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Does Streaming Esports Affect Players' Behavior and Performance?

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Abstract

In this work, we analyze what effect streaming gameplay on Twitch has on players' in-game behavior and performance. We hypothesized that streaming can act as a form of implicit incentive to boost players' performance and engagement. To test this hypothesis, we continuously collected data about all Twitch streams related to a popular Multiplayer Online Battle Arena (MOBA) game, League of Legends (LoL), and data of all LoL matches played during the same time frame, and cross-mapped the two data sets. We found that, counterintuitively, streaming significantly deteriorates players' in-game performance: This may be due to the burden of carrying out two cognitively intensive activities at the same time, namely, playing the game and producing its commentary for streaming purposes. On the other hand, streaming increases engagement keeping players in significantly longer game sessions. We investigate these two effects further, to characterize how they vary upon individual characteristics.

Keywords

esports, behavioral dynamics, streaming, Twitch, MOBA, league of legends

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Introduction

Game streaming platforms like Twitch play a pivotal role in the growing popularity of esports, accounting for a huge cohort of players that daily broadcast their gameplays live, attract viewers, and gather donations. They not only allow players to share their content online but also constitute a possible source of engagement in the game for both players and their audience.

On the one hand, many studies have focused on human engagement in streaming platforms, as well as trying to understand the motivation that users have to stream (Hilvert-Bruce, Neill, Sjöblom, & Hamari, 2018; Hu, Zhang, & Wang, 2017; Sjöblom & Hamari, 2017), and their behavioral patterns on such platforms (Hamilton, Garretson, & Kerne, 2014; Lessel, Mauderer, Wolff, & Krüger, 2017; Zhu, Yang, & Dai, 2017). On the other hand, engagement and motivation has been analyzed from the game perspective, by studying what are the characteristics of the game that drive users to be more engaged, such as the game ranking systems (Kou, Gui, & Kow, 2016), team composition (Kou & Gui, 2014), and that retain them over an extended period of time in online games (Park, Cha, Kwak, & Chen, 2017).

However, whenever a game is streamed, the user is actually engaging on two different platforms: the streaming platform and the game platform. Thus, to better understand what are the factors that affect players in both their engagement and performance when streaming, we need to consider both the streaming and the game platform and identify any change in their behavior that would lead to better performance and engagement.

In the present work, we aim at shedding light on the effects that streaming has on players' performance and engagement by taking into account their behavior in different conditions: streaming and nonstreaming. To this aim, we collect data about players in a popular Multiplayer Online Battle Arena (MOBA) game: League of Legends (LoL). Since its release in 2009, LoL has not only attracted the attention of millions of users that regularly play on the platform but has also become one of the most streamed online games on YouTube and Twitch.tv. Due to its popularity and huge cohort of streamers, we focus on the study of players' performance and engagement in LoL and how they are affected by streaming on Twitch. Moreover, the accessibility to both streamed data and in-game data allows us to compare how streamers' behaviors change when streaming and nonstreaming as well as to study the differences between streamers and nonstreamers.

We are particularly interested in identifying the effects of streaming on performance and engagement at different levels. First, we study the effect of streaming in the long term, by comparing the level of engagement in LoL of streamers and nonstreamers over the entire observation period. Second, we investigate if streaming leads to longer engagement in the game in the short term, namely, during an individual match and over the course of a session, that is, a sequence of matches played consecutively without an extended break. We use an analogous analysis to study the performance dynamics over time and corroborate previous results which show how performance deteriorates over game sessions. Here, we also try to disentangle different aspects that can influence players' performance, for example, popularity and skill level. Finally, we use a mixed effect model to test our hypothesis about streaming impact on performance.

The article is organized as follows. In second section, we introduce the platforms studied and explain our data collection process. In third section, we summarize the methods used throughout the article to analyze the impact of streaming on players' performance and engagement. In fourth section, we outline the results obtained in our study and report the work relevant to our findings in fifth section. Finally, we report our main findings and related conclusions in sixth section.

Data Collection and Preprocessing

Data Sources

LoL. LoL is a popular MOBA game developed and released by Riot Games in 2009. LoL players collaborate with other four teammates or computer-controlled characters to defeat the opposing team. The final goal of the game is to conquer the enemy's base, also known as, nexus, a tower on the opposite side of a symmetrical map which is protected by several defensive structures. Each player in the team is assigned with a specific role and thus impersonates a character, that is, champion, whose characteristics and special powers change depending on the role, or class of the champion, for example, defensive (tanks), offensive (fighters, slayers), support (controllers), and so on.

Since its release, LoL has grown in popularity with a community of players that at the beginning of 2014 reached over 67 M participants playing per month. Of all MOBA games, LoL has so far the largest footprints in streaming platforms such as YouTube and Twitch.[1] Due to its popularity, here, we just focus on Twitch users that stream LoL matches.

Together with the Twitch data (described in the next section), we collected information about LoL players and their matches through the official Riot Games Application Programming Interface (API) (Riot Games API: https://developer.riotgames.com/), which allows us to get data about players' actions, for example, number of kills, number of assists, number of deaths, and so on, per match, and compute the kill and assist to death (KDA) ratio metrics, which we will use as a proxy for in-game players' performance, similarly to previous literature (Sapienza, Zeng, Bessi, Lerman, & Ferrara, 2018).

Twitch

Twitch is a live streaming video platform owned by Twitch Interactive, first introduced in 2011 as a spin-off of Justin.tv. The main focus of the platform is the live streaming of video games, including broadcasts of esports tournaments, individual players' streams, and online game related talk shows, which can be viewed both live and on demand. Since its release, Twitch has attracted the attention of millions of users and rapidly became one of the most popular live streaming video platforms, now accounting for 15 million daily active viewers and over 2.2 million streamers (see official statistics: http://twitchadvertising.tv/audience/). Twitch users can stream popular online games, such as Fortnite, LoL, and Dota 2, share their game content, and collect donations from their viewers.

In the present work, we focus on a specific MOBA game that is usually streamed on the Twitch platform: LoL. To this aim, using the Twitch official API (Twitch API v5: https://dev.twitch.tv/docs/v5/), we collect data of Twitch users that streamed LoL matches. This API gives access to the list of current live streaming, and their broadcasters' metadata, for example, name, ID, number of followers, number of views, and number of viewers at the time of the request. Leveraging this input, we followed LoL streamers over time and gathered their data by updating our API requests every 5 min. The data collection occurred from March 6, 2018, to June 30, 2018. This process allowed us to collect time-varying data and thus understand different aspects characterizing streamers, for example, popularity growth, time spent in streaming, and its frequency.

Mapping and Sessions

As the gaming platform (LoL) and the streaming one (Twitch) are independent, to consistently collect data about the same users, we need to map each user we followed on Twitch (340,230 streamers in total) to their correspondent player in LoL. To this aim, we queried the Riot Games API to get the playing history of Twitch streamers, by using their Twitch user name. Among the original number of streamers, we then successfully mapped 1,426 players in LoL both by their name and matches. In particular, for each player, we marked as "streaming game" any match in LoL that occurred at the same time of a Twitch stream by that user, while any other match in the player's history has been flagged as "nonstreaming game," accounting for a total of over 94,000 matches. Moreover, with the aim of understanding the impact of streaming on players' performance and engagement in the game, we collected data of 2,168 LoL players who were not streamers and played during the same time frame.

Finally, to understand how a player's performance changes over consecutive matches, we divided each player's history of matches in sessions, that is, sequences of matches played consecutively without an extended break (Halfaker et al., 2015; Kooti, Moro, & Lerman, 2016; Kooti, Subbian, Mason, Adamic, & Lerman, 2017; Sapienza et al., 2018; Singer, Ferrara, Kooti, Strohmaier, & Lerman, 2016). To this aim, we set a threshold of 1 hr break to mark different sessions, which covers over 50% consecutive games as shown in Figure 1. Once we identified the sessions, we discarded those having both streaming and nonstreaming games (mixed sessions), as we are interested in identifying the impact of streaming on a player's behavior and wanted to avoid introducing possible confounders like the presence of nonstreamed

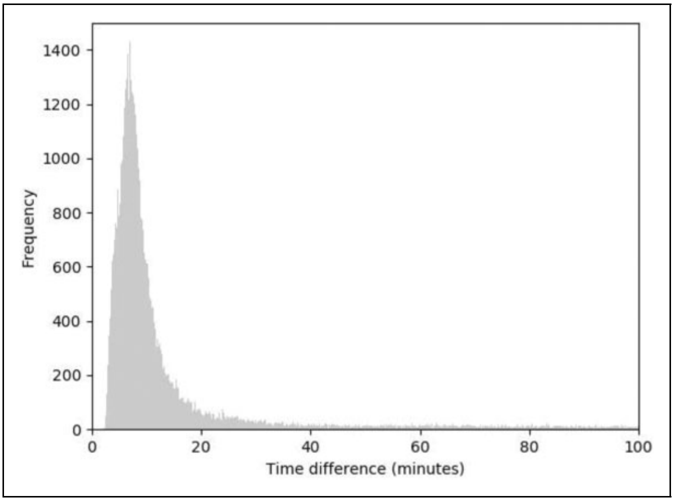

Figure 1. Time difference between consecutive matches.

Table 1. Basic Statistics for Twitch Users.

Statistics	# Matches Per Player	# Session Per Player	Total Play Time Per Player	Total # Followers Per Player	Session Play Time Per Player	Match Duration	KDA
Mean	66.38	35.95	111,726.85	12,010.31	4,072.76	1,683.05	3.23
Standard	47.87	23.47	80,924.55	109,685.60	3,288.48	501.02	3.89
Minimum	1.00	1.00	1,005.00	0.00	191.00	190.00	0.00
25%	29.00	18.25	47,297.75	61.00	1,830.00	1,348.00	1.00
50%	60.00	35.00	101,808.00	157.02	3,081.00	1,677.00	2.00
75%	94.00	50.00	160,211.50	523.97	5,221.00	2,005.00	4.00
Maximum	256.00	148.00	411,961.00	2,235,845.40	48,746.00	4,255.00	51.00

matches within a given session. The same procedure was repeated for LoL players that were not on Twitch (here, any session is marked as a "nonstreaming session"). Additional information about the final data set can be found in Tables 1 and 2, respectively, for Twitch players and non-Twitch players.

Method

In the following, we describe the methods used in the present study to understand both a player's engagement and performance and how these two aspects are affected by streaming. On the one hand, to study the effect of streaming on players' engagement in

Table 2. Basic Statistic for Users Not on Twitch.

Statistics	# Matches Per Player	# Session Per Player	Total Play Time Per Player	Session Play Time Per Player	Match Duration	KDA
Mean	34.26	13.67	51,813.42	3,800.50	1,512.23	3.16
Standard	41.53	16.04	65,239.47	3,166.12	531.64	3.98
Minimum	1.00	1.00	978.00	191.00	191.00	0.00
25%	5.00	4.00	7,973.50	1,690.00	1,124.00	1.00
50%	11.00	6.00	16,150.00	2,863.00	1,445.00	2.00
75%	53.00	18.00	79,039.25	4,909.00	1,863.00	4.00
Maximum	209.00	97.00	340,473.00	50,009.00	7,228.00	119.00

the game, we compare how much time players spend in their matches (when streaming or not), by both looking at the average duration of each match and how many matches in a session they play. On the other hand, we compare performance over the course of sessions of different lengths in three scenarios: Twitch user sessions (streamed and nonstreamed) and non-Twitch user sessions. Finally, we investigate players' characteristics and their relation to in-game performance.

Average Match Duration Difference

The first metric we use to investigate a player's engagement is the average match duration of both streamed games and nonstreamed games. To compare the two cases, we compute the difference Δ^i for each user i as:

$$\Delta^i = \frac{\sum_{t=0}^{M} x_t^{i,l=\text{streamed}}}{M} - \frac{\sum_{t=0}^{N} x_t^{i,l=\text{nonstreamed}}}{N}, \tag{1}$$

where N is the number of streamed matches and M is the number of nonstreamed matches of player i. Δ^i is then the average game duration difference of user i, which is positive if he or she spent more time in streaming matches, and negative otherwise.

Survival Rate

The second metric used to understand users' engagement is the survival rate, which we define as the probability that a user will play another match after the last one. This analysis allows to identify different levels of engagement between players and their relation to streaming. In particular, we can distinguish between a long-term and shot-term survival rate.

The former refers to the probability of having, in the life span of our data set, a certain survival time, which is the temporal distance (measured in days) between the last and first match played in the player's whole records. Thus, if N days separate the first and the last recorded match, then a player's survival time will be N.

The latter is defined as the probability that a player will start a new match after another one in the same session. Analogously to the long-term metric, here, we consider the distance between the last and first match of a session. However, the distance is measured by the match index in the session and thus by the session length, that is, the number of matches in a session.

The computation of the survival rate in both short term and long term helps us understanding the effect of streaming on a player's engagement in the game. By studying the long-term effect, we can indeed measure how long streamers keep playing the game in comparison with nonstreamers, while the short-term effect highlights differences between streamers and nonstreamers (streamed sessions vs. sessions of players not using Twitch) and effects of streaming on individuals (streamed vs. nonstreamed sessions of Twitch users).

Performance Indicator: KDA

To investigate the consequences of streaming on users' performance, we study how a user's performance changes over time, and in particular over the course of sessions of different lengths. To this aim, we use a proxy for in-game performance that is popular between MOBA game players: the KDA ratio. The KDA ratio can be computed as follows:

$$\mathrm{KDA} = \frac{\#\text{of kills} + \#\text{of assists}}{\max(1, \#\text{of deaths})}. \tag{2}$$

In a nutshell, the KDA is a ratio between qualitatively positive actions that a player performs during the game (killing enemies and assisting teammates) and negative actions that are harmful to the player and his teammates (champion's deaths). Thus, if a player kills a lot of enemies (or assists teammates in doing so) but he or she also dies very frequently in such exchanges, the final KDA score will be lower than a player who actually manages to kill or assist while staying alive during these fights.

Performance Over the Course of a Session

Once the KDA of each match in a player's history is computed, we can study how it changes over the course of a session. To this aim, we report the KDA transition from the first to the last match of a session, for sessions of different lengths and user categories. It has been indeed shown in previous works (Ferrara, Alipourfard, Burghardt, Gopal, & Lerman, 2017; Kooti et al., 2016; Singer et al., 2016) that users' performance tends to deteriorate over time due to mental fatigue and the higher effort in keeping focus after a certain period of time. In the following, we compute the average KDA over sessions of the same length in our data and plot them to observe this phenomenon.

We are particularly interested in understanding whether performance deterioration differs in relation with a player's category (streamers vs. nonstreamers) and their characteristics: popularity and skill. Here, the popularity of a player is provided by the number of followers on Twitch, while the skill is computed as the player's average KDA. On the basis of both popularity and skill level, we can further distinguish between players that have high/low popularity and high/low skill level.

Mixed Effect Models

Finally, we aim at identifying the relation between a player's performance and his or her characteristics. To this aim, we use a mixed effect model. Our hypothesis is that streaming and game session length both affect player performance. Streaming might indeed increase players' engagement in the game, as streamers have to demonstrate their abilities in front of an audience. Furthermore, players' performance may deteriorate over time due increased mental fatigue effects. The mixed effect model allows us to assume these two factors to be heterogeneous among users, by incorporating both fixed and random effects.

Given a condition l with $l\,2L$ where, $L = \{\text{session length, streaming}\}$, a user i, and his or her vector of observations $\mathbf{y}_i$ we can compute:

$$E_l(\mathbf{y}_i) = \beta_l X_l, \tag{3}$$

where β is the fixed effect for condition l.

Given the two conditions, we can then write our model for each user i as follows:

$$\mathbf{y}_i = \sum_{l \epsilon L} E_1 + \gamma_{0i} + \beta_0 + \epsilon_i, \tag{4}$$

where β_0 and γ_{i0} are, respectively, the fixed and the random effect intercepts, and ϵ_i is an unknown vector of random errors. Note that the parameter γ varies depending on the user, while β is fixed for each user in the data set.

There are different possible configurations for the mixed effect model, in which we can decide to add a random effect to either one variable X_l or to all of them. Given the condition l in which a random effect is applied together with the fixed effect, its expectation will be:

$$E_l(\mathbf{y}_i) = (\beta_l + \gamma_l)X_l. \tag{5}$$

We tested all the four possible combination of the model. However, as explained in fourth section, we did not find any relevant difference in the results of the different models. Thus, we chose to use the simplest model, where we define the expectation as in Equation 3 under both conditions l. This not only is the simplest model but also does not require us to further manipulate our data as needed in the other models.

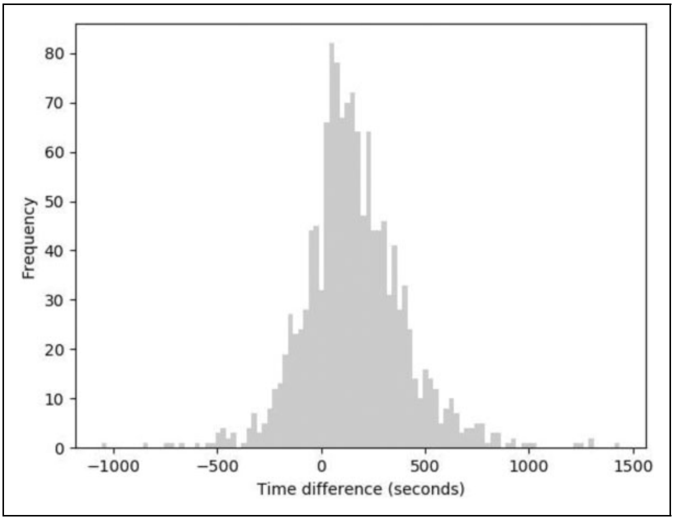

Figure 2. Average match duration differences between each user's streamed and non-streamed matches.

Results

In the following, we report the results of our study on the effects of streaming on both players' engagement and performance. We are particularly interested in understanding how a player's engagement varies in the long term and short term under the effect of streaming, and if streaming can have a positive effect in mitigating the performance depletion that has been shown to affect users that play multiple matches in sequence.

Effects of Streaming on Engagement

A natural metric to measure a player's engagement is the time the player spends in doing different activities in the game. This can be measured at different levels. In the case of MOBA games, players can indeed play longer games when they are highly engaged, display longer sessions (more matches played in sequence), and become regular users of the platform (i.e., have a long-term engagement in the game).

For this reason, we first study how streaming affects engagement at the level of each match. To this aim, we compute the average match duration of Twitch users when they are (respectively, are not) streaming the game and compute the difference as shown in Equation 1. The result of this operation is shown in Figure 2. Here, we can observe that the average match duration is longer when players stream their games, as the distribution is shifted on the right (note that positive differences

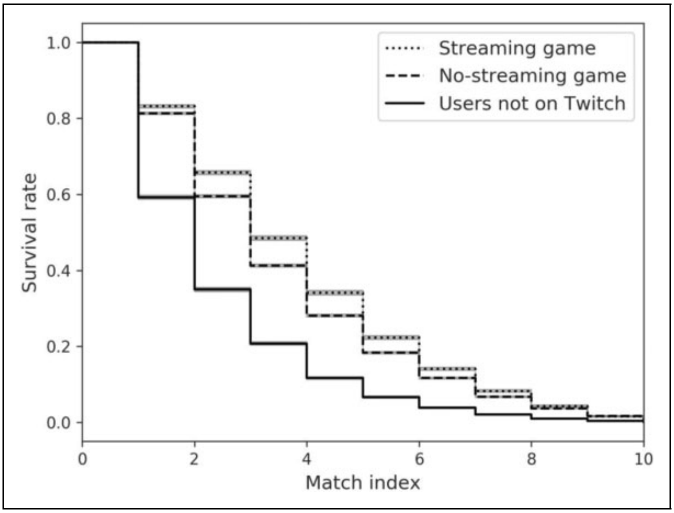

Figure 3. Kaplan–Meier survival rate plot of players for different categories: Twitch user with streaming games and with nonstreaming games and users not on Twitch.

correspond to longer streamed matches). On average, the streamed matches result to be longer that the nonstreamed one of about 5 min.

We then investigate the effect of streaming on the short-term engagement, by analyzing the Kaplan–Meier survival rate over the course of sessions of different length for three categories of matches: Twitch user's streamed matches, Twitch user's nonstreamed matches, and matches of LoL players that do not stream on Twitch.

Figure 3 shows how many times players play their game consecutively under different settings. We can observe that the sessions with streaming are longer than without streaming. When the Twitch users do not stream their videos, they tend to play shorter sessions than when they stream. Even though Twitch users' engagement without streaming is lower, Twitch users still show higher engagement than the users not on Twitch. As we can observe in Figure 3, users who do not stream on Twitch show lower survival rate than the one of streamed and nonstreamed matches. This result unveils the behavior of streamers when they do not stream their matches. Twitch users play a shorter session than they usually do with streaming and average nonstreaming users, but they show higher engagement than users not on Twitch.

We are also interested in the longer term engagement. Figure 4 shows the survival rate in a long term, and analogously to what observed on the short-term effect, Twitch users show higher engagement. Across the entire period, the survival rate of Twitch users is higher than the users not on Twitch. In other words, the duration that Twitch users play LoL is longer than the one of non-Twitch users. Not only in the short term but also in the long term, Twitch users tend to play LoL in a longer period.

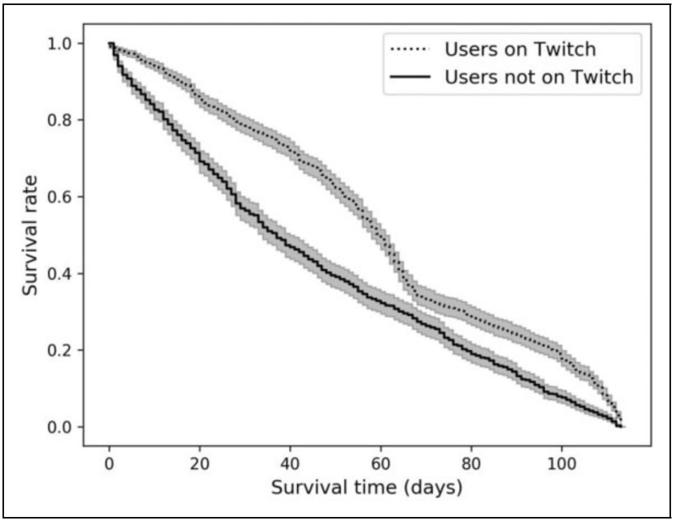

Figure 4. Kaplan–Meier survival rate plot of players for different categories: Users on Twitch and not on Twitch.

Effect of Streaming on Performance

Analogously to what we have done with the match duration, we used Equation 1 to compute the average win rate difference for each user, which is shown in Figure 5. In spite of what we observed with the match duration differences, the distribution of win rate differences does not display any shift and it is instead centered around zero. Therefore, even if streaming has been shown to have an effect on the in-match engagement of players, this does not reflect on a direct effect on players' win rates.

There are however some confounding factors when considering the win rate of players. The win rate is indeed dependent on other aspects of the game, such as teammates cooperation, team composition, and matchmaking game design. For this reason, in the following, we focus on a different proxy for players' performance, which is the KDA ratio.

Figures 6–9 plot game performance transition over the course of a session for each game categories and sessions of different lengths. The transitions of performance over the course of sessions illustrate how the session length affects players' performance. We can observe clear performance deterioration over the session in Figure 6 while the patterns shown in Figures 7 and 8 do not significantly decrease. However, downward transitions of game performance can be still identified. This is not the case for transitions of players that do not stream, as Figure 9 does not show any clear downward performance.

To see whether the users' characteristics matter for the performance transition, we further segment our data by popularity in Twitch and skill in LoL. To this aim,

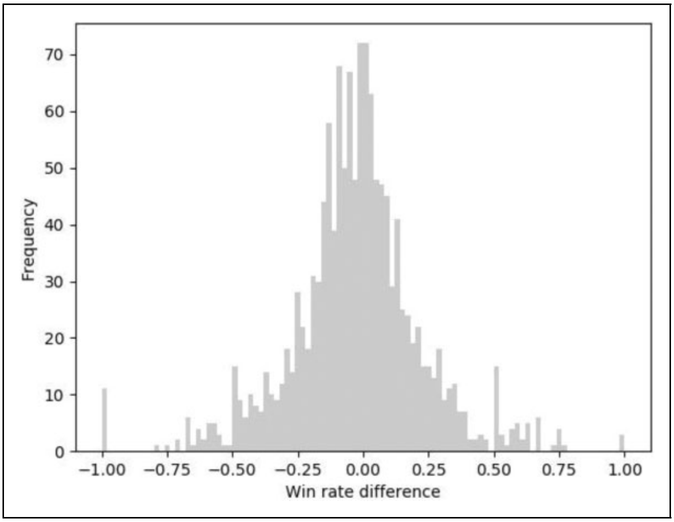

Figure 5. Average win rate differences between each user's streamed and nonstreamed matches.

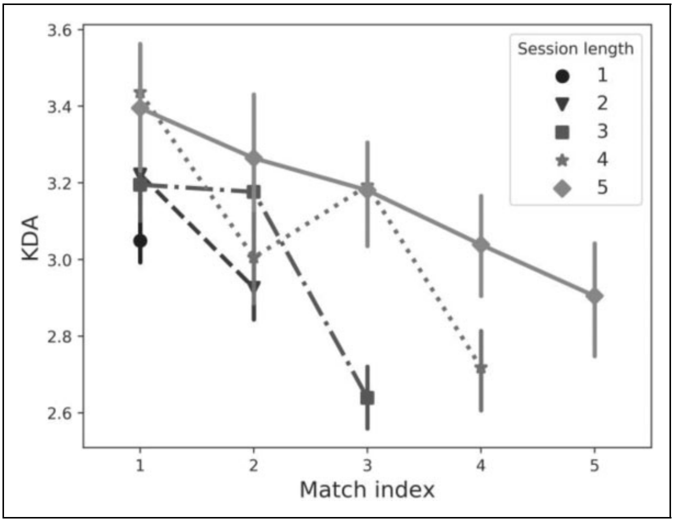

Figure 6. Average kill and assist to death of Twitch users' streaming game.

we divide the game performance data according to users' popularity in Twitch and plot them in the course of a session. We use the number of followers as a proxy variable of popularity in Twitch. While Figures 10 and 11 do not show an evident difference, both of them show performance deterioration. We also compare

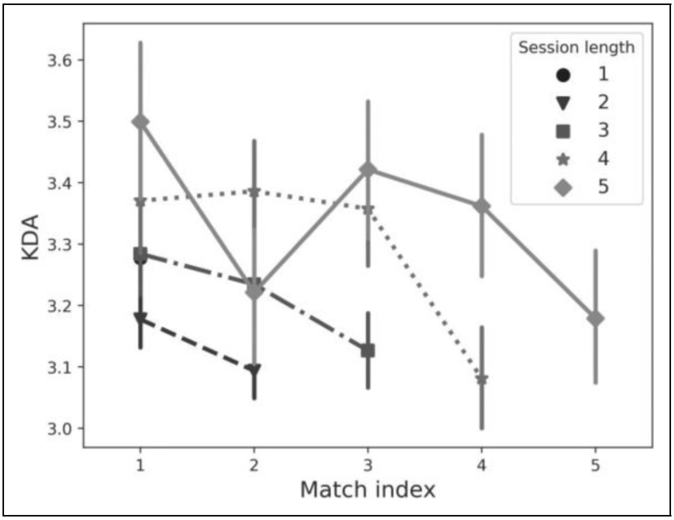

Figure 7. Average kill and assist to death of Twitch users' nonstreaming games.

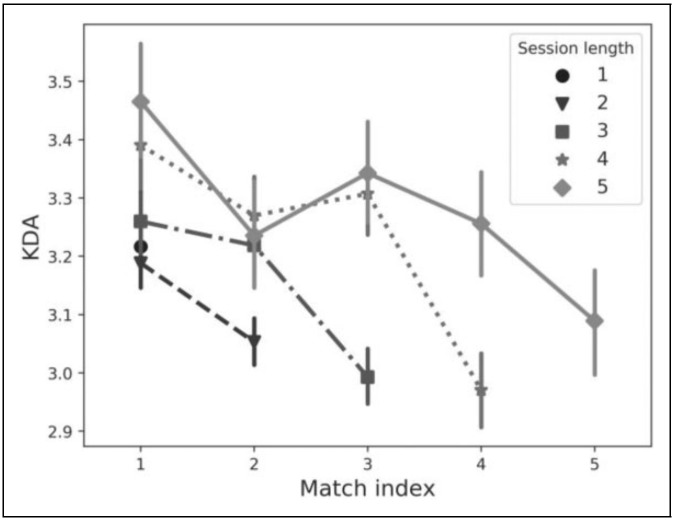

Figure 8. Average kill and assist to death of Twitch users' streaming game.

performance transitions of Twitch users with a lower skill to those who with higher skill in LoL (Figures 12 and 13). These results suggest that high-skill players are less affected by performance deterioration than low-skill players. This can be due to the fact that high-skill players tend to maintain their performance and focus over time better than low performers and amateurs.

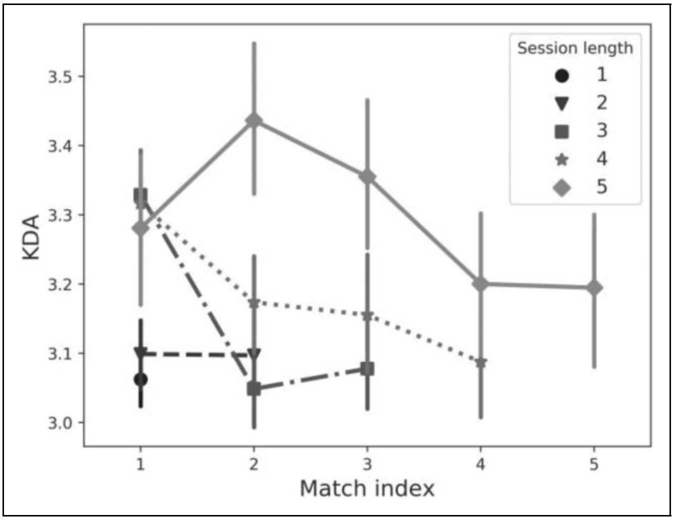

Figure 9. Average kill and assist to death of non-Twitch users' nonstreaming games.

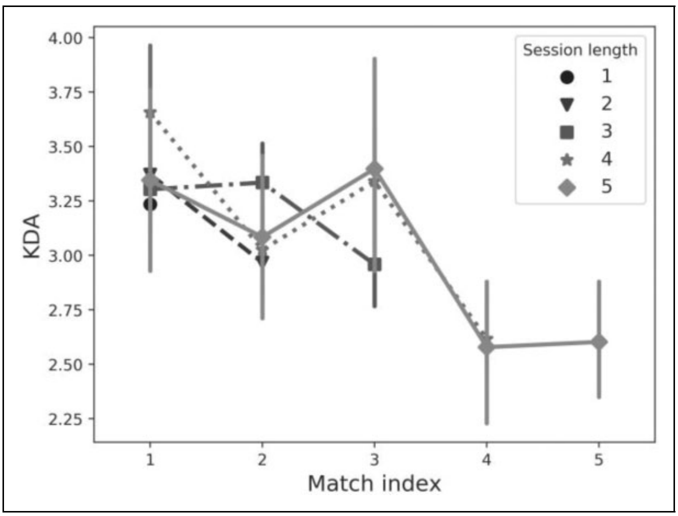

Figure 10. Average kill and assist to death of few follower users' game (bottom 25% follower).

Finally, as we observed that performance during a streaming session deteriorates over time, we want to further investigate the effect of streaming and thus conclude that it correlates with deterioration effects. To this aim, we use the mixed effect model described in Mixed Effect Models subsection.

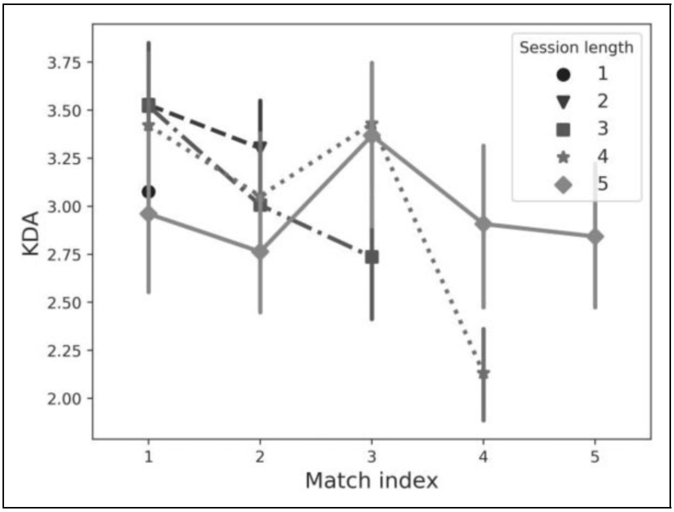

Figure 11. Average kill and assist to death of many follower users' game (top 25% follower).

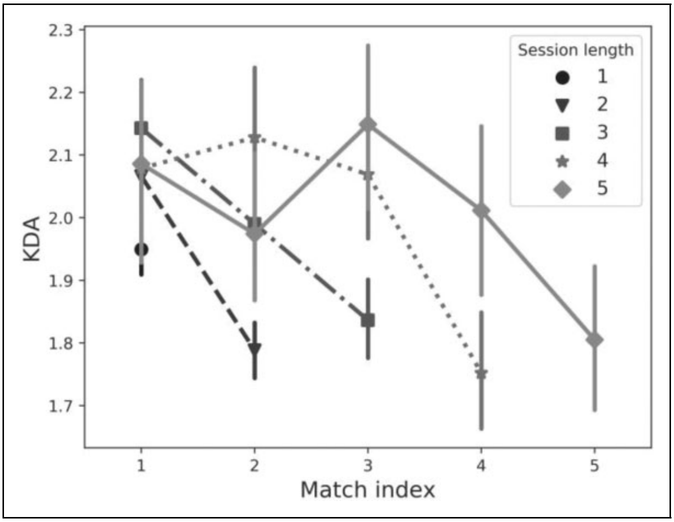

Figure 12. Average kill and assist to death of low-skilled users' game (bottom 25% follower).

As mentioned in third section, we computed four different mixed effects models, by adding on either one or both variables X_l a random effect. We tested all four models on our data, and we found that the results are consistent. Thus, we decided to use the simplest model, by not adding any random effect on the variables.

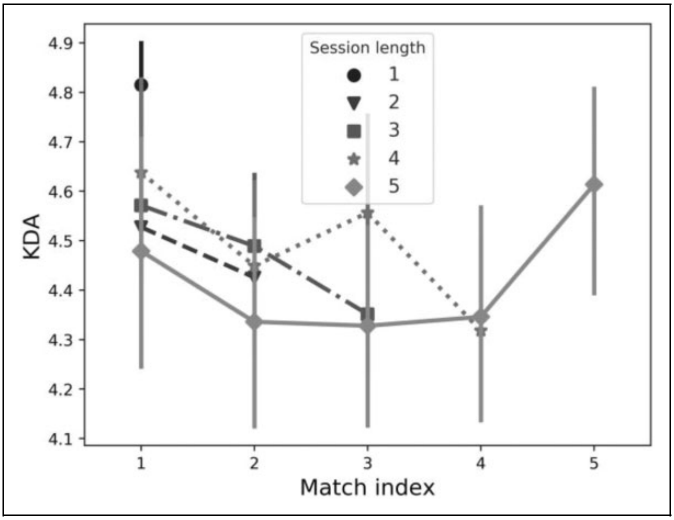

Figure 13. Average kill and assist to death of high-skilled users' game (top 25% follower).

Table 3. Mixed Linear Model Regression Results.

Model	Mixed LM	Dependent Variable			KDA	
Number of observations	73,485	Method			Restricted Maximum Likelihood (REML)	
Number of groups	1,426	Scale			14.2225	
Minimum group size	1	Likelihood			−202,717.2711	
Maximum group size	212	Converged			Yes	
Mean group size	51.5					
	Coefficient	Standard Error	*Z*	*P* > |z|	[0.0255 -> Lower CI 95%	0.975 -> Upper CI 95%]
Intercept	3.330	.040	82.567	.000	3.251	3.409
Match index	−0.057	.013	−4.248	.000	−0.083	−0.031
Streaming dummy	−0.140	.035	−4.024	.000	−0.208	−0.072
Groups random effect	0.858	.013				

Note. LM = linear model; KDA = kill and assist to death.

The mixed linear model regression results are reported in Table 3. As we hypothesized, the results indicate that there is a negative relation between the match index and game performance. Moreover, our streaming variable shows a negative relation with game performance as well. Thus, not only the match index in a session (i.e., the session length) but also the streaming factor have a critical effect on players' performance, which under these two conditions decreases.

In conclusion, we found that streaming has the power of boosting players' engagement in the game, by not only increasing the time spent in both matches and sessions but also committing players to play the game in the long term. However, we observed that streaming has a negative effect on players' performance. We indeed found that players' performance shows a decay that is more marked when a player is streaming a match. This result has been also confirmed by our statistical model, which has clearly shown the negative relation between playing longer sessions, and/or streaming them, with players' performance.

Related Work

This study draws from several research topics: game streaming, game engagement, and performance deterioration. In the following, we describe the literature relevant to our work and highlight the common points as well as differences in the findings.

Game Streaming

Many studies have been devoted to analyze user behavioral patterns in game streaming platforms. Kaytoue, Silva, and Cerf (2012) have done one of the first research studies using qualitative data from Twitch.tv. In this work, the authors characterize the community structures on Twitch and propose a way to rank users by popularity. Other studies have been done to investigate different aspects of live streaming related to user motivations (Hilvert-Bruce et al., 2018; Hu et al., 2017; Sjöblom & Hamari, 2017), detection of the relevant features used to attract viewers (Sjöblom, Törhönen, Hamari, & Macey, 2017), communication between viewers and streamers (Hamilton et al., 2014), and subscription and donation behavioral patterns (Lessel et al., 2017; Zhu et al., 2017). Despite the large amount of work that has been done to study the different characteristics involving live streaming platforms, our work focuses on the impact that streaming has on the game performance and engagement of a player. Thus, unlike prior work, we combine data from both streaming and players' history in the game, to identify whether a player's behavior changes in presence of streaming.

Game Engagement

Game engagement is used to describe a player's commitment into the different gaming actions, which is a crucial factor to retain players in the platform and make them become regular users. Multiple studies have tried to identify the main causes of a user's engagement in playing games. Kou and collaborators focused on game engagement in relation to players' collaboration (Kou & Gui, 2014), by trying to understand how temporary teams of strangers coordinate to reach their common goal. By means of semistructured interviews, they also studied how player ranking mediates social practices in LoL (Kou et al., 2016). In particular, the authors found that the ranking system not only act as a motivator for players' engagement but also contribute to the creation of social stratification and stereotypes, thus affecting the way players learn and collaborate with each other. Other studies focused on investigating long-term engagement mechanisms.

Park et al. (2017) relied on data about Massive Multiplayer Online Role-Playing Game to identify the factors that are indicative of long-term commitment in the game. In particular, they found that these factors change accordingly to the game level: Sense of achievement and the related incentives are fundamental in the initial to the advanced phases of the game, while features related to the social aspects of the game become important to predict long-term engagement when a player reaches the highest levels in the game.

Other studies focused on motivations for playing either online games (Yee, 2006) or watching esports (Hamari & Sjöblom, 2017) and on the underlying causes that brings individuals to stop playing a game (Anderson & Green, 2018). Our research adds on previous work results by using quantitative data of two different platforms to detect a possible external factor that plays a role in driving users' engagement. This is particularly important when considering online games whose majority of players stream on a daily basis.

Performance Deterioration

In the context of analyzing users' performance, an increasing number of works have shown the importance of breaks and the negative effects that extended efforts have on performance. Sapienza et al. (2018) have shown that players' performance in MOBA games deteriorates over the course of sessions. This decreasing trend in performance has been also observed in several online platforms such as Reddit (Singer et al., 2016), Twitter (Kooti et al., 2016), and Stack Exchange (Ferrara et al., 2017).

Kooti et al. (2017) compared the performance down turning among users with different characteristics on Facebook. In particular, they found that the time users spend in doing several activities on Facebook depends on their demographic attributes, the number of friends, and the time spent since the start of the session. Deterioration phenomenon has been also observed in relation to student performance (Sievertsen, Gino, & Piovesan, 2016), driving (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014), data entry (Healy, Kole, Buck-Gengler, & Bourne, 2004), and self-control (Muraven & Baumeister, 2000). Finally, the causes of performance deterioration are a controversial issue that several studies tried to address (Boksem & Tops, 2008; Kurzban, Duckworth, Kable, & Myers, 2013; Marcora, Staiano, & Manning, 2009). However, in their experimental study, Bernstein, Shore, and Lazer (2018) have shown that to improve human performance in complex tasks, the key is to take intermittent breaks.

In alignment with the previous research in the field, we also observed that performance deteriorates over the course of sessions of different lengths. However, we made a step forward in disentangling the factors that lead to performance deterioration, by studying performance of different categories of players (streamers vs. nonstreamers) and by further dividing them based on their popularity and skill level.

Conclusions

In the present work, we studied the effects that streaming has on both a player's performance and engagement in a game. To this aim, we collected data of players streaming LoL, one of the most streamed MOBA games on Twitch, as well as their match information and history through the official Riot Games API. This data set allowed us to study not only the changes in streamers behaviors, by comparing their performance and engagement in streamed and nonstreamed matches, but also the difference between streamers and nonstreamers (we collected additional data of LoL players that do not stream on Twitch).

First, we analyzed engagement differences in these categories of players. We found that streaming a match has a positive effect on players' engagement: Streaming a match leads to play longer matches, and streamers tend to have higher engagement both in the short term and in the long term. We indeed identified that streamers engage in longer sessions than in the case in which they do not stream, thus displaying higher survival rates. This is also true when comparing streamers and nonstreamers. Moreover, we observed higher survival rates in the long term: Streamers tend to engage in the game for long periods of time and have a longer player history than nonstreamers.

Second, we analyzed the effects of streaming on players' performance. We noticed that there is no difference in the win rate of streamed and nonstreamed matches. However, the variable "win" can be biased by other aspects of the game such as composition of teams, teammates abilities, in-game matchmaking design, and so on. Therefore, we used the KDA ratio as a proxy for a player's performance. The KDA ratio of a player indeed reflects the actions that the player performs in each match and thus provides an estimator of the quality of playing in the match.

We studied performance over the course of a session, for each of the three session types: streamed session, nonstreamed session, and sessions of players that do not stream their matches. The results, in line with prior literature, show that in general players are subject to performance depletion when playing a sequence of matches without an extended break.

Performance over the course of a session does decay; however, we observed that streamers are more affected by this mechanism when streaming than in the case in which they are not streaming. This result suggests that streaming might be a source of distraction for players, taking cognitive bandwidth away from gameplay, as players often comment and try to engage with their audience while streaming.

To detect possible factors connected to performance decay, we further analyzed sessions of players segmented by popularity, that is, number of followers, and skill, that is, KDA levels. The results of our analysis led to the conclusion that performance decay is not affected by the number of followers one player has. However, if a player has higher skills, his or her performance does not reflect the typical performance depletion pattern. This mechanism is indeed mitigated by the fact that higher skill players most likely can keep focus on the game for longer time while producing the streaming commentary at the same time.

Finally, we studied what players' characteristics have the strongest effect on performance. In particular, on the basis of our previous results, we assumed that both the match position in a session and streaming can negatively affect players' performance. To test this hypothesis, we used a mixed effect model that allows us to incorporate heterogeneous effects of these two gaming aspects among players. We confirmed that streaming has a negative influence on a player performance even if it boosts engagement in the game.

In conclusion, through the combined study of Twitch and LoL data, we found that streaming has a major impact on a user engagement in the game, by making users both playing longer and more regularly over time. We have also shown how performance deteriorates over sessions, thus corroborating the extant literature. However, we found that performance decay is mitigated in high-skill players, and that it is not affected by streamer's popularity.

Authors' Note

This project does not necessarily reflect the position/policy of the government; no official endorsement should be inferred. Approved for public release; unlimited distribution.

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Note

1. In the top 3 of all platforms in June 2018.

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