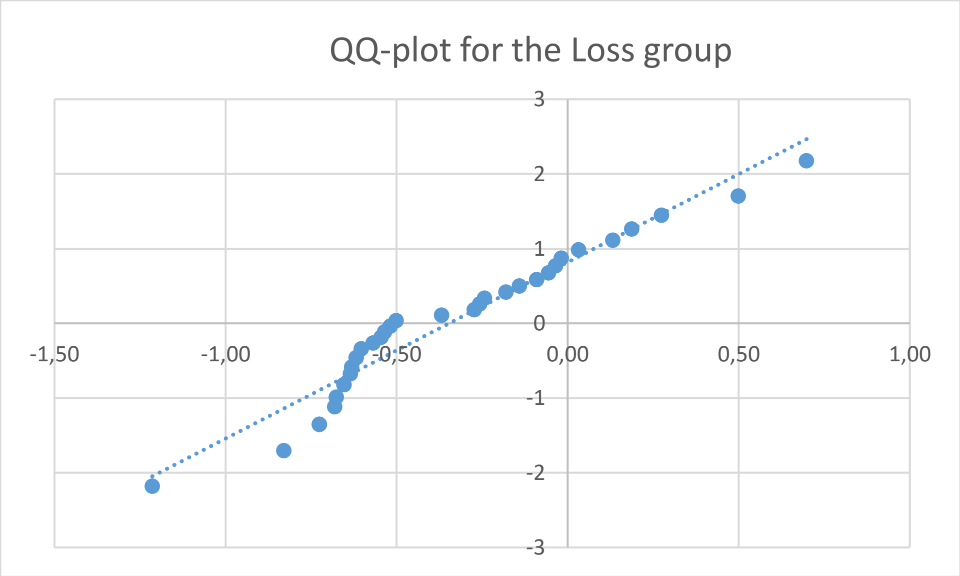

Figure 2-3. QQ-plot for data normality check of the KDA value for the Loss variable

Source: Scatter chart obtained by the author using the Microsoft tool.

With the QQ-plots it was possible to attest data normality and the t-test could be conducted from there.

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Here reference p-value is a stablished reference value that varies according to the number of data (N) and the chosen significance level, it can be consulted in the figure 2-4 below (Shapiro & Wilk, 1965a).

An analysis of variance test for normality 605

Table 6. *Percentage points of the W test* for n* = 3(1) 50

	Level								
n	**0·01**	**0·02**	**0·05**	**0·10**	**0·50**	**0·90**	**0·95**	**0·98**	**0·99**
3	0·753	0·756	0·767	0·789	0·959	0·998	0·999	1·000	1·000
4	·687	·707	·748	·792	·935	·987	·992	·996	·997
5	·686	·715	·762	·806	·927	·979	·986	·991	·993
6	0·713	0·743	0·788	0·826	0·927	0·974	0·981	0·986	0·989
7	·730	·760	·803	·838	·928	·972	·979	·985	·988
8	·749	·778	·818	·851	·932	·972	·978	·984	·987
9	·764	·791	·829	·859	·935	·972	·978	·984	·986
10	·781	·806	·842	·869	·938	·972	·978	·983	·986
11	0·792	0·817	0·850	0·876	0·940	0·973	0·979	0·984	0·986
12	·805	·828	·859	·883	·943	·973	·979	·984	·986
13	·814	·837	·866	·889	·945	·974	·979	·984	·986
14	·825	·846	·874	·895	·947	·975	·980	·984	·986
15	·835	·855	·881	·901	·950	·975	·980	·984	·987
16	0·844	0·863	0·887	0·906	0·952	0·976	0·981	0·985	0·987
17	·851	·869	·892	·910	·954	·977	·981	·985	·987
18	·858	·874	·897	·914	·956	·978	·982	·986	·988
19	·863	·879	·901	·917	·957	·978	·982	·986	·988
20	·868	·884	·905	·920	·959	·979	·983	·986	·988
21	0·873	0·888	0·908	0·923	0·960	0·980	0·983	0·987	0·989
22	·878	·892	·911	·926	·961	·980	·984	·987	·989
23	·881	·895	·914	·928	·962	·981	·984	·987	·989
24	·884	·898	·916	·930	·963	·981	·984	·987	·989
25	·888	·901	·918	·931	·964	·981	·985	·988	·989
26	0·891	0·904	0·920	0·933	0·965	0·982	0·985	0·988	0·989
27	·894	·906	·923	·935	·965	·982	·985	·988	·990
28	·896	·908	·924	·936	·966	·982	·985	·988	·990
29	·898	·910	·926	·937	·966	·982	·985	·988	·990
30	·900	·912	·927	·939	·967	·983	·985	·988	·900
31	0·902	0·914	0·929	0·940	0·967	0·983	0·986	0·988	0·990
32	·904	·915	·930	·941	·968	·983	·986	·988	·990
33	·906	·917	·931	·942	·968	·983	·986	·989	·990
34	·908	·919	·933	·943	·969	·983	·986	·989	·990

Figure 2-4. Reference p-values for Shapiro-Wilk test

Source: Image obtained from Shapiro & Wilk (1965), p.605

The outcome from the Shapiro-Wilk test is displayed in Table 2-4.

Table 2-4. Shapiro-Wilk test outcome for win and loss situations

Outcome	p-value	alpha	Reference-value
Win	0,93870096	0,05	0,927
Loss	0,94629982	0,05	0,933

Source: Scatter chart obtained by the author using the Microsoft excel tool.

We can see that the obtained p-values are higher than the references considering a 95% confidence level, which means that the null hypothesis should not be rejected and, therefore, the data is inside the limits of normality and the t-test can be conducted from here.

The second test used to measure KDA difference between groups was ANOVA. The ANOVA test is used to verify the existence, or not, of statistically significant difference between the mean of three or more independent variables. In this research, it was used to verify the existence of relevant difference between the KDA mean values obtained by the player among the three ranks observed in the game matches dataset (Sthle & Wold, 1989).

To apply an ANOVA test to data groups these groups must follow some prepositions. Firstly, the normalization of the data was checked using QQ-plots for each group and the plots are contained in Figure 2-5, Figure 2-6 and Figure 2-7 below.

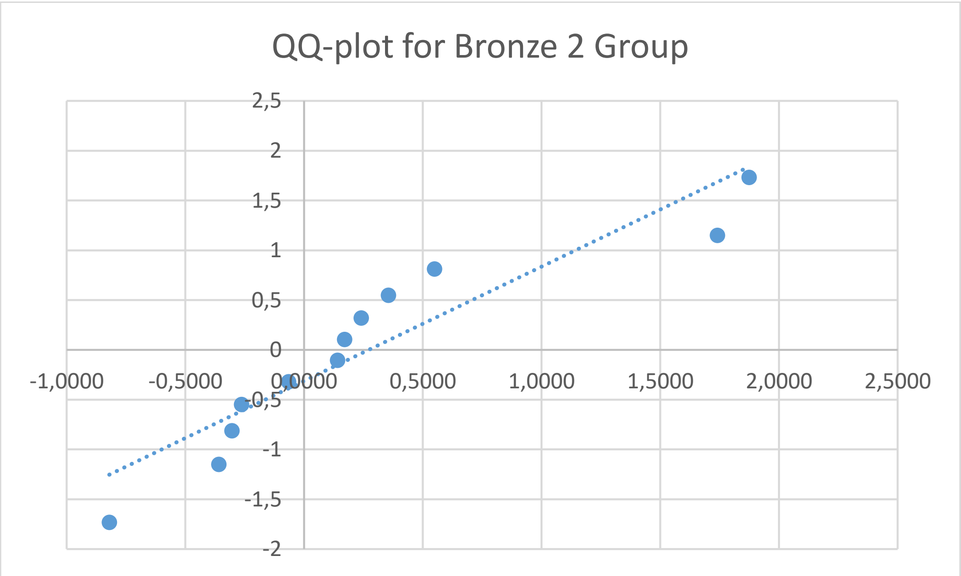

Figure 2-5. QQ-plot to check normalization of KDA values from Bronze 2 group

Source: Scatter chart obtained by the author using the Microsoft tool.

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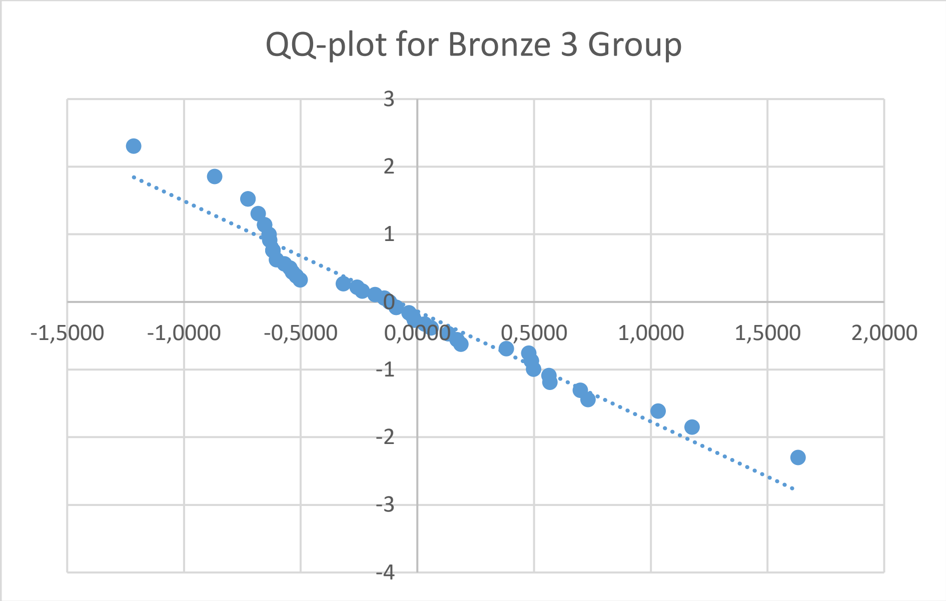

Figure 2-6. QQ plot to check normalization of KDA values from Bronze 3 group

Source: Scatter chart obtained by the author using the Microsoft tool.

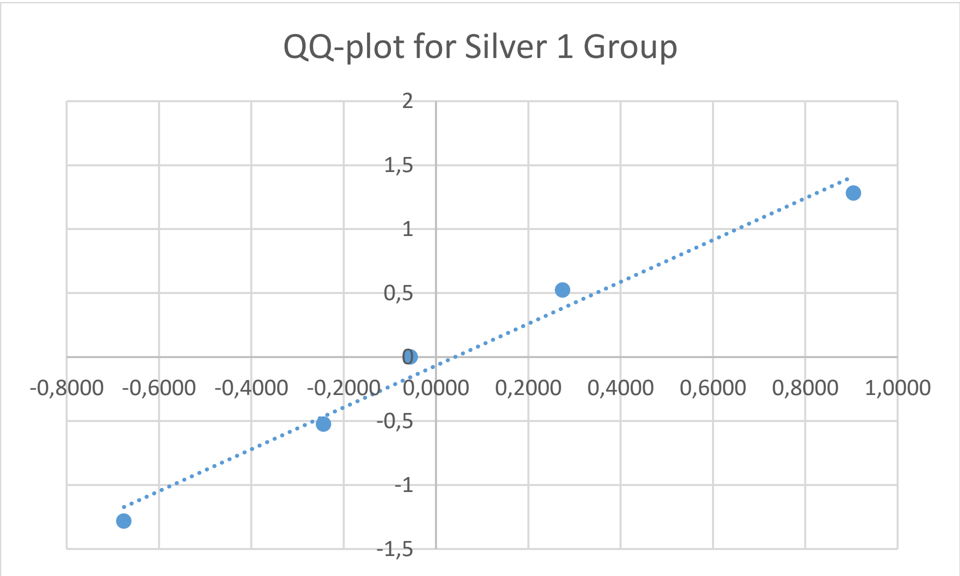

Figure 2-7. QQ plot to check normalization of KDA values from Silver 1 group

Source: Scatter chart obtained by the author using the Microsoft tool.

As we can see in the Figures 2-5 and 2-6, data from Bronze 3 matches and Silver 1 seems to tend to normality while in the Bronze 2 group, the chart was not considered enough to determine the normality of data and a further confirmation was required. The Shapiro-Wilk test was applied to all three groups for further reaffirmation.

Table 2-5. p-values results for the Saphiro-Wilk test conducted for the three groups

Rank	p-value	Significance value	Reference p-value
Bronze 2	0.8736	0.05	0.859
Bronze 3	0.9484	0.05	0.946
Silver 1	0.9836	0.05	0.762

Source: outcome obtained by the author using the Microsoft Excel tool.

We can see that the obtained p-values are higher than the reference considering a 95% confidence level, which means that the null hypothesis should not be rejected and, therefore, the data is, indeed, inside the limits to be considered proper to be used in the conduction of the ANOVA test.

The second assumption is that the variances of the groups must be homogeneous. To test this assumption a Lavene test was conducted using Microsoft excel. The Lavene test was chosen for its good performance for groups that can deviate a little from normality and in groups with small amount of data (Sthle & Wold, 1989). The result is in Figure 2-8.

Fcalc	Ftab	p-value	Conclusion
0,342138	3,147791	0,711604	The variations are homogeneous

Figure 2-8. outcome for Lavene test for the three groups variances

Source: outcome obtained by the author using the Microsoft Excel tool.

Here, the f-value calculated is smaller than the one tabulated and means that the variances are homogeneous, and the ANOVA test can be applied.

2.2.2 Questionnaire data

Firstly, the data containing information about participants gender and server were used to graphics construction for better understanding of the survey participants demographic data.

When analyzing the questionnaire data, the analysis was similar to the ones presented for the practical dataset since the aim was to compare the results from both data sources and either confirm or not the conclusions found from the played matches.

3 RESULTS AND DISCUSSION

In this chapter we present the results of the two analyses carried out, one using the scientific method of participant observation and the other using the survey method with a questionnaire (see Appendix 1), trying to compare these results as closely as possible.

3.1 Participant observation

3.1.1 Toxicity observation

The definition of toxicity fixated to serve as parameter in this research was obtained from the combination of definitions given in previous researches as: any spoken offense or action with the intention to harm, bully or/and offend another player or to disrupt the team work and gameplay in order to prevent their own team from winning (Beres et al., 2021; Reid et al., 2022; Türkay et al., 2020).

Considering toxicity can be displayed in this game by text chat, voice chat and through a toxic behavior such as trolling, matches containing any of these types of toxicity were computed and it was found that from the 64 analyzed matches, 17 contained some kind of toxic behavior, either by text, voice communication or by a behavior in the game, that means that one in each four matches contains toxicity.

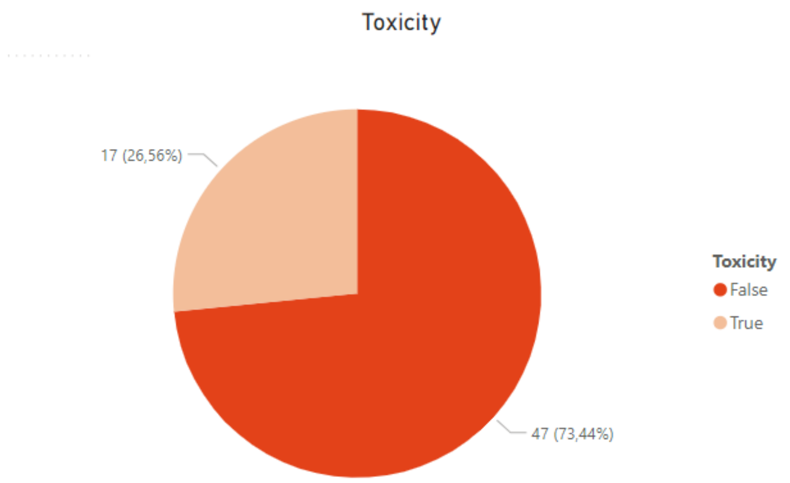

Figure 3-1. Number of matches containing toxic behavior

Source: Pie chart created by the author using the Microsoft Power BI tool.

3.1.1.1 Forms of toxicity

In this research toxicity is considered to be displayed inside Valorant within three forms: by the text chat, voice chat, or through a behavior in the game, with the possibility of happening in more than one form in a same match. In the table 3-1 we can see the frequency each type of toxicity happened.

Table 3-1. Number of occurrences of each type of toxicity

Behavior	Text	Voice	Number of matches
No	No	Yes	8
No	Yes	Yes	2
Yes	No	No	5
Yes	No	Yes	1
Yes	Yes	Yes	1

Source: Data collected by the author from the Valorant game matches.

It is easy to observe that voice chat communication has the biggest number of toxic displays, present in 12 of the 17 matches containing toxicity, which makes sense considering that it is the easiest way to communicate in a match, a player can open their microphone and speak quickly while playing, on the other side, typing something in the text chat takes way longer and the player has to stop playing to type.

The second way is through the behavior known as “trolling”, a troll is a player that sabotage its own team by playing badly on purpose, staying Away From the Keyboard (AFK), which is a term commonly used in video games when the player stays inactive although still being connected in the game, or preventing others from their team to fulfill the game goals. That behavior can happen either because the called “troller” is angry from a bad game or simply because they want others to get “tilted” because they think it is fun. Players interviewed by Türkay et al., (2020) define tilting as “*the breaking point […] the point where you get angry or you just go to the edge and just don’t feel like playing anymore*”, it usually origins from

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game related frustrations and leads to toxic behaviors that most of the times ruins the game for the whole team.

The third possibility is through the text chat, which, as already said before is more time consuming and, as discussed in the topic 3.3 is also easier for the company to monitor and consequently is easier for the offender to get punished.

3.1.1.2 Chi-Square test for variables association

Giving the goal of the research to trace a general panorama for disruptive behavior in Valorant it was relevant to try to verify the existence of an association between toxicity and other variables in the data. It would also be interesting to know if any of these variables could be a suitable predictor for toxicity in a game match. For this goal, a chi-square test was conducted between toxicity and the variables of rank, if the match was played on solo queue or not and if it ended in win or loss. The results are displayed in Figure 3-2.

```
Chi-Square for Rank vs. Toxicity: p-value = 0.5786117257961308
Chi-Square for Solo Queue vs. Toxicity: p-value = 0.7445149903472785
Chi-Square for Win/Loss vs. Toxicity: p-value = 0.0019248357044977626
```

Figure 3-2. Results for chi-square test for toxicity and other variables

Source: Data obtained by the author using the Google Collaboratory tool.

Given the significance level of 0.05, the rank and solo queue variables have a p-value > 0.05, which means that the data suggests there is no significant association between them and toxicity in a game match. That outcome is expectable. We are going to dig further into it in the topic 3.1.2, but the ranks here analyzed are very similar when it comes to the ability level. That means that the same player can easily fluctuate between them within a short period of time, so it was estimated to not have a significant influence on the presence of hostility.

The solo queue variable was also expected not to play a big part in the toxicity presence in this specific research since the number of matches played in solo queue was way greater than the one played in group and, therefore, they could not be compared equally to this end.

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With the win/loss variable, the p-value obtained is less than 0.05 and ended up having a correlation with toxicity. This makes sense considering that more than 88% of the matches containing toxicity ended in a loss. This relation will be further explained in topic 3.1.3.

3.1.2 Toxicity per rank

First, for a better analysis of this specific variable, is important to understand the Valorant rank placement scale and system. As we can see in the Figure 3-3, these are the ranks a player can achieve when playing ranked mode in Valorant, being Iron 1 the lowest and Radiant the highest rank.

Each rank is separated by 100 points between them, and the player earn and lose points in each won or lost ranked game match. The amount of points a player will earn or lose depends on their performance in that match and the rank of their allies and opponents.

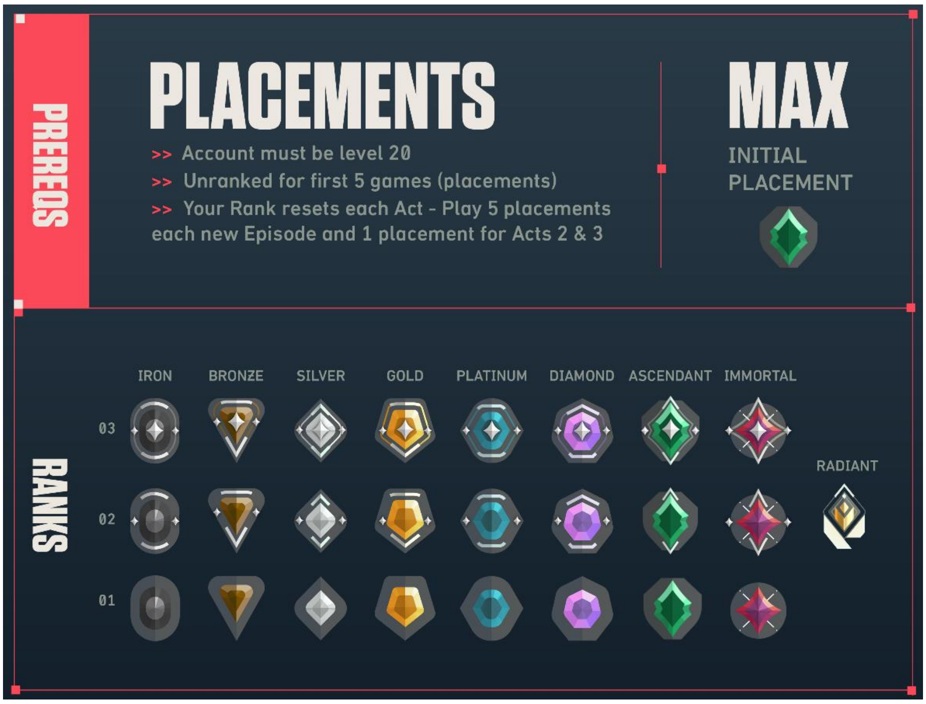

Figure 3-3. Valorant rank placement schema

Source: Image obtained from Valorant official website (https://playvalorant.com/pt-br/maps/).

Here in this research, the player had matches in 3 different ranks, although the quantity of matches in each rank is very unequal since it depends on the number of win and losses the player had and how many points they earned or lost in each one. The ranks were bronze 2, bronze 3 and silver one. Since the outcome of a match does not rely on a single player performance, it is easy for the same player to fluctuate between these three ranks even when playing consistently. That means that the same players that play in Bronze 3, can play in Silver 1 or Bronze 2 in a couple of days difference and vice-versa.

To prove this point, the KDA ratio was used as a performance indicator and an ANOVA test was conducted to analyze the KDA of the player in these three ranks to see if there is a relevant difference between them that indicates a difference in the performance level of the player. The result is shown in Figure 3-4:

	SS	df (GL)	MS	F	P
Between groups (c)	1.161302835	2	0.58	1.422381089	0.2490228072
Same group (t)	24.90	61	0.41		
Total	26.06	63			

Figure 3-4. ANOVA test results for the KDA ratio in each rank

Source: Outcome obtained by the author for an ANOVA test using the Microsoft Excel tool.

The p-value found is bigger than 0.05 which means that there is no statistically significant difference between the performance of the player in the ranks and, therefore, does not present a relevant association to toxicity in the context of the data presented.

These results confirm the other one found in the chi-square test indicating no real association between the rank and toxicity in this present research.

3.1.3 Win and Loss variables

3.1.3.1 KDA influence in match outcome

When analyzing causes for the toxicity to happen in a specific game match we can consider player performance as one of them, since the most common reason for flaming in cooperative games is an ally bad performance (Jerabeck & Ferguson, 2013; McLean et al., 2020). Here, we are going to analyze the author performance in a match by its KDA ratio and see the impact it has on the match outcome. In this research, we are simply going to consider KDA>1 as associated to a good performance, since that means that the player killed and assisted in kills more than they died in the match, and KDA<1 associated with a bad performance since it means the player died more than they killed and assisted in that match. This is a simplify approach but will server to the purpose of this research.

However, is important to say that this is the data collected from only one player in a team of five and does not represent the performance of the entire team in that match. In Figure 3-5 we can see that, as expected, the KDA mean is smaller in matches that ended in the defeat for the players team.

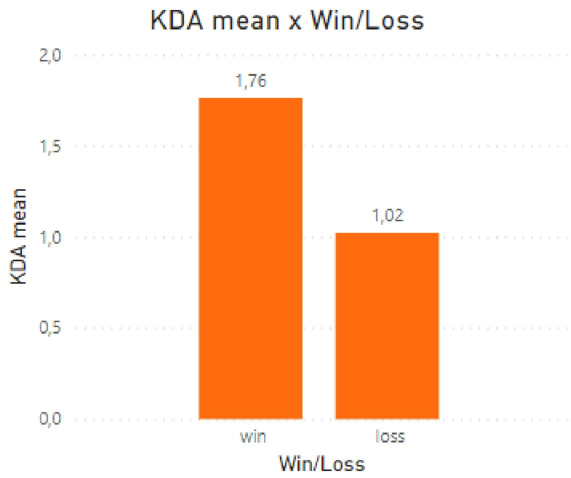

Figure 3-5. Bars graphic of the relation between the players KDA mean and the match outcome

Source: Graphic obtained by the author in the Microsoft Power BI tool.

Applying a t-test to the KDA ratio means in win and loss situations, the p-value found for it was lower than 0.05 (Figure 3-6), which means that the null hypothesis must be rejected and, therefore, there is a statistically significant difference between the KDA value is these situations.

KDA Win	KDA Loss
2,10	0,69
1,05	1,19
1,28	2,07
1,71	0,75
1,53	1,35
3,00	1,33
1,50	1,00
1,43	0,15
1,29	0,71
3,10	0,83
1,50	0,71
1,91	1,87
1,13	0,54
1,94	0,75
3,83	0,87
1,60	1,56
1,06	0,64
1,86	0,64
1,54	0,74
1,25	0,76
1,36	1,10
2,40	0,85

Mean W	1,66
Mean L	1,02
stdv W	0,692605772
stdv L	0,403525253
p value	3,94158E-06

Figure 3-6. t-test result for the KDA mean in win and lost matches

Source: Results obtained by the author using the Microsoft Excel tool.

This result means that the player performance in each game did have an impact on the match outcome, which, as we are going to see in topic 3.1.3.2, can affect the team gameplay and have an impact on toxicity occurrence.

3.1.3.2 Win and Loss x Toxicity

As we can see in Figure 3-7, from the 17 matches containing toxicity, 15 resulted in a loss match and only two in a win.

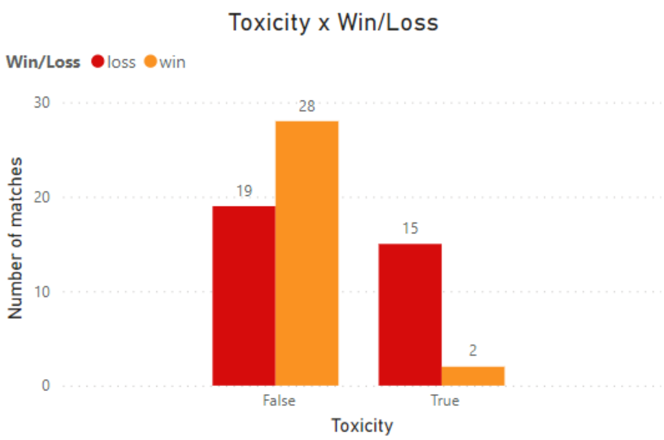

Figure 3-7. Outcome of the matches containing toxicity

Source: Bars chart obtained by the author using the Microsoft Power BI tool.

From this outcome it is possible to stablish an association between losses and toxicity. Digging further into this relation we have two possible theories: a match that tends to a loss outcome since its early stages, resulting in players tilting and, therefore, being toxic towards their teammates, or that a player being toxic in the beginning of a match leads to the demotivation of the entire team and, hence, the loss. The presence of hostility and disruptive behavior in a match leads to a shrinking in team cooperation, which disturbs team play and tends to bad performance (McLean et al., 2020).

The effect tilting and toxicity have in a game outcome has been approached in previous research by Türkay et al. (2020) where players defined unsporting behaviors as a form of toxicity where the toxic player stop cooperating with the team and take actions that are detrimental to the teamwork. This behavior is usually originated from, or leads to tilting and the results in this present research corroborates with existent literature.

3.1.4 Toxicity per server

When an account region is set to Europe the player can choose to play in one of these servers: Frankfurt, Madrid, Paris, Stockholm, Istanbul, London, Warsaw, Bahrain. The name of the server is the city where is located and the player can choose based on where the latency is smaller for them, meaning that they have a smaller delay time from the other players actions.

The player chose to play in Frankfurt, London, Madrid and Paris since these servers offered a latency of less than 50ms, which is a good value for First-Person-Shooter (FPS) multiplayer games.

The relation between the toxic matches and the server can be seen in Figure 3-8.

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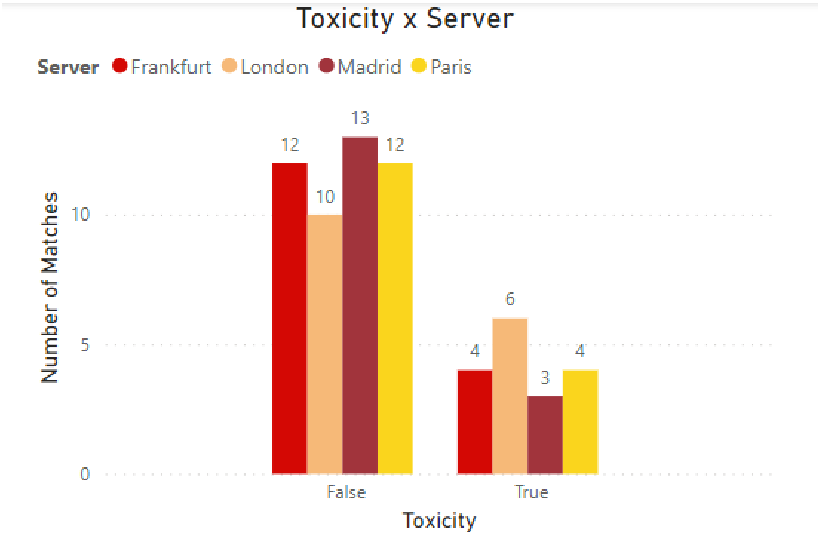

Figure 3-8. Toxic matches occurrences by server

Source: Graphic obtained by the author using the Microsoft Power BI tool.

The London server was the one containing the biggest number of matches with toxicity, followed by Paris and Frankfurt, and Madrid was the one with less toxic occurrences between the analyzed matches. We can conclude that toxic behavior can happen in any server, however, to measure the different levels between them to define if there are server that are more toxic than others is hard in the context of these research given the small amount of data in general.

3.1.5 Sexism

It was found that six from the 64 matches played by the author contained a behavior considered sexist, which means that a certain behavior or said profanity was directed specifically to a person exclusively because of their gender. This results in a statistic of almost one in each 10 matches containing sexism. In five of these cases the phrase said by the offended was recorded in the dataset. Analyzing further into these phrases, it is possible to relate them to concepts previously discussed above and attest that they match with most of the reports from other players in previous research. They also falls right into place with the concept of hegemonic masculinity presented before by Connell, R. W. (2005) and show clearly how the principals of this hegemony are still present in this online gaming environment.

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It is possible to divide these phrases into 2 categories. The first two ones: "go wash the dishes" and "a girl? We are going to lose", are related to the common prejudice that a girl playing videogames is out of place, that games are a manly activity and should remain that way and represent the principle of patriarchy. The origin of this way of thinking comes from way before the internet and digital world, it dates back to the XIX century when debates about what should be considered men roles or women roles. In that time, for an example, a society dictated by men decided that a woman's mind could not tolerate the academic pressure and, therefore, women should not have access to universities. Of, course, the world has come a long way since then and basic rights had been granted to women in many places around the world, but the idea that the two gender should not coexist in various environments is still spread and gain force inside the gaming community (Connell, 2020).

It becomes clear that the stereotype that women should be responsible for the domestic work, and that is what they should be doing instead of playing video games, and the implication that women are "so bad" in videogames that is impossible to win a match when you have a girl in your team, still persist in the video games community (Madden, Liu, et al., 2021).

The last three phrases "are you a girl? Can I fuck you?", "hey beautiful, mommy", "hey baby girl", imply sexual harassment and are considered to be part of a bigger problem that has impacts that go way beyond the gaming community. That is the woman sexualization and constant harassment culture, already addressed above (Sørensen et al., 2022). Here we can see that women are directly connected to sex even in environments with totally different meanings and context.

This is the result of a normalization cycle where men assume that is acceptable to make sexual comments or about one's appearance just because they are women, even when you don't even know what they look like. Situations like these are very likely to make people uncomfortable and creates an environment that is not inviting for women unless they also normalize that behavior and accept it as a part of gaming, which just contributes for the perpetuation of this said culture (Madden, Liu, et al., 2021; Sørensen, 2022).

This also reflects into another problem discussed before that affects not only players in game but also female streamers, with the reduction of women to their physical appearance, where even when women are just trying to play something or to do some hobby for fun, they often receive, especially when streaming, comments about their appearance or/and sexually suggestive ones that are extremely inappropriate considering the whole context (Sørensen, 2022).

3.1.5.1 Sexism occurrences per server

In Figure 3-9 is the visualization of the occurrences of the sexist offenses in each server.

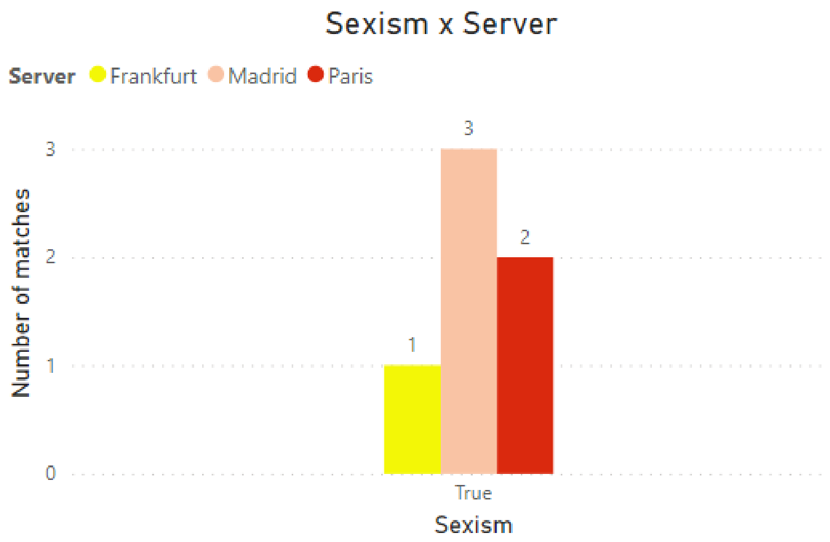

Figure 3-9. Matches containing toxicity per server

Source: Graphic obtained by the author using the Microsoft Power BI tool.

In the topic 3.1.4 we can see that Madrid was the sever with less toxic occurrences when compared to the other ones, however, it was the one with most sexist occurrences, and the London one, although having most of the toxic matches, had no sexist occurrence in it. In the London server, since the most spoken language is English, is very common to find players from very varied nationalities in a same match, while in Madrid is more likely to have only Spanish, and sometimes Portuguese, people in a match, which makes sense considering that playing in a closer server lowers your latency and you can play in your native language, which is usually more comfortable.

Previous research from Gómez-Gonzalvo et al. (2020) conducted in Spain already pointed to the sexism problem in the video games community specifically in Spain. They attest to exist big gender gap when it comes to gaming due to:

> *"divergences in the socialization of boys and girls within the video games culture, mainly due to negative female experience. For instance, female players experience comments and ridicule for their video game skills, suffer sexual harassment when they interact with other users, they are afraid of being considered unfeminine or androgynous"* - (Gómez-Gonzalvo et al., 2020, p. 6)

3.1.5.2 Sexism vs game performance

As approached in the topic 3.1.3, a player performance can be a trigger to toxicity, however, when analyzing only the matches containing sexism, the profanities were, in fact, directed to the player whose KDA we have information about, so we can verify the existence of that relation directly.

As we can see in Table 3-2, from the 6 analyzed matches, in three of them the player had a performance considered to be good and in the other three, a performance considered bad.

Table 3-2. KDA values for matches containing sexism

Index	Sexism	KDA
18	True	0,71
24	True	0,87
32	True	0,74
56	True	1,31
59	True	1,13
63	True	1,40

Source: Data obtained by the author.

This suggests that there is no real connection between player performance and sexism occurrences during the game. This proposes an assumption that sexist insults are motivated only by previous prejudices and not by a in game specific situation.

3.2 Survey

3.2.1 Demographic data about the questionnaire research participants

Participants were questioned about their gender, the server(s) they play mostly in and the current rank they have achieved in Valorant.

From the 120 participants, 89 of them (74,17%) identify themselves as men, 29 (24,17%) identify as woman, 1 as non-binary (0,83%) and 1 preferred not to say (0,83%). As we can see in Figure 3-10:

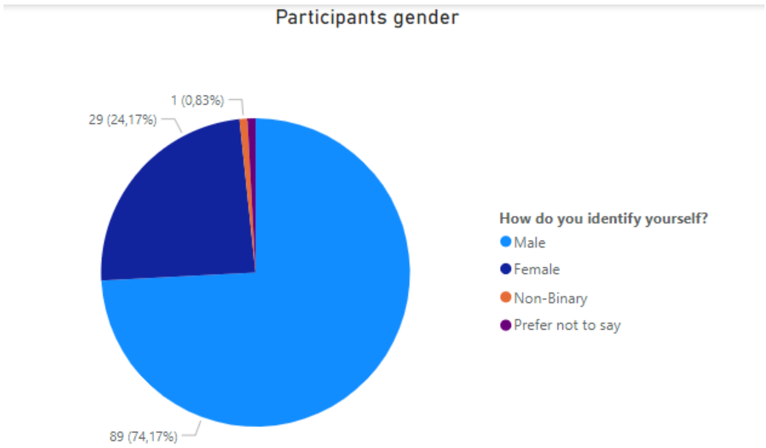

Figure 3-10. Gender which each participant identify with

Source: Chart obtained by the author using the Microsoft Power BI tool.

Analyzing the answers about in which server they usually play, it is safe to conclude that most participants play in the Brazilian server, situated in São Paulo. The rest of the participants play in Europeans servers, variating between playing in only one of them or in more than one. One thing to notice is that this possibility of choosing between servers is possible in Europe, but not in Brazil, if you region account is situated to Brazil you can only play in São Paulo server. This fact can server as an indicator that most players who claim to play in São Paulo probably lives in Brazil. The distribution is displayed in Figure 3-11.

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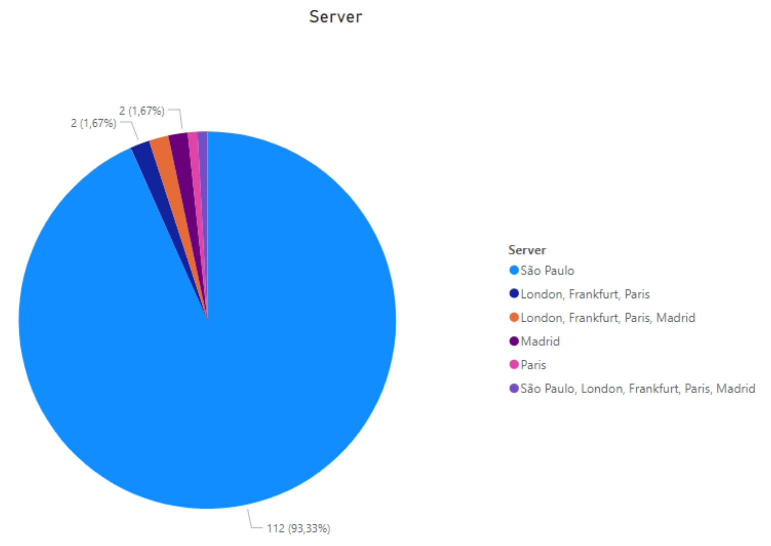

Figure 3-11. Number of participants by server

Source: Chart obtained by the author using the Microsoft Power BI tool.

The ranks of the participants have been a very varied data, going from the lower rank possible until the highest one.

Another question was about since when they have been playing Valorant (Figure 3-12). Most of the players reported playing since 2020 when the game was launched, some of them even playing since the game beta stage.

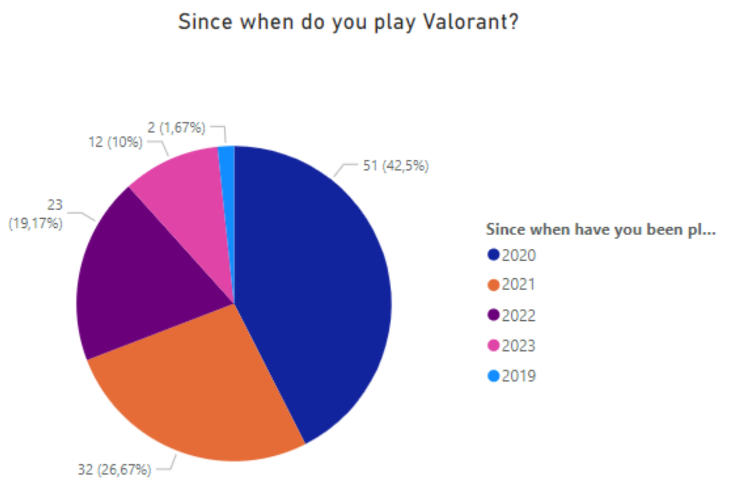

Figure 3-12. The years in which each player has started playing Valorant

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Source: Chart obtained by the author using the Microsoft Power BI tool.

Here we can see that two participants reported playing Valorant since 2019, which is impossible given that the game has only launched in 2020. The data was included in this chart for visualization, but it was discarded in further analysis.

3.2.2 Toxicity

Considering the data obtained from the questionnaire (Figure 3-13), it was found that only one of the 102 participants considered not to have ever experienced toxicity in a Valorant game match, representing only 0,98% of the total.

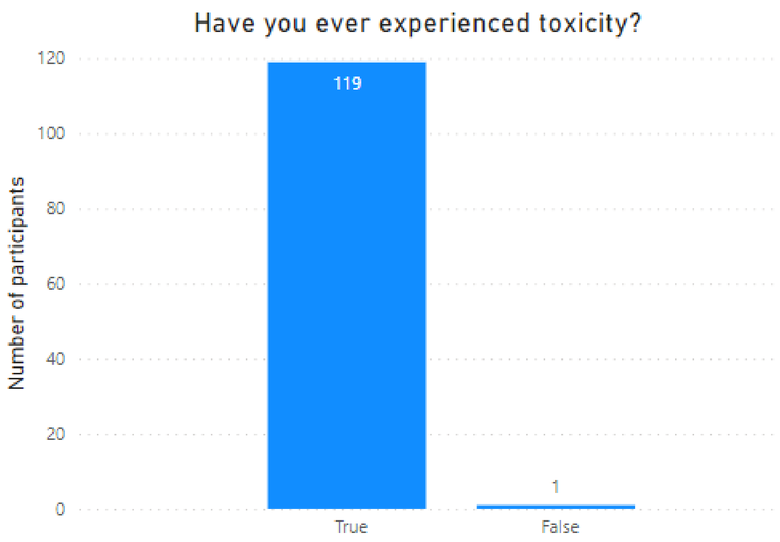

Figure 3-13. Answers from participants about experiencing toxicity in Valorant

Source: Chart obtained by the author using the Microsoft Power BI tool.

Now, since this data was obtained from a questionnaire survey and the answers were anonymous, it is not possible to know the criteria the participants used to determine a toxic behavior or to know if it is compatible with the one defined in this work.

3.2.2.1 Toxicity per rank

In the graphic in Figure 3-14 is possible to see the distribution of players per rank and we can see that the only player who did not report having experienced toxicity in the game plays in Bronze.

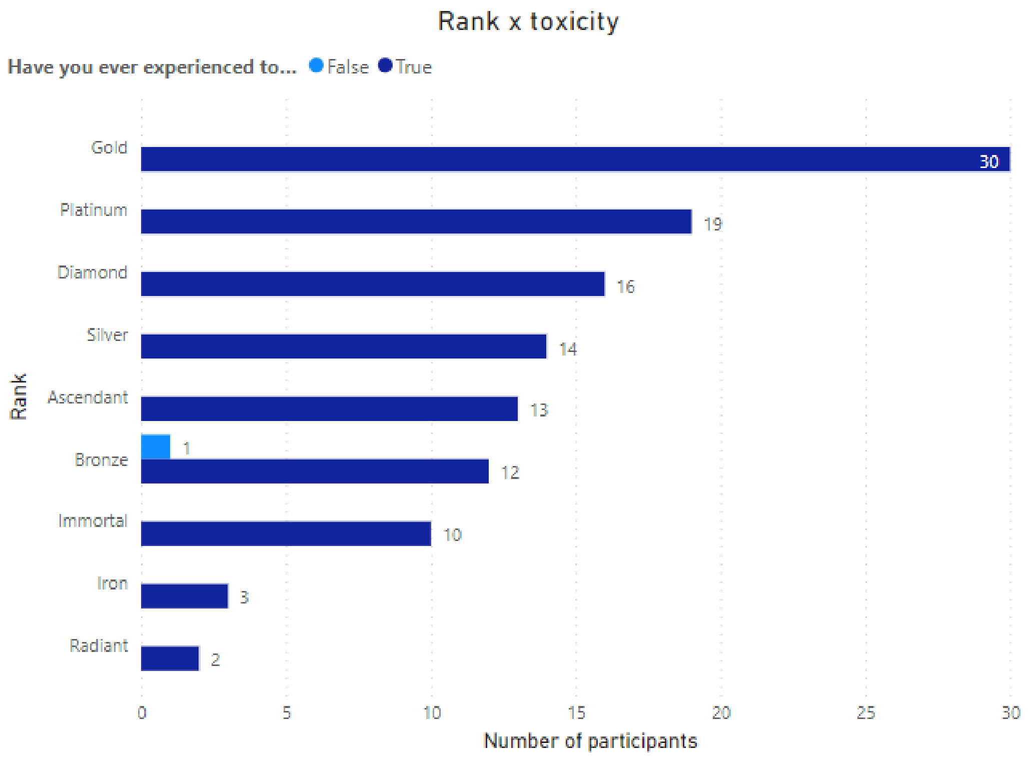

Figure 3-14. Toxicity reports from rank

Source: Chart obtained by the author using the Microsoft Power BI tool.

Despite that, 12 other players from bronze reported having encountered some form of toxic behavior in the game, and, in general, toxicity seems to be a common occurrence for all players, despite their rank.

3.2.3 Sexism

In the answers it was found that 90,83%, 109 from the 120 participants, reported having experienced some kind of sexist behavior, either towards them or another member of their team. The visualization is contained in Figure 3-15.

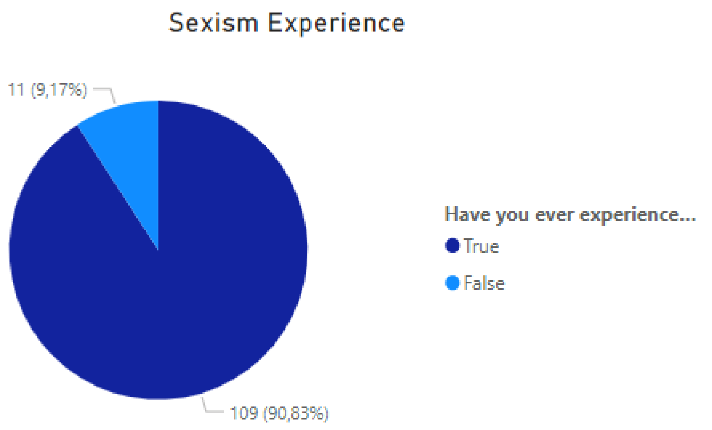

Figure 3-15. Number of players who have experienced toxicity

Source: Chart obtained by the author using the Microsoft Power BI tool.

That is a very high number and leads us to another analysis, that is the display of these sexism experiences by gender, contained in Figure 3-16.

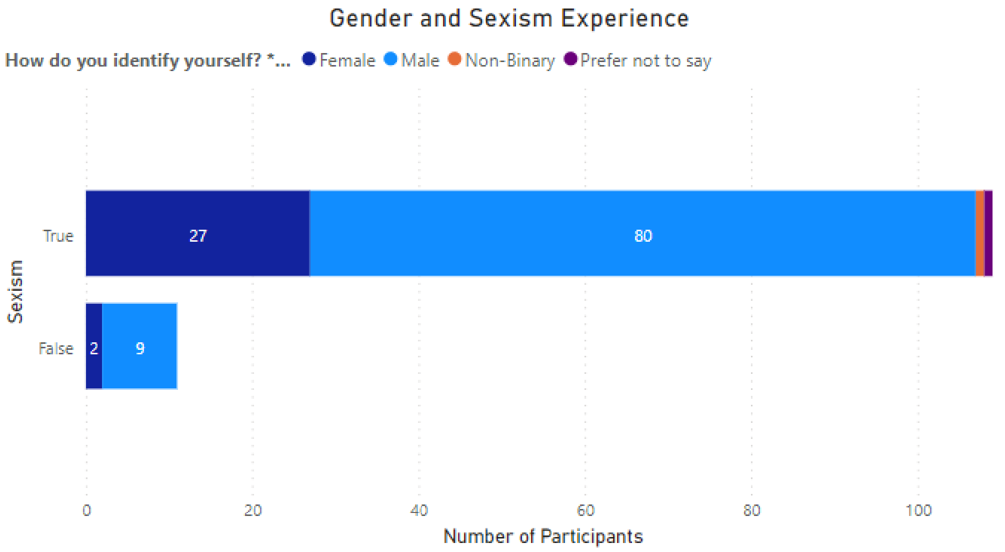

Figure 3-16. Sexism experience by gender

Source: Chart obtained by the author using the Microsoft Power BI tool.

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Here we can see that most players who reported not having experienced any kind of sexist behavior identify themselves as men, while only two of those who identify themselves as women reported the same. Both participants who identified themselves as non-binary or preferred not to say their gender answered positively to the question.

This can suggest in a way, that instead of simply never having experienced sexism in the game, men simply have more difficulty perceiving it than minorities who usually suffer with it. Their privileged position in society makes it harder for them to identify situations that can be uncomfortable or harmful for others that are not in this same position (Connell, 2020).

3.3 Comparison of data and final discussion

3.3.1 Toxicity: general Panorama

Both data from the game matches and the questionnaire pointed toxicity as a current issue in the game, with ¼ of the played matches containing some type of toxicity and more than 99% of the players reporting having experienced some kind of toxic behavior while playing.

The causes for this kind of disruptive behavior can be diverse, but some conclusions about its enhancers can be drawn tracing a parallel between this and previous research. In Jerabeck & Ferguson (2013) work it was found an inverse proportional relation between competitiveness and enjoyment and a very solid directly proportional relationship between competitiveness and toxicity. Evidence shows that the competition feeling promoted by the game is accountable, at least partially, for the hostility between players, a much bigger effect than the one observed from the violence contained in the game itself. That becomes relevant when connected with the fact that all matches observed were played in ranked queues and all players who took part in the questionnaire also play the game competitive mode, even if not exclusively.

3.3.2 Toxicity per rank

In previous research from Leiman et al. (2019) the toxicity level was measured in the game League of Legends between three different ranks. The author found that, although having different toxicity levels, in all ranks the player was very likely to find at least one hostile remark in each match. Albeit being different games, both LOL and Valorant belong to Riot

Games company and are very comparable when talking about toxicity and with a lot of common players between them.

In this train of thought, the results found in this study corroborates with previous research since, in the matches data, it was found toxic matches in all three ranks and, the KDA analysis proved that there was no significant difference in player performance between these ranks, indicating that the toxicity is not dependent on a player's rank. Now, this is a very limited analysis since only contained data from one player in matches performed in a short period of time, which indicated very little to no difference in this sense.

However, the finding that toxicity can happen independently of the rank was confirmed by the questionnaire results, where players from all ranks reported having experienced toxicity inside the game.

3.3.3 Sexism

The analysis of the data collected from the matches played showed that sexism continues as an issue inside the Valorant community, and albeit not occurring with such frequency when compared to toxic behavior in general, it happens in a very aggressive and threatening manner, as we can see from the phrases here collected, suggesting that women do not belong in games and never will, or with sexually suggestive remarks. This shows that, although toxicity being a common denominator between all players, the kind of hostility can vary according with the victim's gender, women being more susceptive to sexual harassment, stalking and being sent inappropriate content (Bryter, 2022).

The thought is confirmed with the questionnaire answers where more than 90% of the players, men, women, and non-binary, reported having experienced some situation with a sexist behavior inside the game.

It is important to say that Valorant, when compared to other big games in the scenario, had made significant improvements when it comes to women representation in esports since Riot Games had put on some effort to assure representativeness inside the game. But as one can see in this research results, while in the game there are many characters with different

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genders, colors and nationalities playing all kind of roles, inside the player's community sexism continues to be an issue and should be addressed as such (Quinn, 2022).

3.4 The racism occurrence

In one of the matches two players presented racist behavior. The first player used the word "nigga" in the game text chat in the beginning of the match and it was instantly restricted from communicating for the rest of that match and a report feedback saying that the player was later punished was received, showing that Valorant do have a real time toxicity detector for the text chat that takes action immediately when detecting a trigger word even if it was said just once. However, the other player used the voice chat to say racial slurs and was not punished, although having saying things like "nigga" and "you, black people destroying my game" many times during the game match.

It is important to remark that, in an online game, unless the players know each other, it is not possible to know other player's visual appearance, which can make one think that a racial insult makes no real meaning or sense in this context, however, this can relate to the disinhibition effect, where one feel protected by the internet anonymity to say insults that they would not be allowed or would feel ashamed to in real life even when they want to (Kordyaka et al., 2020).

3.5 Report and punishment System

All toxic situations faced in the course of this research were reported, and some observations can be done through the report feedback received. Analyzing communication abuses, most of the text chat toxic communication received feedback saying that the offender player had some kind of punishment, while that number was way lower when considering voice chat abuses.

When talking about toxic behaviors, such as trolling their own team or sabotaging through being AFK, none of the reports had feedback, which probably means that none of the occurrences had a punishment related to it.

It is reasonable to say that, although Riot Games has made its text chat surveillance and toxicity detection better along the years, the same cannot be said for the voice chat or when

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it comes to identify trollers. The text chat has an in-real-time hostility detection mechanism that instantly censor some considered swear words like “shit”, “fuck”, “bitch” etc. As for words considered to be severely offensive, like “nigga”, the game gives the player who sent it in the chat an instantaneous ban from that match communication[1]. But seems not to have a similarly efficient system for the voice chat feature.

This becomes clear when we see a situation like the one match containing racism, where two players said the same things, one said a racial insult once through the text chat and was banned from the communication system until the end of that match and the other said the same thing various times during the match and was not punished at the end, albeit being reported several times. That checks out with recent studies that also points out the limitations of big companies when it comes to identify toxic behaviors in real-time especially when it comes to voice chat features (Reid et al., 2022).

The problem becomes even bigger when talking about the detection of toxic behavior. Even for a player inside the game match it is hard to determine if another player is really trolling on purpose, or is simply having a bad game, or really do not know about a game feature or strategy, so, for the company employee that was not playing that match, but is responsible for verifying the existence of toxicity, it must be even harder, having to consider not just an isolated action but the whole context in which it was inserted in the game. For all the toxic behavior reports contained in the dataset, none report feedback was received about it.

[1] It is important to say that the parameters used by Riot Games to define and measure the toxicity level of a word is not known by the author and the examples cited here were obtained from real situations.

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CONCLUSION

With this research it was possible to trace a general panorama of toxicity in Valorant. In conclusion, toxic and disruptive behavior is still a strong issue inside the game community and is displayed in many forms, but mostly by the voice chat and through behavior inside the game that aims to disrupt team play.

Players from servers in Brazil and Europe reported having experienced toxicity inside the game, with less than only 1% of the survey participants declaring to not having observed hostility. The toxicity reports came from players from all game ranks, showing that disruptive behavior is a problem that affects players independently on their gender, rank or server.

When talking about gender bias in the game it became clear that this still has a strong effect in a player behavior. Most players answered to have had contact with some kind of sexist occurrence in the game. In the game matches data, text evidence of common prejudices and serious problematic situations involving a player gender was collected and reinforce the idea that, although moving in the right direction, the actions taken by big companies are still not enough to mitigate the sexism effect and it is still a point that can severely affect one's experience inside a game.

This research was faced with some barriers and limitations through its course:

- Data collection: data collection, especially for academic researchers proved to be a very time demanding activity that limited the analysis in this research, since all the data from the Valorant matches was collected by the same player. For future works it is suggested that a greater variety of players, from different ranks and servers contribute with the research so more variables can be analyzed and aggregates more liabilities to toxicity params, especially in order to compare the experience had here by a female player with a male one.
- Bias: the practical data collected was also under a biased interpretation of toxicity from the player who judged the presence of toxic behavior taking that was an established truth to the purpose of the research.

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- Number of data: the sample here collected was small and, therefore, this limited the kind of analysis that could have been done with it and determined the research to a more exploratory approach.

In conclusion, toxicity detection and report system in Valorant still need some work in order to improve player experience, especially when it comes to voice chat surveillance, research presented in the theoretical framework of this work give us a place to start and find a solution for a more effective voice chat toxicity detection system similar to the one presented on the text chat feature.

Efforts supporting female participation in esports and in the gaming scenario in general, as well as to maintain diversity inside the community should also be taken more seriously since the hostility and obstacles found both by casual and professional players can be severely demotivating and really affect one's experience inside such a nice game.

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APPENDIXES

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APPENDIX 1: QUESTIONNAIRE

Toxicity in Valorant

Hey, this is a form for my Master studies research and the goal is to better measure and understand toxicity inside the game Valorant. Please be true to your answers and thank you for your time.

How do you identify yourself? ** Como você se identifica? *

- Female - Feminino
- Male - Masculino
- Non-Binary - não-binário
- Prefer not to say - prefiro não dizer
- Other...

Since when have you been playing Valorant? (put the year below) ** Desde quando você joga Valorant? (Coloque o ano abaixo) *

Short-answer text

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Which server do usually play in? ** Em qual(is) server(s) você costuma jogar? *

- [ ] São Paulo
- [ ] London
- [ ] Frankfurt
- [ ] Paris
- [ ] Madrid
- [ ] Other...

What is you current rank? ** Qual o seu rank atual? *

- ○ Iron
- ○ Bronze
- ○ Silver
- ○ Gold
- ○ Platinum
- ○ Diamond
- ○ Ascendant
- ○ Immortal
- ○ Radiant

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Have you ever experienced toxicity in a Valorant game match? ** Você já observou toxicidade em uma partida de Valorant? *

- ◯ Yes
- ◯ No

Have you ever experienced gender related (sexism) toxicity in game (either directed to you or another member of your team)? ** Você já observou algum tipo de comportamento sexista em jogo (direcionado a você ou a alguma pessoa do seu time)? *

- ◯ Yes
- ◯ No

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