Audience and Streamer Participation at Scale on Twitch

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ABSTRACT

Large-scale streaming platforms such as Twitch are becoming increasingly popular, but detailed audience-streamer interaction dynamics remain unexplored at scale. In this paper, we perform a mixed methods study on a dataset with over 12 million audience chat messages and 45 hours of streamed video to understand audience participation and streamer performance on Twitch. We uncover five types of streams based on size and audience participation styles, from small streams with close streamer-audience interactions to massive streams with the stadium-style audiences. We discuss challenges and opportunities emerging for streamers and audiences from each style and conclude by providing data-backed design implications that empower streamers, audiences, live streaming platforms, and game designers.

KEYWORDS

Twitch, Audience Participation, Games, Data Analysis

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1 INTRODUCTION

Live streaming platforms, such as Twitch, Youtube Gaming, Periscope, and Hitbox, have become considerably popular in recent years [3]. Streamers on these platforms each have a channel where they generally live stream themselves engaging in various entertaining activities such as playing video games while interacting via chat messages with an audience who can be globally distributed [3].

There is vast HCI research on audience and spectator engagement, including within gaming [2], but our understanding of how audiences and streamers collectively participate in live game streaming platforms is still limited [2, 5].

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We conduct a large scale data analysis on Twitch and identified the following research questions to understanding audience participation in the platform: *RQ1. How does audience participation on Twitch vary across different sized audiences?, RQ2. What type of techniques do streamers use to drive audience participation and how do these techniques vary?*

We explored these research questions using one month of data from 130 randomly selected Twitch streams.

2 METHODOLOGY

We used Twitch's API to scrape data from all English-language streams that allowed free, public participation between April 10, 2017 and May 17th, 2017. See Table 1 for details.

Days Collecting Data	44
Number of Streamers (Twitch streams)	226,658
Minutes of Analyzed Video Stream	2,700
Number of Viewers Participating in Chat	651,664
Number of Chat Messages	12,150,866

Table 1: Twitch Data Collection

We focus our analysis on understanding interactions between streamers and their audience at different *scales*. For this purpose, we: (1) use a mean shift algorithm to group streams with similar sized audiences to group and uncover the different audience sizes (scales) present in Twitch; (2) use textual and sentiment analysis [6, 9] to model the participation of audiences within each cluster; (3) using an approach informed by ethnomethodology and conversation analysis [8] we conduct qualitative analysis on the video of streamers from each cluster to understand how streamers perform differently and similar for different sized audiences.

3 RESULTS

We summarize the findings as follows:

Cluster 1 (Clique Streams): Streams in this cluster had small audiences (up to 6 live viewers on average). These streams had a relationship-driven nature. We hypothesize that streamers were attempting to create a stronger bond with them, similar to the behavior that is observed on Facebook when individuals are tagged or mentioned in posts [7]. Among our five clusters, this cluster had the most difficulty with retention. 65% of the audience that participates in chat stays active for only one day, and 90% of visitors appear in chat on only two or fewer days.

Cluster 2 (Rising Streamers): Despite high turnover, the streams in this cluster presented a relatively large audience size: 339 audience members per stream on average. These streams also start a

Cluster	AvgLive Stream Viewers	Audience Members in Chat	Audience Messages Collected	Min. Video Analyzed	Avg. Num. Bots	%Positive Messages	%Negative Messages.	%Exit Rate on Day 1	Avg. Words per Message
1: Clique	0-6	1,374	49,909	438	1.25	23.98	9.86	65.21	6
2: Rising Streamers	6 - 1,879	54,526	723,928	1,071	1.57	21.25	10.15	64.74	5.71
3: ChatterBox	1,879 - 7,703	169,546	3,166,399	506	2.12	14.38	7.44	56.51	4.36
4: Spotlight Streamers	7,703 - 21,678	329,279	3,925,338	881	1.87	11.27	6.05	58.06	3.82
5: Celebrities and Tournaments	21,678+	189,737	3,884,273	1,101	1.5	13.97	7.17	51.49	3.99

Table 2: Overview of the characteristics of each cluster

formal integration of bots to facilitate moderation. Streamers in this cluster still struggle with retention. We observed that 64% of the audience participates in chat for only one day and an additional 19% of the audience participates for a maximum of two days. Streamers built community around shared identity or experience (e.g. streamers who stuck to a specific game). Streams that belong to this cluster can apply to the "Affiliate Program," to monetize their streams.

Cluster 3 (The ChatterBoxes): Streamers in this cluster used slang and stream-personalized emoticons meaning that in this cluster the audience might be building a sense of community and identity around the stream. Compared to previous clusters, the exit rate on day one decreases dramatically, from 64% to 56%, meaning that streamers here were able to hold their audience's attention. Channels had an average of over 4,468 individuals per stream. We observed channels with one streamer playing the game live, while another reads aloud the messages from the audience and initiates discussions with them.

Cluster 4 (Spotlight Streamers): Streams in this cluster had a massive number of concurrent viewers, ranging from 7,703 to 21,678 live viewers on average. They presented the largest proportion of the participatory audience on Twitch. The total number of active audience members was 329,000. All the streams in this cluster were highly promoted by Twitch and had large audiences but retained relatively few of their new viewers, 58% of the audience members in these channels would only participate in chat for one day. Streamers belonging to this cluster talked the most about their struggle with playing the video game and interacting with the audience.

Cluster 5 (Celebrities and Tournaments): Streams in this cluster retained on average over 1,000 audience members for more than 20 days per stream. They presented enormous live audience sizes (21,678+ participatory audience members). Streamers in this cluster were typically professional Twitch streamers with verified accounts. These streamers were the most consistent in their live transmissions: their schedule was posted on their profile, and during the study period they never missed a day of streaming. On tournament streams, they always presented a host whose job was to narrate the actions the players were doing on the match. The streams implemented multiple sections of the stream that include, interviews with the players, short brakes between matches, game analytic, discussions and sponsored content.

4 DISCUSSION

Implications for Streamers. Our results showed that streamer attention is split between playing the game, and playing to the audience. Designers can create visualization tools that in real-time can show streamers and audience analysis. For example, the tool could show when a large number of newcomers join the stream, or provide real-time text mining to help them understand what their chat is talking about, which political trolls do to drive engagement [4]. It might also be helpful for designers to consider creating tools that can detect streamer behaviors (e.g. reading chat messages out loud) and identify the best practices (i.e., behaviors) that are most likely to help foster engagement.

Implications for Game Designers. Through our study, we identified that many streamers struggled to perform for their audience while effectively playing their game. It can therefore be important for game designers to envision tools that help streamers to effectively manage all of these elements: to maintain the "persona" or image they want to convey for their audience, keep their audience engaged, and still adequately and effectively play their game. Designers might use phase-based design strategies [1] to allow both streamers and audiences to participate differently during different phases of play.

Implications for Platform Designers. In our study, we identified that some streamers lost a large number of their audience members over relatively short periods of time. It can, therefore, be useful for platform owners and designers to think about providing training or onboarding help for streamers, perhaps exploring in collaboration with researchers to study which stream behaviors or tools are most effective at retaining viewers. This especially can provide value for platform owners as it can facilitate engagement and retention on their sites and systems. Best practices could also be embedded directly in interfaces that adapt as audience sizes change; for example, the traditional chatbox could be designed to look and function significantly differently for different sizes of streams.

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