The Panorama of Steam Multiplayer Games (2018-2020): A Player Reviews Analysis

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ABSTRACT

People approach video games for a multitude of reasons, such as connecting with others, escaping reality, or challenging their abilities. As a consequence, video games have reached an increasingly broader audience and their consumption was even more pronounced during the COVID-19 pandemic. Recent studies have shown how playing video games together improved the well-being of people during period of movement restriction and how video games were an important tool for connecting with physically distant people. However, little is known about how the relationships of people with video games have changed across the years. In order to answer this question, we collected data from the Steam platform and analyzed players' opinions about multiplayer video games as stated in the respective reviews. The reviews analysis showed that players had played more and in addition their reviews had not been influenced by the difficulties of this significant moment. Their contribution, however, had been less relevant for the community when compared to the situation in the years before the pandemic. Finally, an increase in players choosing to play more casual and amusing games became evident.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **User studies**.

KEYWORDS

Steam, Multiplayer games, Review Analysis

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1 INTRODUCTION

Video games are now both extremely popular and have become a well-established form of entertainment in our society and culture, especially among the younger generations. The number of people playing video games is constantly growing, as is the value added of this industry, which exceeds the economic value added of the movie and music industries combined [34]. With the growing popularity of video games, numerous studies have explored the effects of gaming in our daily lives. Further research proved that playing can have the beneficial effects of reducing stress and anxiety and improving moods, especially when playing with other people [29, 30]. Recent studies have also suggested that multiplayer games can arouse a feeling of connectedness [28], enjoyment [10] and other positive emotions [22, 25]. The positive effects of games became even more tangible for many during the COVID-19 pandemic, which appeared suddenly, globally and impacting us all. It forced social distancing, causing people to feel stressed and lonely, along with other serious detriments to our physical and mental health [18]. People around the globe were forced to change their daily routine due to the severe restrictions and stay-at-home orders adopted by all countries [1, 9]. Video games proved a popular way to cope with the pandemic situation, and we have seen a huge increase both in players and correlated activities [31]. A remarkable example is related to *Animal Crossing: New Horizons* which became an important social hub to meet and interact with other people at a time when this was not possible in real life [17]. A similar trend could also been observed in more competitive games. For example, League of Legends, which helped to strengthen and create new relationships between players during the pandemic [24]. The sudden spike in player activities generated a great quantity of data in the form of reviews, especially on platforms such as Steam, which reported its highest number of concurrent users of all time [35]. Since reviews have always been a means for understanding the opinions and attitudes of customers (i.e. the players), our intention was to take advantage of this unprecedented event, and to exploit games reviews on Steam as a means of exploring how player opinion and the community as whole changed in 2020 compared to the previous two years.

Research Questions and Contributions

In this paper, we aim to determine how players' relationships and opinions in connection with gaming have evolved in recent years, especially in conjunction with the COVID-19 pandemic. We investigated the possible effects using players' reviews from the years 2020, 2019 and 2018 as our data pool. The data gathered was then analyzed according to the following research questions:

- RQ.1 How have the turnout and activities of players evolved through the years?
- RQ.2 Has the pandemic situation changed the approach of players to video games?
- RQ.3 Have player preferences changed over the years?

Answering these research questions contributes to the field of Games User Research (GUR). First, with RQ.1, we aim to verify how the turnout and activities of players in multiplayer gaming have changed in as a result of COVID-19. In RQ.2 we explore how player considered video games throughout the years and what kind of messages they conveyed in their reviews. Finally, in RQ.3 we aim to determine how players' preferences evolved and what reason could have led to those changes.

2 BACKGROUND

In this section, we discuss the power of reviews as a tool to understand user opinions and perspectives. Furthermore, we show how Steam data can be used to explore trends, measure a game's success, and evaluate player communities.

2.1 Review Analysis

Online platforms that offer products or services usually embed review sections in which users can share feedback and opinions regarding what they acquired [8]. Thus, reviews can be seen as an online version of word-of-mouth but with a wider reach. For this reason, they have assumed a central role in electronic commerce. Reviews are beneficial for both the prospective customers and the service (or product) provider. On the one hand, potential customers can use the information in the reviews to make a more conscious purchase choice. On the other hand, reviews have become increasingly important for businesses, as positively reviewed goods are more likely to be successful on the market [21]. In addition to the economic worth of (many) positive reviews, they are also a valuable, independent source of information. People review their purchases voluntarily, hence their opinion is generally considered honest and based on personal experience [7]. Moreover, when reviewer opinions are detailed, they can contribute to improve the product and, ideally, reach a broader market. It follows that researchers have unceasingly become interested in reviews (i.e., review analysis) to gain information on the market, retain feedback on how to acquire more customers, as well as provide targeted suggestions to potential buyers. Review analysis has already been used to highlight important requests from the customers and generate knowledge for product manufacturers, especially concerning critical product defects [26]. Other research includes using text analysis to polarize reviews and achieve satisfactory accuracy [12] and explore temporary (positive) turnout and its causes (e.g., "holiday effect" in restaurants [11]). These are merely a few examples showcasing the potential of a review analysis, but, review analyses of video games have even greater potential. Specifically, reviews can be assessed to extract meaningful information on the game player community, existing trends, and variations in playtime. In this regard, Steam is a precious data source.

2.2 Data Analysis on Steam

Steam[1] is an online platform for distributing and storing video games. Games on Steam are usually uploaded by game developers, game studios, or video game publishers. Every game has its own page with information about the game, such as release year, genre, tags, a list of user reviews, and a user rating obtained from the user reviews. Gamers can review the games by submitting either a positive or negative recommendation and textual information. The ratings are then grouped by Steam to compute a global rating on a scale from overwhelmingly negative (0%-19% of positive reviews) to overwhelmingly positive (95%-100% of positive reviews).

Analyzing the Steam community can provide meaningful information on current trends, patterns in the player activities, and their opinions on the game available on the platform. So far, researchers have investigated Steam data to better understand players by extracting their opinions [20, 37] and play patterns [32]. Other studies analyzed the community by modeling Steam friendships in a graph [4], showing how similar players are often connected [23]. The network was also investigated to uncover social influence on purchasing of digital goods and how different video games were affected differently (and to varying degrees) by the market [15].

Besides behavioral and interaction patterns, the value of analyzing Steam data lies in the possibility of gaining interesting insights into player experiences and expectations by investigating the topics discussed in the reviews. Many authors use data available on Steam, and the considerable data volume from the coherent user reviews [3, 33]. In [20], the authors examined 6,224 video games and their associated reviews and discussed the general structure as well as content of the reviews. One of the essential findings is that negative reviews in particular, often address more aspects of game design than technical bugs. In comparison to positive reviews, they are also often longer. This already implies that negative reviews are an excellent source to learn how to improve the game itself or even future games. Sifa, Drachen, and Bauckhage [32] focus on understanding player behavior using Steam data along with analyzing game ownership and playtime. In [37], the authors use sentiment analysis to gain a better understanding of Steam reviews. They describe the use of Naive Bayes and Decision Tree Classifiers. Their results show that most games have less than 20 reviews and that the top five most popular games received about 30% of all reviews. Social interactions between Steam users have also been investigated using social network analysis methods [5].

These earlier studies demonstrate the potential of research using the data available on Steam to gain a better understanding of both the videogames and the players. Hence, this data can be exploited to investigate how gamers and their opinions changed throughout

[1] https://steampowered.com

the years (2018-2020), as well as the impact external events (i.e., the COVID-19 pandemic) had on the Steam user community.

3 METHOD

To answer our research questions, we analyzed a set of multiplayer games and their reviews with the aim of extracting and understand player engagement and opinions in the year 2020. In this section, we detail the process through which we gathered and analyzed the information on these games.

3.1 Data Collection and Structure

We collected data from the multiplayer games available on the platform Steam to determine the scope of this paper. The selected games were all marked as *Multiplayer* both in the official game description and *Steam tags*. *Steam tags* are labels defined and assigned by the player community with the aim of clarifying the game's contents (e.g., *Arcade*, *Difficult*, *Survival*). Through the official Steam API [2], we collected a) general game information b) all English language reviews from 2018 to 2020 for each video game. General game information typically includes the game's name, developers, genres, Steam tags, and released date (if available); the second contains detailed metadata regarding the written reviews and the reviews themselves.

3.2 Metrics

In this study, we exploit game reviews to evaluate player changes in activities and opinion in 2020 compared to previous years. This was accomplished using statistical methods and natural language processing tools. When comparing data, we evaluated statistical differences through the Wilcoxon signed-rank test because our data can be considered a dependent sample [27]. In each case, we want to verify: i) if there is a significant difference between 2020 and the previous years ($p < .05$), and ii) the alternative single-tailed hypothesis (one population higher than the other). The study thus focuses on a smaller number of metrics provided with the reviews or calculated from them. We define the following metrics:

- *TBefore*: the time played before the user wrote a review for a specific game. Provided for each review.
- *Helpfulness*: a coefficient between 0 and 1 that defines the usefulness of a review for the player community of a specific game. This coefficient is provided for each review directly by Steam.
- *PRatio* and *NRatio*: calculated as the #positiveReviews or #negativeReviews divided by the #reviews.

In addition to these metrics, we also looked also at the general #reviews and how they split into positive and negative evaluations. Finally, we explored which games have been played looking at genres and *Steam tags*. In the context of analysis done by natural language processing tools, we rely on the well-known and widely used NLTK [3] and the sentiment analyzer VADER [13]. For data visualization and exploration, we used the WordCloud package [4]. For each sentiment in the sentiment analysis, we computed:

- *PosSRatio*: defined as #positiveSentiment over #reviews.
- *NegSRatio*: defined as #negativeSentiment over #reviews.
- *NeuSRatio*: defined as #neutralSentiment over #reviews.

4 ANALYSIS AND RESULTS

In this section, we detail the results of our analysis. In accordance with the previously outlined research questions, we explore how the turnout, activities and opinion of players on the platform changed from 2018 until 2020

4.1 Affluence on the Platform

Affluence was measured through the number of reviews (#reviews) left by the users. With the aim of identifying the presence of unexpected change in the players during the first year of the COVID-19 pandemic (2020), we focused our attention mainly on games that were available throughout each of the years under investigation (i.e., since 2018). This ensures that a comparison between years is more consistent and we can analyze the evolution of the same games in the course of the years. The games are grouped in the group *persistent games*; It includes 2467 games, and their reviews cover 80% of all reviews done in 2019 and 70% of 2020. For the group *persistent games*, Table 1 shows the total number of reviews written in each year and the percentage of positive/negative reviews. To assess a first statistical difference among the *persistent games*, we compared the #reviews. Since we refer to same paired population we used the Wilcoxon signed-rank test [27] ($p < .05$). A first analysis of the #reviews showed that there is a significant difference between the years 2018 and 2019 and the year 2020, with 2018 and 2019 having fewer reviews ($W = 1,052,715.5, p < .0001$; $W = 675,697.0, p < .0001$), however, we did not find a statistical difference between the year 2018 and 2019($W = 1,334,321.5$, $p > .55$). Next, we evaluated whether there was a real growth among the years, comparing the *PRatio* and *NRatio* (introduced in Section 3.2) for each of the *persistent games* using the Wilcoxon signed-rank test [27] ($p < .05$). The results show that the positive reviews percentage for 2018 and 2019 was lower than for 2020 ($W = 842,637.0, p < .0001$; $W = 916,971.0$, $p < .0001$), while the year 2018 showed a lower ratio of positive reviews compared to 2019 ($W = 1,102,349.5, p < .0001$). We then looked at the ratio of negative reviews. The years 2018 and 2019 had a higher percentage of negative reviews than the year 2020 ($W = 1,872,726.0, p < .0001$; $W = 1,541,622.5, p < .0001$), while, the year 2018 showed a higher ratio of negative reviews compared to 2019 ($W = 1,680,738.0$, $p < .0001$). To summarize, a growing trend towards positive reviews and a decreasing trend towards negative reviews could be noticed. The results are summarized in Table 2. Finally, we explored genres and *Steam tags* with the help of Fig 1, 2. As expected, the large number of games resulted in a great variety of genres and *Steam tags*. Among genres, *Action* (64%), *Indie* (54%), and *Strategy* (24%) had the highest frequency, while the other genres occurred for less than 20%. Among *Steam tags*, as expected, we find *Multiplayer*, which is our game selection criteria, together with *Action* (74%), *Indie* (57%), *Singleplayer* (55%). All other *Steam tags* were used for less than 35% of the games.

4.2 Player Reviews and Sentiment

We rely on two different approaches for exploring how games have changed during the pandemic. These are i) reviews metrics and ii)

[2]https://steamcommunity.com/dev
[3]https://www.nltk.org/
[4]https://amueller.github.io/word_cloud/

Table 1: Persistent games - Positive and Negative reviews

	Tot. rev.	Pos. rev.	Neg. rev.
2018	1,660,205	76.34%	23.66%
2019	2,221,516	88%	12%
2020	3,716,974	90.20%	9.80%

Table 2: Metrics evolution through the years. The - indicate non-significant difference between two years.

	2018	2019	2020
#reviews	-	-	higher
PRatio	lowest	medium	higher
PNegative	higher	medium	lowest

Figure 1: Persistent games - Genres

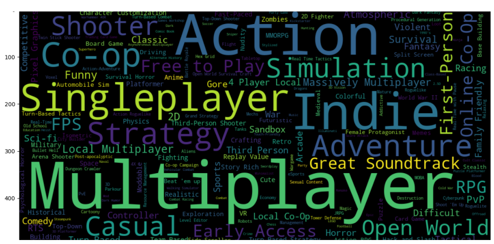

Figure 2: Persistent games - Steam tags

sentiment analysis metrics. Both approaches are introduced in Section 3.1. We calculate the *TBefore* and the *Helpfulness* for each year and game using the Wilcoxon signed-rank test [27] because data are paired and similar to the previous analysis. This also allows us to verify if there is a statistical difference between the years. Results show that gamers played more in 2020 and 2019 compared to 2018 before expressing an opinion on a game ($W = 688,552.0$, $p < .0001$; $W = 663,047.0$, $p < .0001$), however, there is no statistical difference between 2019 and 2020 ($W = 1408638.5$, $p = 0.58$). Looking at the helpfulness coefficient of the reviews, the results for the year 2018 show a higher helpfulness level than those for the years 2019 and 2020 ($W = 2,307,280.0$, $p < .0001$; $W = 2,533,311.0$, $p < .0001$). Similarly, 2019 shows more helpful reviews than 2020 ($W = 2,012,411.0$, $p < .0001$). In the sentiment analysis, we calculated the sentiment in the reviews using the tool VADER [13]. The sentiment analyzer produces a *compound value* for each review that estimates the sentiment. Following the use suggested by the authors of the tool, we identified the three sentiments by dividing the *compound value* in different ranges:

Table 3: Sentiment analysis on *persistent games* percentage of neutral, positive and negative reviews

	Neu. rev.	Pos. rev.	Neg. rev.
2018	25.66%	56.34%	18%
2019	36.35%	52%	11.65%
2020	41.62%	48.38%	10%

Table 4: Sentiment reviews evolution through the years.

	2018	2019	2020
PosSRatio	higher	medium	lowest
NegSRatio	higher	medium	lowest
NeuSRatio	lowest	medium	higher

- Positive: compound value > 0.1.
- Neutral: compound value between -0.1 and 0.1.
- Negative: compound value < -0.1.

Text data do not need any preprocessing before being analyzed, since punctuation or other symbols (like emoji) help to achieve a more truthful result. However, if a review was too long, we first divided the review using a tokenization process, then we calculated the *compound value* of each token. Finally, we calculated the average compound among the tokens. This was done following the tool guideline, proving to be more effective on short texts [13]. Table 3 shows the sentiment calculated for each review divided by year. As done in the previous analysis, we compared the positive, negative and neutral sentiment growth using their respective ratio as anticipated in Section 3.2. The results show a smaller percentage of positive sentiment in 2020 compared to 2018 ($W = 2,031,732.5$, $p < 0.0001$) and 2019 ($W = 1393340.0$, $p < .0001$). A similar result can also be seen in the negative sentiment compared to 2018 ($W = 1,948,542.0$, $p < .0001$) and 2019 ($W = 1,233,749.5$, $p < .0001$). Looking at neutral sentiment, however, we see that 2020 has a greater percentage of neutral reviews compared to 2018 ($W = 479,633.5$, $p < .0001$) and 2019 ($W = 749,155.5$, $p < .0001$). Table 4 summarizes the above results.

4.3 Impact of the pandemic on game reviews

We are interested in exploring what effect the Covid-19 pandemic left on players through the reviews they wrote. In this case, we looked at the ten most reviewed games in 2020. Among them, we found eight games released before 2018 (part of the *persistent games* set) and two games released in 2020. We looked for the reviews containing direct reference to the pandemic then we verify the sentiment of these reviews. Finally, we visualize their content through two word clouds. We looked for all the reviews containing at least one of these words: pandemic, pandemia, corona, coronavirus, virus, covid, and lockdown. The reviews found are 1268, which is a very small percentage of reviews from the top 10 most reviewed games in 2020. Table 5 contains all the details regarding these corona-related reviews. While Fig 3,4 show words frequencies in positive (game: 71%, fun: 37%, friend: 36%, play: 35%, pandemic: 29%) and negative(game: 66%, corona: 37%, covid: 26%, play: 26%, get: 25%) corona-related reviews.

Table 5: Top10 most reviewed 2020 games. Corona-related reviews details.

Top 10	Corona reviews (% total 2020)	#Positive	#Negative	#Neutral
Counter-Strike: Global Offensive	199 (0.05 %)	107	45	47
Among Us	351 (0.12 %)	314	15	22
Rainbow 6 Siege	49 (0.03 %)	31	10	8
Terraria	80 (0.05 %)	60	4	16
Fall Guys	139 (0.11%)	93	16	30
Phasmophobia	91 (0.07 %)	62	12	17
Grand Theft Auto V	98 (0.09 %)	56	17	25
Dota 2	109 (0.11 %)	46	30	33
Garry's Mod	32 (0.03 %)	24	3	5
Team Fortress 2	70 (0.08 %)	42	11	17

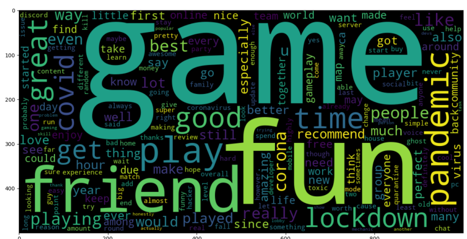

Figure 3: Top 10 most reviewed. Corona-related reviews positive word cloud

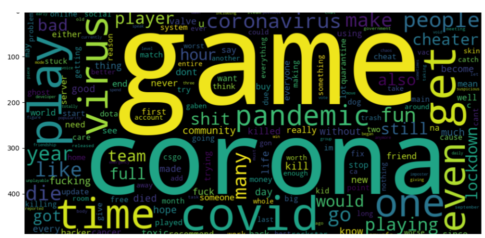

Figure 4: Top 10 most reviewed. Corona-related reviews negative word cloud

4.4 Exploring players' preference

Finally, we had a qualitative focus to the most reviewed games of 2020 compared to the past. For this purpose, we looked at *Steam tags* and genres of the TOP 10 most reviewed games of 2018, 2019, and 2020. Six of the games were available throughout all three years(Counter Strike: Global Offensive, Rainbow 6 Siege, Grand Theft Auto V, Dota 2, Garry's Mod, and Team Fortress 2). Looking at the Top 10, the main genres are *Action*, *Free To Play* and *Adventure*. However, we find two extra genres only in 2020: *Casual* and *Sport* (the games Among Us and Fall Guys, respectively). Taking the *Steam tags* only into consideration, we found an additional tag strictly related to the concept of multiplayer mechanics: in 2018 Multiplayer, Competitive, Co-op; in 2019 Multiplayer, Competitive; and in 2020 Multiplayer, Competitive, Co-op, Online Co-op. (TOP 10 2018: Counter Strike: Global Offensive, PlayerUnknowns's Battlegrounds, Rainbow 6 Siege, Dota 2, Monster Hunter World, Team Fortress 2, Warframe, Grand Theft Auto V, Rust, Garry's Mod; TOP 10 2019: Counter Strike: Global Offensive, Rainbow 6 Siege, Terraria, Dota 2, Rust, Grand Theft Auto V, Team Fortress 2, Garry's Mod, PlayerUnknowns's Battlegrounds, Stardew Valley; TOP 10 2020: see Table 5).

5 DISCUSSION

In this paper, we examined available multiplayer games in both a quantitative and qualitative way. We analyzed the reviews written by players in the years 2018, 2019, and 2020, calculating the sentiment of these reviews. We then focused on the most reviewed games of 2020, analyzing also reviews related to the pandemic. In the following section, we discuss our findings and what can be learned about community from the reviews gathered.

5.1 Player Affluence and Sentiment

While the number of reviews increased in 2020, these showed a change in balance with a growing trend towards positive reviews and a decrease in negative reviews shown in the results. The results in terms of the increased reviews are as expected. During 2020, people around the world spent most of their time at home or reduced their contact outside their households to a minimum. This in turn brought about an increase in the opportunity for game playing [24]. Moreover, playing videogames became a valuable method for connecting with friends and for overcoming the lack of opportunities for social contact [30]. Looking at the trend in positive and negative reviews, we can partially explain the increase in positive game evaluation as a consequence of having more time to play. These results are also supported by the metrics relating to how much the players had played a game before reviewing. Reviewers in 2020 played more than those in 2018 before expressing their opinion about a game, eventually leading to more truthful evaluation. While there is no statistical difference between 2019 and 2020, the year 2020 nevertheless showed a greater number of reviews following a positive trend. Both old and new players might also have evaluated games more positively because video games provided a way to connect and interact with friends. Following the same trend, we can also observe how reviews in 2020 were less useful than those of the previous years. This may be connected to the increased player turnout, especially in relation to new players who have a smaller frame of reference due to less experience gaming and thus produced less helpful reviews for the community. For some communities, reviews are in fact identified as more helpful not because they accurately review the game itself but because they describe a game's peculiarities or the community that populates the game itself (often sarcastically). Another possible reason for the increase in reviews may be that due to the COVID-19 pandemic and the resulting lockdowns, players have had more time to finish or lose interest in a game, deciding to leave a quick review and move on to the next game. This also seems to be in line with the findings of our sentiment analysis. Here, the results showed that compared to the previous years, the sentiment in the reviews players wrote is simultaneously less positive and less negative. What was defined as a neutral sentiment in this paper has increased significantly compared to 2018 and 2019. This leads us to the conclusion that while gamers wrote more reviews, they were less likely to express a strong and clear opinion. This conclusion is also supported by our findings, in fact, when examining what are defined as neutral reviews more closely, it becomes apparent that they represent all reviews consisting mostly of only a few words (e.g., *ok*, *good game*, *fun to play*) or less than 15 characters. Here, the increase in reviews of this kind may be strongly related to previous results concerning the decreasing helpfulness of reviews. While these phenomena were more pronounced in 2020, they can also be observed on a smaller scale in 2018 and 2019 as a result of an increased interest in video games in the last decade.The COVID-19 pandemic has in a sense only accelerated these processes, as evidenced by the massive increase in players and activities across gaming genres during the pandemic [24]. Finally, we took a deeper look at the effect of the COVID-19 pandemic on gamers by focusing on the most reviewed games of 2020. We immediately noticed that reviews referring directly to the pandemic made only a very small percentage of these. Operating under the assumption that players use games as a way to have fun and cope with outside problems, such as the pandemic and its accompanying restrictions, this is not unexpected. Exploring the sentiment of these reviews, we noticed that most of them have a positive sentiment (Table 5). In fact, positive sentiment reviews relative to the COVID-19 pandemic refer to the opportunity provided by the game for keeping in touch with friends, joining a community, or simply spending time doing something fun. In contrast, reviews with a negative sentiment often refer to the toxicity of the community, game bugs, racist comments about the Asian community or even death threats. The subjects of negative reviews were often compared to the disease or to the threat of being infected with the virus. Insults directed at other people only occurred in reviews for competitive games (i.e., Counter-Strike: Global Offensive, Dota 2), while in other/more casual games (i.e., Among Us, Terraria), reviews with a negative sentiment refer mostly to game or player problems. Fig. 3, 4 illustrate the difference between the positive and negative sentiment. Words related to COVID-19 are far more visible in the negative reviews. In fact, on average negative reviews contain at least two words related to the virus. Moreover, words such as *friend* and *fun* (in 7% and 14% of reviews, respectively) appear less often than extremely negative words such as *kill* or *die* (in 9% and 16% reviews, respectively). Some negative words (not related to COVID-19) also appear among the reviews with a positive sentiment but with an occurrence of less than 1%, which suggests they may be related to the content of the game rather than to a threat. As shown in previous research, even though we are looking at a small data sample, the reviews with a positive sentiment show how games can help players to overcome tough situations. In fact, the game becomes a medium through which the player can relax, get in touch with a friend or forget about bad events.

5.2 Player Opinions

In regards of players' preferences, we have focused on the TOP 10 most reviewed games in 2018, 2019, and 2020 looking for changes. As first noticed in the analysis section, more casual games entered in the TOP 10 in 2020 compared to 2018 and 2019, which only had games with either complex game mechanics or a competitive playstyle. 2020 saw the addition of two casual games such as *Among Us* and *Fall Guys*. Both games have been an import protagonist of the first year of pandemic [6, 36], owing their success to game mechanics that allow all kinds of players, experienced or not, to enjoy the game in an easy and quick way. Their design encourage players to interact each other without pushing on a competitive aspect making easy to make new friends or communicate with others. However, the most famous games still remained in the TOP 10. These games either have a strong and long-living community (e.g., Counter-Strike: Global Offensive and Team Fortress 2 with over 10 years of activities) or are strongly supported through mods or popular among streamers. (e.g., Grand Theft Auto V, Garry's Mod). Casual games like *Among Us* and *Fall Guys* have also become extremely popular also thanks to streaming platforms such as Twitch or Facebook, which similarly saw a peak in new users during the pandemic [16]. Another reason linked to the success of casual games can be found inside their gaming community. Especially in competitive games, the player community can often be more aggressive and toxic [2, 19]. In a period where people already felt lonely and mentally stressed, it may have been harder to deal with this kind of behaviors. Casual games may have offered refuge to anyone who was in need of a moment of relaxation and enjoyment, as also suggested by previous research on *Animal Crossing* [14].

6 LIMITATION & FUTURE WORK

While this paper provides starting points for future studies, our research has several limitations. Firstly, our hypothesis is based on a specific set of games and reviews. Secondly, when exploring data related to the COVID-19 pandemic, we only focused on the TOP 10 most reviewed multiplayer games of 2020. Thirdly, sentiment analysis tools can experience some problems when dealing with for example sarcastic reviews or when negative words are used to reinforce a positive opinion. While we fine-tuned the tools to produce the best possible results for our text data, some reviews may still be categorized wrongly. This paper could nevertheless serve as a starting point from which to explore if player numbers and engagement can be retained once the COVID-19 restrictions are decreased. Furthermore, the numerous examples of angry and violent reviews for competitive games suggest a further study on toxicities and racism in these communities may be necessary.

7 CONCLUSIONS

Our aim was to learn more about players' activities and opinion during the pandemic year. We collected and analyzed reviews of games played in 2018, 2019 and 2020 looking for significant differences between them. We then focused on the sentiment expressed in these reviews. Finally, we explored the sentiment of reviews that explicitly refer to the COVID-19 pandemic and what people played during the same period. Our findings show an increase of people playing and reviewing games during the first year of the pandemic in which stay-at-home orders and other restrictions were implemented. Contrary to what we expected, we did not find a strong negative sentiment among reviews. In fact, reviews written in 2020 during the pandemic were shorter and less helpful for the community, suggesting an influx of new/casual players and a general increase in activities. Furthermore, gamers played more casual games, which had a lower barrier of entry and could be enjoyed even with friends who may not have had any prior gaming experience.

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