Developing Feedback Systems For Live Stream Communities Using Large Language Models

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Abstract

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Live streaming has become a key mode of community engagement, enabling real-time interaction between creators and audience. Platforms like Twitch have transformed content creation into a participatory, performative practice that blends entertainment, emotional labor, and community building. Despite its cultural and economic significance, little research has examined how streamers interpret and act on audience feedback in ways that support sustained growth, well-being, and meaningful interaction.

This dissertation explores how large language models (LLMs) can power intelligent feedback systems that help streamers manage content production and community engagement. Through three studies, it examines feedback from multiple angles: streamers' existing information practices, proactive strategies for soliciting input, and reactive techniques for interpreting audience response post-stream. This research demonstrates how LLMs can synthesize audience input into insights that are actionable, emotionally supportive, and strategically meaningful. The work contributes both deployable systems and design principles for building feedback tools attuned to the demands of live stream communities.

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Chapter 1

INTRODUCTION

1.1 Overview

In recent years, content creation and consumption have surged, accelerated in part by the COVID-19 pandemic, which provided people with more time for online engagement as in-person activities diminished [62]. While the pandemic has subsided, live streaming platforms such as Twitch and YouTube Live continue to thrive, with millions of users worldwide turning to them for entertainment, information, and community interaction [56]. Within these environments, audiences often coalesce into micro-communities, initially forming around specific streamers or topics and gradually developing their own norms and practices [81].

Human-Computer Interaction (HCI) researchers have long studied the dynamics of online communities, exploring how they form, sustain themselves, and sometimes decline [108]. Key areas of inquiry include supporting long-term community sustainability, fostering commitment, moderating behavior, managing newcomers, and designing for resilient engagement [108]. In the context of live streaming, research has addressed motivations, parasocial interactions, audience moderation, and the use of multimedia tools to enhance experience and community governance [158, 156, 189, 113, 193, 117].

Alongside this work, a parallel stream of literature focuses on feedback exchange, the processes through which individuals seek, give, and receive feedback to support community cohesion, creative development, and personal well-being. Within creative and educational domains, feedback is recognized as critical for maintaining productive environments and fostering sustainable participation [105, 60, 124]. Studies have compared peer and crowd-sourced feedback, examined help-seeking behaviors in academic settings, and explored the use of guiding questions to support deeper engagement [142, 14, 33, 138].

Despite extensive research on online communities and feedback practices, little is known about how feedback is exchanged within live stream communities. The unique features of live streaming—real-time interaction, overlapping social roles, and dynamic audience participation—pose new challenges and opportunities for designing meaningful feedback systems. Moreover, the intense labor involved in live streaming can impact streamers' emotional and physical well-being, highlighting the need for tools and practices that support sustainable community involvement without overwhelming creators.

This dissertation bridges these two strands of research—online community sustainability and feedback exchange—by introducing a framework for studying and supporting feedback within live streaming communities. Specifically, I aim to:

- Investigate the current practices and challenges of feedback exchange in live streaming contexts;
- Develop tools and strategies to facilitate more effective and sustainable feedback in these environments; and
- Evaluate the impact of these interventions on community sustainability, content development, and streamer well-being, with attention to emotional and physical dimensions.

This research explores the role of feedback mechanisms in supporting the long-term sustainability and well-being of live streaming communities, focusing on their impact on engagement, retention, and the quality of social interactions. It contributes to research by empirically examining feedback dynamics within live streaming ecosystems and by developing tools that promote healthier, more intentional, and feedback-rich interactions.

To explore this space, I conducted three studies:

1. Semi-structured interviews with streamers to examine how they interpret, act on, and wish to improve the information they receive from their communities.
2. Design and deployment of a conversational agent for constructive feedback collection and synthesis.
3. Development of a post-stream analysis tool to help streamers retrospectively review

chat interactions and identify actionable feedback.

Together, these studies explore both proactive and reactive approaches to feedback, supporting streamer decision-making, community management, and content planning. This dissertation provides design-based insights into the evolving relationships between streamers and their communities. It contributes to our understanding of the social and technical infrastructure required to sustain vibrant online communities and proposes practical pathways for creating healthier, more sustainable, and emotionally supportive feedback environments on live streaming platforms.

1.2 Dissertation Structure

The remainder of this dissertation is organized as follows: I begin by reviewing the relevant literature on online community dynamics and feedback exchange. I then present the research questions that guide this work, followed by a detailed description of the three studies. Each study includes its motivation, relevant background, methodological approach, and key findings. I conclude with a synthesis of the contributions and implications for research and platform design.

1.3 Research Questions

Live streaming platforms are complex social environments that foster ongoing interactions between streamers and their audiences. These interactions present opportunities to explore how feedback is exchanged, understood, and acted upon.

This dissertation is guided by the following research questions:

RQ1: What does the information ecosystem of live streamers look like, and how does it shape their content and community relationships?

RQ2: How can feedback mechanisms be designed to support constructive, timely, and meaningful exchanges within live stream communities?

RQ3: How can feedback systems be developed to help streamers manage information while minimizing emotional and cognitive labor?

By investigating these questions, this research draws from and contributes to literature in HCI, drawing on studies of feedback systems in managerial and educational contexts, as well as work that examines online collaboration and community dynamics.

Figure 1.1: Diagram of how study 1 informs study 2 and 3; and how this work contributes and extends our understanding of feedback exchange through the lens of proactive and reactive feedback mechanisms.

Chapter 2

BACKGROUND

Online communities refer to any virtual space where people come together to converse, exchange information and other resources, learn, play or just be with each other [108]. This term ranges from small close-knit communities to larger sites with millions of participants. Different types and subsets of online communities attract different subsets of participants, leading to varying affordances. There are often different levels of engagement within these communities, such as the primary content contributors, secondary content contributors, and view-only participants [144]. The common feature among online communities is the ongoing interaction between people over time, with most of the interactions being technologically mediated.

The literature review will be structured as follows, first I will discuss the related literature on feedback exchange as a theory, its growing importance in online communities and HCI research, and an introduction to the framework for feedback exchange. Then, I will describe prior research on live streaming, its dynamics as a real-time feedback environment, and associated motivations and challenges.

2.1 Understanding Online Feedback Exchange

Online feedback exchange (OFE) is a method for requesting and receiving information from distributed users online to improve the quality of creative work including design. OFE systems have gained recent attention from researchers because of their abilities to help creatives collect constructive feedback quickly from as hundreds of people in as short as 24 hours. While OFE systems' ability to collect feedback efficiently provides a cost-effective solution to populations without access to face-to-face feedback, many systems struggle to maintain high quality across all critiques, and these systems come with their own limitations.

In the rest of this section, I will discuss what feedback and feedback systems mean within the space of human-computer interaction research, and an overview of prior work exploring feedback exchange within online communities including designers, fanfiction communities, and small businesses.

2.1.1 HCI Research and Feedback

In this work, I will look at both feedback-seeking and help-seeking behavior within HCI research. Help seeking is a process that involves multiple steps in self-awareness and communication skills. In academic help-seeking literature, prior work describes a five-step process to seeking help 1) awareness, 2) deciding to seek help, 3) identifying potential helpers, 4) employing strategies to seeking help, and 5) reacting to the help-seeking process [15, 45]. There are a lot of overlaps between prior work in the education context and other domains that can be applied to online communities.

Systems designed to support feedback at scale play a crucial role in various domains, including education, content creation, and collaborative work. These systems leverage technology to facilitate the collection, management, and utilization of feedback from large and diverse groups of users. For instance, Kulkarni et al. (2017) discuss the PeerStudio platform, which supports scalable feedback in online learning environments by enabling rapid, peer-generated evaluations [111]. This system enhances the learning process by allowing students to receive timely and diverse feedback on their work, which is essential for iterative improvement and deeper understanding. Similarly, systems like Taskr [25] aim to optimize the feedback process in large-scale online courses by using machine learning to prioritize and distribute feedback tasks among teaching assistants, ensuring that students receive high-quality and prompt responses. These HCI systems address the challenges of feedback at scale by integrating advanced algorithms, user-friendly interfaces, and collaborative mechanisms, ultimately enhancing the efficiency and effectiveness of feedback processes across various settings.

Existing Approaches to Manage Harsh/Negative Feedback

Existing approaches to controlling harsh or negative feedback in HCI systems focus on fostering a supportive and empathetic environment for feedback exchange. One such approach is the use of narrative empathy and ingroup framing as explored by Wu et al, their study demonstrates that by framing feedback interactions within a narrative context and emphasizing shared group identities, individuals are more likely to provide constructive and less harsh feedback [192]. Narrative empathy involves encouraging users to consider the perspectives and experiences of those receiving feedback, which promotes understanding and reduces the likelihood of negative comments. Ingroup framing, on the other hand, highlights commonalities and shared goals among users, fostering a sense of community and mutual respect. These techniques leverage social-cognitive mechanisms to mitigate the impact of anonymity and distance in digital communication, ultimately leading to more positive and productive feedback exchanges.

Existing Approaches to Improve Feedback Quality

To improve the quality of feedback in HCI systems, prior work has identified several effective strategies. One key approach is the implementation of structured feedback frameworks that guide users in providing specific, actionable, and balanced comments. For example, research on peer review systems has shown prompts that encourage reviewers to highlight both strengths and areas for improvement can lead to more comprehensive and useful feedback. Additionally, training users on effective feedback techniques, such as using descriptive language and avoiding personal judgments, has been shown to enhance feedback quality. Incorporating elements of narrative empathy, as discussed by Huang et al. (2017), can encourage users to consider the context and emotional perspective of content creators, which can in turn lead to more thoughtful and considerate insights [42]. Another effective strategy is the use of automated tools to analyze and suggest improvements to feedback in real-time, ensuring that comments are constructive and relevant. These methods, grounded in empirical research, contribute to creating a feedback culture that supports learning, growth, and positive engagement.

2.1.2 Feedback Exchange in Online Communities

Feedback-seeking behavior in online communities is a multifaceted phenomenon influenced by various factors, including the creation stage of the artifact, the nature of community comments, and the perceived role of the feedback provider. For instance, Cheng et al. found that writers actively seek feedback from peers to improve their work and build a sense of community [46]. This feedback is often detailed and constructive, given in a supportive environment where writers share common interests and goals.

Another critical aspect is the creation stage of the artifact. Guo highlights that creators are more receptive to feedback during the early stages of their projects [73]. At this stage, they are still forming their ideas and are open to making significant changes based on the feedback received. The characteristics of community comments, such as their specificity, relevance, and tone, also play a significant role in how feedback is perceived and acted upon. Positive and constructive comments are more likely to be valued and integrated into the creator's work, fostering a culture of continuous improvement and engagement.

Factors Influencing Feedback-Seeking Behavior

The approach to seeking feedback can significantly impact the quality and utility of the feedback received. Krishna et al. shows that setting clear goals and understanding the feedback provider's role can enhance feedback-seeking behavior [109]. Creators who set specific goals for what they hope to achieve through feedback are more likely to engage in meaningful revisions and improvements. Additionally, perceiving the feedback provider as a knowledgeable and supportive figure increases the likelihood of seeking and valuing feedback.

Creative small businesses face unique challenges in seeking feedback on social media, as explored by Kotturi et al. [103] These businesses often rely on social media platforms for customer interaction and feedback but may struggle with the volume and variability of responses. The informal and public nature of social media feedback can sometimes make it difficult to extract actionable insights. Despite these challenges, social media remains a crucial tool for small businesses to engage with their audience, gather diverse perspectives, and refine their offerings based on customer feedback.

Impacts of Feedback-Seeking Behavior

The impact of feedback-seeking behavior on creators can be profound, as highlighted by Cheng et al. [46]. This study found that public requests for feedback often lead to a higher volume and diversity of responses, which can provide creators with a wide range of perspectives and suggestions. Such public critique not only helps in improving the quality of the work but also fosters a sense of accountability and transparency within the community. Moreover, creators who actively seek feedback tend to experience greater engagement and motivation, as the interaction with their audience and peers can validate their efforts and inspire further creativity. The visibility of feedback processes also encourages community members to contribute constructively, enhancing the overall quality of interactions within the platform.

Given these gaps, there is a pressing need to explore both explicit and ambient feedback as a means to better support live streamers. This exploration aims to develop a comprehensive understanding of how these forms of feedback can be harnessed to foster growth and enhance participation in live stream communities.

2.2 Live Streaming Within Online Communities

Online communities have evolved significantly since the early bulletin board systems on the internet. These communities were originally popularized as text-based exchanges such as forums or discussion sites, which are similar to sites that exist today like Reddit [18]. Over time, this landscape has expanded to include a wide array of multimedia formats, even expanding from computer-based to phone-based interactions, additionally giving rise to video-based communities [169]. Even within video-based communities, there are still a variety of subsets such as video-on-demand (vod) and live-stream based communities. My investigation particularly focuses on the live-stream based communities that thrive on real-time interactions, focusing on the dynamic and immersive experiences offered to streamers and their viewers.

Video sharing communities began with platforms such as Youtube, a large-scale video sharing service that offers asynchronous viewing of videos for social connection through channels, following, and comments. Large scale video sharing sites such as Youtube store huge amounts of data across video recordings and linked textual data. While people have conversational interactions on YouTube, most of the social interaction is limited to textual experiences. Additionally, while a video recording is an engaging medium, the asynchronous nature of viewing recorded videos also further limits social engagement [177]. And so, the emergence of live video streaming services emerged that allows for a more specialized relationship between user community and the streamer.

As the landscape of content consumption evolves, numerous studies have explored different facets of community interactions within live streaming. For example, Weisz et al., explore the combination of chatting over text while watching a video together, finding that chatting improves the social experience, despite the distraction and dividing attention [185, 184]. Pires and Simon study how YouTube Live and Twitch offered a wide variety of live content at all hours of the day [145]. Through a logging study on Twitch, Zhang and Liu found that viewers were heavily skewed to the most popular fraction of broadcasters [197].

As live streaming platforms continue to grow and evolve, they increasingly offer a rich, real-time environment for interaction and engagement, shaping a unique form of online community distinct from traditional text-based or asynchronous video platforms.

2.2.1 What is the Creator Economy?

This evolution in live streaming has significantly contributed to the rise of the creator economy, encompassing a wide range of modern creators and influencers. In this section, I will explore the creator economy in detail and examine its impact.

Digital platforms have become a central infrastructure for many facets of public and private life. Within cultural and media industries, sites leveraging user-generated content have significantly lowered barriers of entry for a large number of creators. As researchers have noted, advances in computing and decreases in production costs have led to an increase in production, distribution, and transaction in the web [130]. These days, individuals can easily shoot a video with a cheap smartphone, upload for free, and potentially reach a large and diverse audience [169]. This form of content creation and sharing can lead content creators to earning income without having to deal with a middle man or advertisers. In recent work of Johnson and Woodcock, they note the process of professionalization and career development of those who pursue Twitch streaming as their primary source of income [95].

More recently, the term "creator economy" has emerged as a way to refer to the ecosystem that is formed around content creators who produce and distribute content directly to their audiences through digital platforms [27]. These creators include individuals such as bloggers, podcasters, influencers, live streamers, and other creators who monetize their work through various means such as advertising revenue, sponsorship, merchandise sales, memberships, and direct fan support.

Within the Human-Computer Interaction (HCI) and Computer-Supported Cooperative Work (CSCW) communities, researchers have explored various interconnected aspects of the creator economy, which can be organized into three main levels: platform, creator, and community.

At the platform level, the focus is on design, user experience, and technological innovations that shape the environment in which creators and communities interact. Platform design significantly influences content creation and discovery, as studies on YouTube's algorithmic visibility management reveal how platform algorithms impact content visibility [29]. Similarly, research on deep neural networks highlights their role in shaping YouTube recommendations [49]. Technological advancements, such as the power of algorithms on social media platforms and the unintended consequences of AI in creators' workflows, continue to shape the creator economy landscape [31, 89]. It is worth noting that socio-technical platforms all function very differently and the associated nature of algorithmic pressure significantly varies across platforms like Twitch, Youtube, and TikTok.

At the creator level, the focus is on individual creators, including their work practices, monetization strategies, and identity management. Research has highlighted the socio-technical architecture of digital labor on platforms like YouTube [147] and the evolving governance models in social media entertainment [50]. The labor dynamics and work practices of creators reveal challenges such as job precarity and emotional labor. Studies have examined the complex work practices of creators and the pressures they face in maintaining their online presence [54, 28]. Identity and self-presentation are central to creators' work, and research explores the complexities of digital identity and the quest for authenticity in online spaces, highlighting how creators navigate their online personas [129, 10].

At the community level, the focus is on the interactions and relationships between creators and their audiences, including community building, support mechanisms, and ethical considerations. Community building and collaborative work are supported by platform tools and participatory practices. For example, Twitch fosters mixed media communities and supports creators through both emotional and financial contributions from viewers [75, 188]. The ethical and social implications of content creation include content moderation practices and their impact on creators. These practices shape the online community environment and affect creators' experiences, emphasizing the need for fair and effective moderation [67, 37]. By examining these levels, platform, creator, and community, I can gain a comprehensive understanding of the creator economy within online communities. Each level interacts with and influences the others, creating a complex ecosystem that shapes the experiences of creators and their audiences.

2.2.2 The Growing Significance of Live Streaming

In 2007, Justin Kan created Justin.tv, where he would broadcast his life 24/7. Eventually, he stopped broadcasting himself and relaunched it to a network of thousands of channels. One of the most popular branches of justin.tv was its gaming section which moved to a site called Twitch.tv in June 2011. Since then, Twitch has been the most popular gaming live streaming channel boasting 35 million+ average visitors, 2.5 million+ viewers at any given moment, and 7 million streamers going live every month [Twitch].

Live streaming refers to the broadcasting of audio and video to an audience in real time.

Viewers are able to watch and listen to the streams, and can also interact with and respond to the streamers' actions through a text-based channel. This facilitates a two-way interaction where the streamers can directly respond to and acknowledge viewers, and viewers can participate and influence the contents of the broadcast. The unique form of interaction and culture particularly changed the gaming community, the most popular type of content among live streams, which drew the attention of both investor, and researchers.

Community in Live Stream Communities

Live streaming has been examined within the broader context of online communities. Kraut and Resnick define online communities as virtual spaces where individuals come together to interact, share information, learn, play, and more [108]. This broad definition covers diverse social configurations and technology platforms, such as email lists, forums, blogs, wikis, social networking sites, and live streaming platforms like Twitch. However, live streaming represents a unique context by fostering “micro-communities.” Wohn et al. describe micro-communities as “channels centered around a single or small group of streamers who engage with their audience, where chat interactions are slow enough for participants to follow conversations.” Unlike other online communities, these micro-communities revolve around an individual or a small group, with viewers often referring to the streamer as “my streamer.” Despite this focus, the relationship between viewers and streamers differs from traditional parasocial relationships with celebrities, as it is typically more interactive, involving mutual exchanges between both parties.

Live Streaming has been an interest of HCI researchers (e.g., [115, 180]) given the unique dynamics between live streamers and their platforms. The two main streams of HCI research about this community are focused on motivation and behavior.

Motivation in Live Stream Communities

Questions on motivation have often focused on two parties, the streamers and the viewers. For the streamers, research has been done on asking why do people live stream [79, 36]? Both intrinsic and extrinsic motivations for why individuals live stream. Research has shown that streamers live stream for a variety of reasons, including social connection, self-expression, and financial gain. Intrinsic motivations are those that come from within the individual, such as the enjoyment of streaming or the desire to make friends and grow a community. Extrinsic motivations are those that come from outside the individual, such as the desire for fame or financial gain. Brundl and Hess examined top streamers to find that live stream content is often influenced by streamers' motivation, while the intention to continue streaming is determined by a streamers' social capital [30]. The prospect of earning a considerable income also attracts more users to become streamers.

Researchers have also explored the question of why individuals watch live streams? Before answering the question, I note that live streamers produce content in a range of different domains, such as video games, real life, cooking, education and more [112, 160, 58]. Viewers are drawn to live streamers due to a unique set of personality traits exhibited by the streamers. These traits include a sense of humor, openness to questions, and overall charm, which create an engaging and enjoyable viewing experience [163, 79, 43]. Additionally, the novelty of the streams plays a significant role in attracting viewers, as streamers often provide new and original content that captures interest [163]. The content of the streams themselves contains features that entertain and relieve stress for viewers, further enhancing the streamers' appeal). Finally, the emotional impact of the streamers, expressed through their moods, expressions, and attitudes, inspires and connects with viewers on a deeper level.

Another aspect influencing viewership is the professionalism and skill level of the streamers. Viewers often seek to acquire knowledge in a specific domain such as gaming, art, cooking, and communication [70, 79].

Finally, the social affordances provided by live streamers and their community is an important factor in engaging viewers. The live interactivity of the stream and the willingness of streamers to communicate, answer questions, show appreciation for gifts highly entices viewers and their interactions. The use of advanced technologies for real time broadcasting adds a layer of curiosity for viewers. And finally streamers provides a sense of community and belonging for the viewers.

Challenges in Live Stream Communities

While there has been work exploring motivation, behavior, and community dynamics within live stream communities, there are still gaps and challenges faced by the streaming community, and opportunities for research to make significant contributions. I use insights from prior work to help inform the questions I explore and the challenges I to address in my work.

Pellicone et al. identified that in order to be successful, streamers need to have technical proficiency in streaming technology, need to apply different strategies to build and grow their community, and need to have the right gameplay attitude [143]. They found that new streamers particularly struggle to develop these skills, and hence struggle to grow their community. Hilvert-Bruce et al. also found that streamers wanting to grow their community need to be able to properly address their viewers' needs, specifically social needs [79]. These studies highlight the importance of addressing community growth and engagement challenges not just from the perspective of individual streamers, but as a collective issue within the streaming community

To further understand and address these challenges, I examine the role of feedback exchange within online communities. Feedback plays a crucial role in facilitating growth, engagement, and learning within communities. The next section will delve into related work on online feedback exchange, exploring how feedback mechanisms have been studied and implemented in various contexts, and how these insights can be applied to live stream communities.

2.3 Live Streaming as a Unique Context for Feedback Exchange

2.3.1 Understanding Feedback Dimensions in Live Streaming

Social Exchange Theory (SET) has been widely used to explain relationship-building and feedback dynamics, particularly through constructs such as Leader-Member Exchange (LMX) [68] and Team-Member Exchange (TMX) [44]. These frameworks are useful in structured environments, such as workplaces or team-based creative settings, where feedback occurs within clearly defined social roles and hierarchies. However, the interaction between streamers and viewers in live streaming environments presents a fundamentally different dynamic, one that resists simple categorization into hierarchical or peer-based exchange.

In creative professions like design, LMX often describes the exchange between designers and clients or managers, where high-quality feedback relationships foster trust, autonomy, and creative output. TMX, on the other hand, captures peer feedback in platforms such as Behance or Dribbble, where designers offer critique to one another, encouraging growth through mutual support.

Streamer-viewer relationships are neither strictly hierarchical nor peer-based. Streamers occupy a hybrid role: both performer and community facilitator, while viewers are simultaneously audience members, co-creators, and informal critics. Feedback in this space is shaped by the *performative, participatory, and real-time* nature of live streaming. Viewer feedback is often unsolicited, contextually fragmented, and delivered mid-performance, contrasting with the more structured, deliberate, and curated feedback found in design or educational platforms.

This asymmetry complicates traditional feedback models but also introduces opportunities for new forms of engagement. Feedback in live streaming is inherently more dynamic and unpredictable, requiring streamers to respond in the moment or later synthesize large volumes of chat-based input. As such, this environment pushes us to expand SET to account for feedback exchanges within *asymmetrical but interactive relationships* that are not only functional, but also socially performative.

2.3.2 The Role and Opportunity of Feedback in Live Stream Communities

Foong et al. [60] introduced the Online Feedback Exchange (OFE) framework to model the socio-psychological factors that influence how people seek, provide, and respond to feedback in online environments. OFE identifies five core activities in the feedback loop:

1. Deciding when and whether to seek feedback

2. Effectively presenting work and asking for feedback

3. Incentivizing others to provide feedback

4. Adapting feedback to one's own work

5. Making sense of and integrating feedback into future revisions

While OFE has been influential in designing platforms for creative and learning domains, its assumptions are rooted in *asynchronous, curated, and often static* displays of work, such as portfolio websites, shared documents, or staged critiques. Live streaming breaks many of these assumptions.

Unlike designers or writers who choose when and what to share, streamers receive feedback continuously, often without solicitation. There is little opportunity to "present" their work in a structured way for critique. Instead, they are improvising in real time, reacting to evolving audience input while managing entertainment, technical performance, and personal presence. The temporality of live content and the fragmented nature of chat, makes it difficult for streamers to apply traditional models of feedback-seeking behavior.

In response to these challenges, I conceptualize two complementary modes of feedback engagement for streamers:

Proactive Feedback Seeking: Structured, intentional efforts by streamers to request audience input outside the flow of performance. This includes purpose-built tools or agents that help streamers ask targeted questions, guide community reflection, and synthesize input that might otherwise be lost in the live stream.

Reactive Feedback Interpretation: Analytical processes that help streamers make sense of the spontaneous, high-volume feedback already embedded in their content, such as chat logs, viewer responses, or sentiment trends. These mechanisms work post hoc to distill meaning from otherwise chaotic or overwhelming interactions.

Together, these approaches expand the design space for feedback systems in live streaming. By considering both proactive and reactive feedback channels, this work explores how streamers can better manage audience interaction, make informed decisions about their content, and foster stronger community engagement.

Chapter 3

METHODOLOGY OVERVIEW

In this work, I employ a mix of explore, design, and evaluation methods and I briefly outline what they are and how they are used in the subsequent studies I present in this work.

3.1 Research Context

3.1.1 Target Community

This research focuses on a specific segment of the live streaming ecosystem: small to mid-sized streamers, particularly those with fewer than 200 concurrent viewers. These individuals often fall within the "rising streamers" category identified by Flores-Saviaga et al. in their analysis of audience-streamer interactions, which characterized streamers in this group as having between 6 and 1,879 live viewers on average [59]. While this dissertation narrows its focus to the lower end of that spectrum, many attributes of the "rising streamer" still apply.

Streamers in this range often exhibit early signs of community growth and platform engagement, such as being enrolled in Twitch's Affiliate program or using automated moderation tools like Nightbot or StreamElements to manage chat interactions. These streamers are not novices, they have established some level of consistency and audience loyalty, but they are not yet professionalized or operating at large-scale visibility. As such, they face a distinct set of challenges around audience engagement, feedback interpretation, and community development, which makes them an ideal group for studying feedback exchange and tool interventions.

It is important to recognize that streamers, even within this relatively narrow band of viewer size, are not a monolithic group. They are deeply shaped by their unique cultural backgrounds, personal experiences, and individual goals, which in turn influence how they engage with their audiences and interpret feedback. These differences manifest in varied understandings of what success means, distinct motivations for streaming, and diverse preferences for how data and insights are presented to them. Consequently, designing tools and analytics systems for this community requires sensitivity to these multifaceted identities, ensuring that feedback mechanisms can be tailored to support their specific aspirations and emotional contexts rather than applying a one-size-fits-all approach.

By centering this group, this work aims to support creators who are in a critical stage of growth, navigating both the technical and emotional labor of streaming, without the infrastructural support often available to more established creators.

3.1.2 Researcher Positionality

I chose to study this community because I have been a part of this community for a long time. I have been an affiliate streamer on Twitch since 2019, and have been a long-time viewer on the platform with my longest subscription to a streamer nearing the 6th-year subscriber anniversary. I have been parts of local organizations such as the Seattle Online Broadcasting Association (SOBA) and the 1000 Dreams Fund, who have supported and participated in some of the studies. My prior experiences in the space influenced how the research questions are framed, facilitated access to participant, and informed the translation and interpretation of data collected in the subsequent studies.

3.2 Design and Development Methods

3.2.1 Brainstorming, and Affinity Diagramming

Brainstorming is a generative method used to explore design opportunities, research questions, or problem spaces through open-ended idea generation [186]. Affinity diagramming is a qualitative analysis technique where observations or user feedback are grouped by themes to reveal patterns and relationships [120].

In this dissertation, these methods were used for both the formative stages of tool development, but also to analyze and synthesize qualitative data from interviews and feedback sessions. These activities were conducted collaboratively with other researchers, including student researchers, many of whom were familiar with live streaming as viewers or creators themselves. Their insights helped ensure that emerging design directions were relevant and grounded in community realities.

3.2.2 Prototyping of Tools

Prototyping refers to the process of creating preliminary versions of a system and interfaces to explore ideas and gather feedback. Prototypes can range from low-fidelity sketches to high-fidelity functional systems [153].

This work involved designing and developing two functional prototypes. In study 2, I developed Streamfeed beginning with Figma wireframes evolving into full-stack application using React, Node.js, PostgreSQL, and OpenAI API. Similarly, in study 3, I created PostChat, a post-stream reflection tool built using Flask, HTML/CSS¡ and OpenAI's LLM. These tools were evaluated in real-world streaming environments.

3.2.3 Applications of Large Language Models (LLMs)

Large Language Models (LLMs) are machine learning models trained on massive text corpora to perform language understanding and generation tasks [136]. In HCI, LLMs are increasingly used to power chatbots, summarize text, classify sentiment, and scaffold user reflection.

In this dissertation, LLMs, specifically OpenAI's GPT-4 and GPT-4o, were used to support multiple feedback-related tasks. In Streamfeed, LLMs helped synthesize structured viewer feedback into digestible summaries. In PostChat, they supported persona generation and chain-of-thought reflections, as well as classification of tone and intent in chat logs. Prompt engineering and iterative evaluation helped tune these systems for streamer interpretability and trust.

3.3 Exploration and Evaluation Methods

3.3.1 Interview Studies

Interview studies are a foundational qualitative research method used to explore participants' perspectives, experiences, and practices in depth. Semi-structured interviews combine a consistent set of core questions with the flexibility to follow up on emergent themes [183]

In this dissertation, interviews were conducted with streamers to understand how they interpreted feedback, what types of analytics they rely on, and what technical and emotional challenges they face. Thematic analysis was then use to identify recurring patterns and inform the design of feedback tools. These interviews provided a rich understanding of both individual and shared experiences, which shaped the conceptual framing of proactive and reactive feedback.

3.3.2 Remote Usability Testing

Usability testing is a method used to evaluate how real users interact with a system in order to identify problems, assess functionality, and gather feedback [55]. Remote usability testing allows participants to use tools in their own environments, which is particularly useful for studying live streamers who operate in context-specific, performance-based settings [76].

All tool evaluations in this dissertation were conducted remotely, allowing streamers to use the tools naturally during or after their broadcasts. Evaluation methods included screen recordings, structured feedback forms, and follow-up interviews. This approach helped assess both usability and emotional impact, ensuring that tools were not only technically functional but also aligned with streamer needs and workflows.

Chapter 4

UNDERSTANDING ANALYTICS NEEDS OF LIVE STREAMERS (RQ1)

This first study is the informational foundation of the dissertation, focused on how streamers interpret, utilize, and seek feedback through platform-provided and community-driven signals.

4.1 Introduction & Related Work

To attract streamers and good content, social media platforms, such as Youtube and Twitch offer financial incentives in the form of donations or subscriptions from audiences, advertisements, or sponsorships. Ninja, arguably the most popular live streamer, had around 1.5 million subscribers on Twitch before switching to Mixer, and reportedly earned about 5.5 million USD per year [66]. However, while top streamers may receive millions of viewers and earn millions of dollars annually, most streamers struggle to grow and engage their community. In their work, Pellicone et al. identified that in order to be successful, streamers need to have technical proficiency in streaming technology, need to apply different strategies to build and grow their community, and need to have the right gameplay attitude [143]. They found that new and smaller streamers particularly struggle to develop these skills, and hence struggle to grow their community. Hilvert-Bruce et al. also found that streamers wanting to grow their community need to be able to properly address their viewers' needs, specifically social needs [79]. These prior works have emphasized the importance and challenges that streamers face around community growth and engagement.

One potential solution to help streamers host more successful streams is to provide them insight through analytics. This is akin to businesses or education institutions leveraging analytics to make more informed decisions [80, 162]. While existing stream platforms do offer analytics to their viewers, little is known around the validity and efficacy of these tools. This leads us to our research questions (1) How do streamers utilize the current information provided to them by their respective streaming platforms? (2) What additional information do streamers need and why? (3) What are some challenges and opportunities to support live streamers and their viewers?

To answer these questions, we first analyzed existing streaming analytics to identify key types of information made available to streamers. For scope, we focused on video game streamers, who represent the largest category of online streamers [170]. We conducted semi-structured interviews with 18 video game streamers from Twitch and Mixer to understand their current practices and needs. We also explored these streamers' respective Discord servers to understand the types of information they seek and solicit from their communities. Overall, we make the following contributions:

- We outline the current ecosystem of analytics and tools that video game streamers use for information seeking
- We describe key information types that address game streamer's identified marketing, content, and community needs.
- We show that there is need for developing human-centered analytics for live game streamers, given the current limitations of internal and external tools.

The goal of this work is to add to the existing knowledge of live streaming by focusing on the analytics aspect of their practices. This paper begins by discussing prior work on live streaming analytics and analytics in other contexts, followed by a qualitative method of interviewing 18 streamers and an exploration of their community, results and insights from these interviews, and a discussion of our findings with design implications.

4.1.1 Live Streaming

While live streaming continues to attract new broadcasters everyday, becoming a successful streamer is not easy. As found in Johnson and Woodcock's study, professional live streamers generally use the number of viewers and subscribers to determine the success of a given stream [95]. This is not surprising as live stream platforms often have a minimum requirement with regards to viewers and followers for creators to be eligible to monetize their content, which is referred to as the affiliate status on Twitch and partnership status on Mixer. As of 2018, Twitch has reported only approximately 220,000 have reached affiliate status on their platform, which represents less than one percent of their then 3 million creators [9].

We should note that monetizing content, or having a large viewership, is not the only definition of success on streaming platforms. As explored in prior work, aside from those extrinsic factors, live streamer's motivation can also consist of intrinsic factors, such as joy and social interaction [79]. However, even these streamers' view of success are dependent on having a group of viewers (even if small), and unfortunately, many streamers end up broadcasting to no one [78]. Hernandez found that streamers often felt disheartened, exhausted, and found it hard to stay positive after streaming for hours with no social interaction.

In Pellicone and Ahn's work, they identified that streamers need to have (1) the technical proficiency in the hardware, software, and graphic design elements of a broadcast; (2) the right gameplay attitude in adopting a fun, casual, and naturalistic attitude to streaming; and (3) the skills to build a community to increase viewership and potential revenue, and also to retain a consistent group of regular viewers. [143]. However, they found that new streamers often lack the information to develop these skills and would retire soon before they hit their goals. They also found that streamers find streaming to be burdensome because of the unanticipated competition for viewership. Similarly, Wohn and Freeman noted how streamers utilized internal and external tools to discover information about their audiences for management [190]. Similar work has also outlined other challenges that streamers face, such as knowing what content to prepare for their stream, or how to stand out amongst other streamers and attract specific viewers [63, 58]. All of this points to an opportunity to provide streamers with useful information and insights to help them improve their streams.

4.1.2 Research on Analytics in Other Contexts

Though minimal research exists on analytics for live streaming, analytics are increasingly used in fields such as business and learning to help develop actionable insights. Business analytics (BA) is primarily concerned with transforming different sets of data into creating useful insights for organizations [80]. Business analytics uses structured data from simple reporting to forecasting; uses unstructured data such as audio and video to support knowledge acquisition, insight generation, problem finding, and problem solving; and uses qualitative data to support decision making with methods such as cognitive mapping and robustness analysis. The overall goal of business analytics is to advance systems and mechanisms for acquiring, generating, assimilating, selecting, and producing knowledge relevant to making business decisions. Similarly, the field of learning analytics (LA) is primarily concerned with utilizing data about learners and their context in order to optimize learning and their environments [162]. Learning analytics can be applied and studied in different levels from the individual learner, the classroom, the institution, and more. These levels afford different sets of data for techniques and applications of learning analytics. Learning analytics techniques are reflective of machine learning and AI methodologies, while applications involve user modelling, knowledge domain modeling, personalization and adaptation [162].

While business and learning analytics focus on different contexts, these analytics have been broadly categorized into: descriptive, predictive, and prescriptive [122]. (1) Descriptive analytics uses data to figure out what happened in the past. Then, it uses and analyzes historical data to identify patterns from samples for reporting trends. Techniques that enable descriptive analytics include dashboards, scorecards, and data warehousing. (2) Predictive analytics uses data to figure out what could happen in the future. It uses a variety of models and techniques to predict future outcomes based on historical and current data. Predictive analytics is what translates big data into meaningful, usable information by allowing decision makers to learn from data how to predict the future behavior of individuals. Techniques that enable predictive analytics include data mining, text mining, and statistical time series forecasting. (3) Prescriptive analytics uses data to prescribe the best course of action to increase the chances of realizing the best outcome. These algorithms may rely solely on data, or expert knowledge, or both. The main outcome of prescriptive modeling is either the best course of action for a given situation, or a rich set of information and expert opinions to provide to a decision maker that could lead to the best possible course of action. Techniques that enable prescriptive analytics include optimization modeling, simulation modeling, expert systems, and group support systems.

However, despite the potential of these analytics, both business and learning analytics still face problems of adoption [110, 151]. Researchers and practitioners have noted that for these analytics to be useful, they need to be human-centered [32, 83]. Applying insights from human centered design, Shum et al. argues that designs of (learning) analytics "should therefore take into account the range of people who will engage with them (who?), what all those people will do with them (what?), the various occasions on which these interactions will take place (when?), the ways in which the analytics will form part of interaction and discourse (how?), and the meanings that these analytics, interactions, and discourse will have for stakeholders (why?)" [32].

Therefore, the goal of this work is to explore the use of analytics for streamers, and to explore their analytics needs. Specifically, we decided to focus on video game streaming. We do so for two key reasons: (1) video game streaming represent a large proportion of live streamers since key popular platforms, e.g. Twitch and Mixer, were initially designed specifically support live game streaming; (2) furthermore, analytics in this space remains underdeveloped and under explored, as an industry that's increasingly embedded in daily lives.

4.1.3 Twitch, Mixer, Discord and Existing Analytics

Twitch is the premiere and largest platform for live streaming [101]. It originally prioritized video game content, but its increasing popularity attracted content creators across different domains, generating new categories over time to support the content production on the platform [8]. A recent report shows that Just Chatting, a category dedicated to streamers talking with their community without any other content or gameplay shown on stream, continues to be the top category on Twitch with around 175 million hours watched in July

2020 followed by League of Legends and Fortnite [41]. As the dominant market leader in the live streaming industry, the streamers on this platform provide great insights about their experiences regarding community building, content creation, and media production.

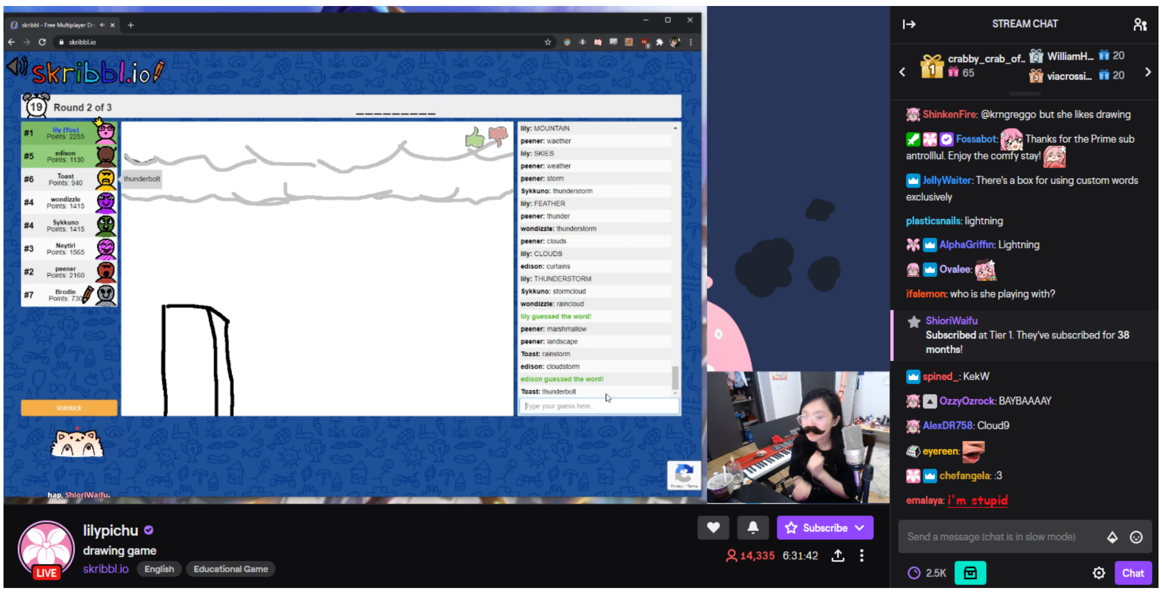

Figure 4.1: This figure shows the interface of Twitch.tv, specifically lilypichu's channel. The left panel consists of an image of skribbl.io, a multiplayer drawing and guessing game; a camera showing the streamer and her background; the title of the stream with its associated category and tags (english, educational game); viewer count (14, 3350; stream duration (6:31:42). The right panel shows the stream chat, which consists of the top 3 gifters in the community; a running text channel that shows usernames: messages, and stream activities such as a subscription event; and a text box to send a message.

Figure 4.2 shows a snippet of the stream analytics provided by Twitch over the course of 30 days. This snippet is mostly centered on 4 key metrics regarding the streamer's viewers, followers, subscribers, and revenue. The stacked histogram also shows the breakdown of revenue sources such as from different types of subscribers. On the rest of channel analytics page, Twitch also offers further information such as (1) the breakdown of revenue streams (i.e. paid subscriptions, prime subscriptions, gifted subscriptions, ads, and more), (2) breakdown of subscriber tiers (number of tier 1, tier 2, and tier 3 subscribers), (3) source of views within Twitch (i.e. views from other channels, views from followers or browse page), (4) channels with similar viewers, (5) reach of Twitch notifications, (6) breakdown of top clips in the channel, and (7) breakdown of tags used to find the channel.

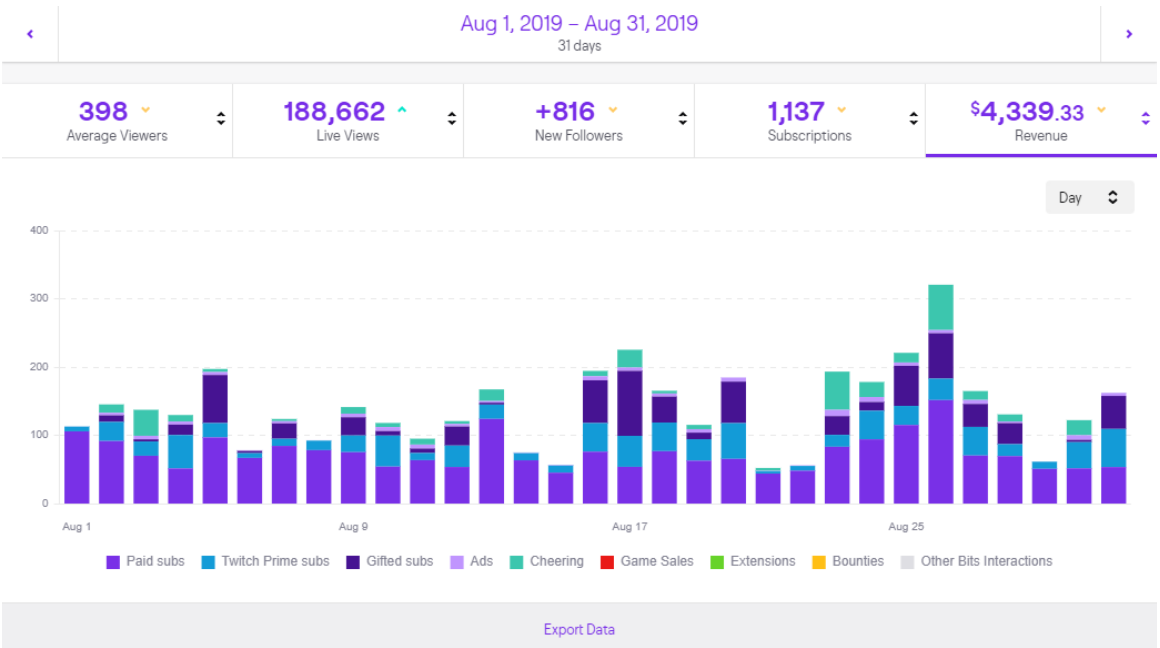

Figure 4.2: This figure shows a snippet of Twitch stream analytics. At the very top, it shows the duration of the statistics from Aug 1, 2019 - Aug 31- 2019. It also shows statistics on average viewers (398), live views (188, 662), new followers (816), subscriptions (1137), revenue ($4339)[2].

Similarly, Mixer was a competitive and increasingly popular live streaming platform primarily focused on video game content. In 2019, Mixer acquired several large streamers from Twitch, including Ninja, which included reportedly around a $40 million contract over three to five years [66]. These partnerships signaled a large investment in streamers that potentially increased the platform's potential. During the process of interviewing streamers, we found value in the perspective of Mixer streamers with this resurgence and growth. However, not long after we completed our study, Mixer was unfortunately shut down and no longer exists as a live streaming platform.

Other large platforms in this space include Facebook Gaming and Youtube Gaming. In our work, we decided to focus on Twitch and Mixer because of their emphasis on video game

Figure 4.3: This figure shows the interface of Mixer, specifically showing Ninja's channel. The left panel consists of an image of Fortnite, a battle royale shooter game; a camera showing the streamer and his background; the title of the stream; and the number of viewers. The right panel shows the chat with the viewer's username and message.

live streaming, as opposed to YouTube that has an emphasis on video-on-demand service and less on live interaction, and Facebook, where user accounts are too closely associated with their personal information.

We inspected the analytics offered by Twitch and Mixer, and categorized them into metrics related to stream performance, viewer engagement, and revenue. Table 4.1 shows the current set of statistics available on either Twitch, Mixer, or both. These are a combination of information presented to streamers in real time, and also information presented to streamers as an after-stream summary. While we found that both platforms had overlapping metrics, we found that Twitch offers more insights regarding viewer engagement analytics. On the other hand, Mixer offers a platform level statistic, top games streamed, while Twitch does not offer any platform level insights to their creators. We also noted how both platforms provided a thorough account of revenue-related analytics.

Another important tool that streamers may be using to communicate with and understand their audience's needs is Discord (Fig. [4.4]). Discord is a free VoIP, instant messaging, and a digital distribution cross-platform designed for creating and supporting communities in the form of servers [1]. Every user can create their own servers that range from the size of a small group of friends to larger communities with hundreds and thousands of members [92]. We will also examine the use of Discord by streamers in our work.

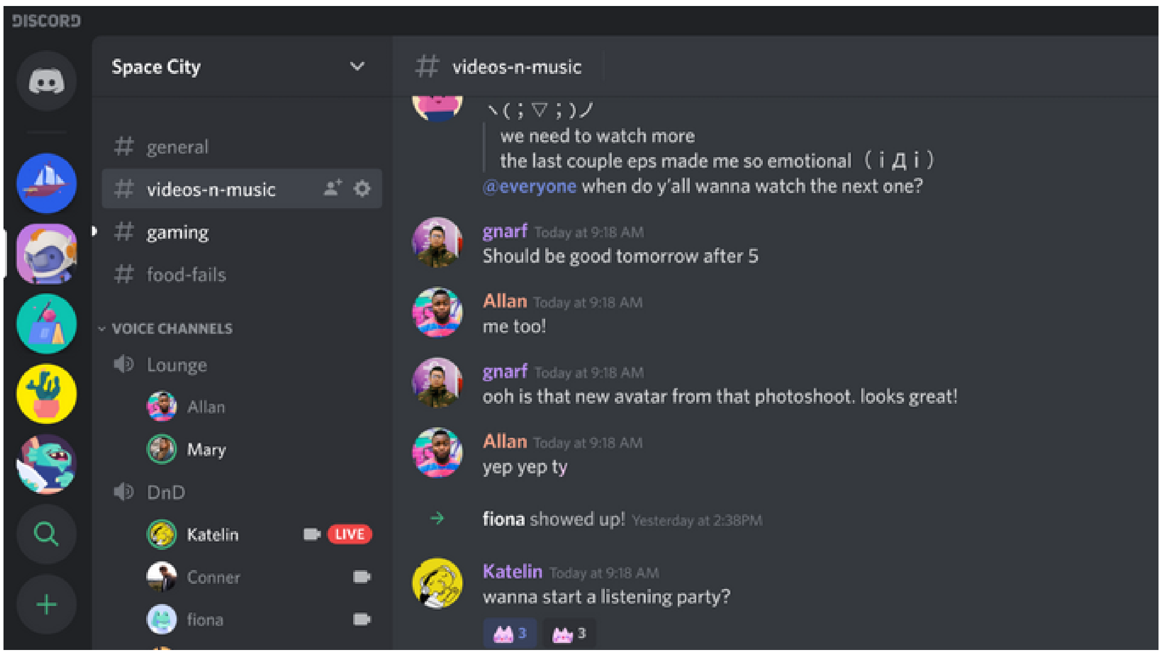

Figure 4.4: This figure shows a screenshot of Discord. The leftmost column shows the list of servers the user is a part of. The following section shows the list of channels in the specific server including both text and voice channels, and the rightmost section shows the exchange of messages in the “videos-n-music” channel.

4.2 *Interview Study*

Below, we describe our interview study with streamers from Twitch and Mixer to have a better understanding of their practices and needs.

4.2.1 Methods

We recruited video game live streamers who regularly streamed on Twitch or Mixer with a range of experiences (6 months to 9 years) and community sizes (129 followers to 67,934

Table 4.1: Twitch and Mixer Analytics

Category	Metric Description	Twitch	Mixer
Stream Performance	Live views: Total number of views of all the channel's live streams	✓	✓
	Clip views: Total views from clips created from the channel	✓	
	Minutes watched: Total time the live stream was viewed across all viewers	✓	
	Average viewers: Concurrent viewers in a given stream	✓	
	Max viewers: Peak viewers the channel received in a given timeframe	✓	
	Unique viewers: Number of unique viewers in a given timeframe	✓	
	Host/Raid viewers: % of viewers from a host or raid	✓	
	Time streamed: Total time the streamer broadcasted	✓	
	Top games: Most streamed games at a given moment		✓
	Platform: Breakdown of viewer platforms (e.g., mobile, desktop)		✓
	Countries: Geographic breakdown of viewers		✓
Viewer Engagement	Subscriptions: Number of subscriptions received in a given timeframe	✓	✓
	Follows: Number of new followers	✓	✓
	Unique chatters: Number of unique users who chatted	✓	
	Chat messages: Total number of chat messages sent	✓	
	Clips created: Number of clips created from a stream	✓	
Revenue	Revenue: Total revenue generated	✓	✓
	Ad breaks: Total duration of ad breaks during stream	✓	
	Ad time/hour: Average ad time per hour	✓	
	Notification engagements: Followers who engaged with stream alerts	✓	
	Promotion impressions: Views during promotional periods	✓	
	Promotion clicks: Clicks from promotional content	✓	
	Leaderboards: Top currency contributors on the channel		✓
	Plotlines: Amount of sparks/embers spent over time		✓
	Milestone report: Status of sparks milestones		✓
	Sparks from streaming: Total sparks earned during streaming		✓

followers). The authors reached out through social media platforms and also through in-person streamer meetups. We informed the participants that this study is voluntary and that they would not be compensated for their participation. All interviews were semi-structured and conducted as a voice call on Discord, and all but one consented to being recorded. Each interview lasted from 30 to 60 minutes. We notified the participants that they would remain anonymous, and that they had the option to refuse to answer any question or leave the interview at any moment.

We began by asking interviewees to recall their most recent streaming experience on their respective platforms, and then asked questions around their general streaming experiences, including things such as their motivations and routine. Next, we asked them about their interaction and engagement practices with their viewers, and inquired about positive and negative experiences on the platform. Then, we asked about their current and desired information about their viewers. Lastly, we asked them if there was anything they wanted to share that we did not touch upon.

To gain a better picture of their practices, the authors also investigated and analyzed the messages in the participants' discord servers. All of our participants ran Discord servers as an auxiliary community platform for their streams. The primary goal of this analysis was to understand the types of questions that streamers asked their community. This process was conducted after our interviews to supplement our initial findings regarding information seeking behavior of streamers.

4.2.2 Participants

From November 2019 to February 2020, we recruited 18 participants with a range of experiences and audience sizes to have a broad understanding of their use of analytics. The final sample included: one gender-fluid, three female and 14 male; age ranged 21 to 34 (broadly representative of Twitch streamer demographics [95]); 17 streamers from USA and one from Germany; and 5 Mixer streamers and 13 Twitch streamers (see Table 4.2). These streamers primarily broadcasted video game content, from single-game streamers to variety streamers. While some of our interviewees considered live streaming as a full time job, most of our interviewees only considered live streaming as a part time occupation and had a different job as their main source of income.

Table 4.2: Participant Demographics of Study 1

Participant ID	Gender	Age Range	Country	Platform	Followers	Experience	Stream Employment	Occupation
s1p1	M	22–28	USA	Twitch	1,000–5,000	2 Y	Part-time	Digital Marketer
s1p2	M	29–38	USA	Mixer	10,000–50,000	3.5 Y	Full-time	Content Creator
s1p3	M	29–38	USA	Twitch	10,000–50,000	5 Y	Full-time	Content Creator
s1p4	M	22–28	USA	Twitch	0–1,000	2.5 Y	Part-time	Delivery Driver
s1p5	M	29–38	USA	Twitch	50,000+	9 Y	Part-time	Content Creator
s1p6	M	29–38	USA	Twitch	0–1,000	3 Y	Part-time	Webinar Producer
s1p7	M	18–21	USA	Twitch	10,000–50,000	1.5 Y	Full-time	Content Creator
s1p8	M	18–21	USA	Twitch	50,000+	1.5 Y	Part-time	College Student
s1p9	M	22–28	Germany	Twitch	50,000+	6 Y	Part-time	Esports Coach
s1p10	GF	29–38	USA	Twitch	0–1,000	6 M	Part-time	Voice Actor
s1p11	F	22–28	USA	Twitch	0–1,000	2 Y	Part-time	Veterinary Technician
s1p12	M	22–28	USA	Twitch	0–1,000	8 M	Part-time	Security Guard
s1p13	M	29–38	USA	Twitch	0–1,000	6 M	Part-time	Software Engineer
s1p14	M	18–21	USA	Twitch	5,000–10,000	6 Y	Part-time	Personal Trainer
s1p15	F	29–38	USA	Mixer	10,000–50,000	1 Y	Full-time	Content Creator
s1p16	M	22–28	USA	Mixer	50,000+	1.5 Y	Part-time	Software Engineer
s1p17	M	22–28	USA	Mixer	50,000+	2.5 Y	Full-time	Content Creator
s1p18	F	29–38	USA	Mixer	10,000–50,000	6 Y	Part-time	Community Manager

4.2.3 Analyses

For our analyses, we followed the Grounded Theory Coding process discussed in Charmaz [38]. We collected two types of data, interviews and data from discord servers. For data from discord servers, we collected around 8000 streamers' messages from our participants' channels within the past 6 months, ranging from as little as 110 messages to 600 messages.

In analyzing the interview data, the first step was for each author to analyse a subset of the first six interviews, generating a set of open codes. After collating these into an initial set of codes, the authors then engaged in an iterative process of reviewing and labeling the data with emerging codes. During this process and prompted by the emerging themes, the authors reached out to the participants to follow up on the current usage of stream analytics and their perceptions on predictive and prescriptive analytics. The authors then repeated the process for reviewing and labeling the follow-up results based on the existing codes. Once the codes were established, similar codes were used for analyzing the messages collected from Discord servers, paying extra attention to messages that were pinned (messages that were particularly flagged as special) or messages that tagged everyone in the channel. The results were interpreted based on their relation to the current usage of analytics and the types of information needs.

4.3 Video Game Live Streamer's Uses of Current Analytics

In this section, we present findings about current practices of live streamers before, during, after, and outside of live streaming.

Before a stream starts, streamers often announce to their followers and community members that they are about to go live through social media platforms such as Instagram, Discord, Twitter, and Facebook. When a streamer goes live, platforms also provide in-app notifications and pop-ups to their followers. Streamers utilize social media platforms to maximize the reach of current and potential viewers. Some streamers also tend to look at platform trends to inform the type of content that they are about to broadcast. One of our interviewees who had experience with streaming on Twitch and Mixer shared:

"I mostly use [Mixer analytics] to track trends rather than specific numbers [because] it's helpful for game to game comparison." (s1p2)

Per Table 4.1, Mixer offers information on the top games streamed on the platform that gives insights to streamers about the most popular game being streamed at a given moment.

Once the broadcast starts, streamers utilize the chat to receive information from their community such as various types of feedback, to converse with their community, and to view dialogue between community members. The chat feature also lets streamers know about new members of the stream whenever they come across a new or unfamiliar name. Additionally, streamers have an associated dashboard with their broadcast that shows them an activity feed and statistics for that specific broadcast. The activity feed informs the streamers about new followers, new subscribers, raids/hosts, and bits (twitch currency) donations. Some of these events could also have an associated message directed either to the streamer or fellow viewers. Moreover, streamers also have access to statistics such as length of stream, viewers, total views, followers, subscribers and bitrate (the speed of upload and download). These statistics allow streamers to view the progress of a given stream, such as seeing increase or decrease in followers and subscribers, or the progression of viewership throughout a broadcast.

“[Twitch Analytics is] so much more easier to use for new streamers. I can basically find anything I need so fast from changing the stream name or game to checking my stats per stream or even checking how much income you’ve made that month” (s1p12).

Internal analytics are appealing to new streamers because of its accessibility and simplicity. It allows the streamers to manipulate various content features such as title and category very easily, and also presents analytics in a digestible manner.

Outside of internal analytics, streamers also utilize external analytics during a broadcast such as StreamElements, which is an all-in-one platform providing tools for stream production, monetization, engagement, marketing, and sponsorships [167]. Particularly, StreamElements enable streamers to receive donations from external payment platforms, such as PayPal, and allow viewers to send a message with the donation. Amongst other platforms, StreamElements also provides a chatbot that can blacklist keywords for moderation, and can occasionally post messages often used for promoting other social media links.

Immediately after a stream, streamers are provided with an after-stream summary of their progress, which includes statistics from Table 4.1. Streamers primarily utilize this to visualize the progress of a given stream, and also to compare their progression over a period of time. This aggregate view of statistics of one or multiple streams enable streamers to look at trends about their content and viewership. This also provides an in-depth analysis of their revenue statistics outside of subscriptions and donations, since streamers also receive monetization from ads, or partnerships with game developers.

Similar to their practice during a broadcast, streamers also utilize external platforms to track growth as a streamer and progress towards platform milestones immediately at the end of their stream. One of our interviewees identified Arsenal.gg as a platform that provides more details than the internal analytics.

“[Arsenal] gives me stats about peak viewership for that stream or a couple of streams. It gives me very good analytics. That’s actually what I used in order for me to get partner [status] because it let me know whether or not I should apply for partnership.” (s1p15)

Arsenal provides viewership statistics that are broken down by the types of games, which is not currently offered by current existing internal platform analytics. These game-specific insights enable streamers to narrow down appealing features about their stream content and also enable streamers to track down self-defined game-specific goals. Additionally, Arsenal offers prescriptive analytics by recommending when streamers should apply for platform partnership from the set of statistics that they collect.

Outside of this time frame, streamers are primarily active on social media platforms and Discord servers to continue interaction with their community. This interaction allows them to solicit and receive direct feedback from their audience such as asking what games should be played for the next stream, or insights about a new feature embedded on the stream. The time spent outside of streaming is mostly dedicated to community interaction to support stream production and community growth.

To summarize, we found that streamers utilize a variety of tools to support the growth of their stream and their community. During a stream, we found that streamers primarily have access to viewer engagement through chat and viewer statistics, and also have access to revenue information through internal and external donation channels. After a stream, we found that streamers primarily look at visualizations of analytics to see their progression towards milestones and growth as a streamer. Outside of stream, we found that streamers prioritize community interaction and management through external communication channels.

4.4 Information Types To Support Analytics Needs

Through our interviews, streamers defined information needs around improving their content, improving their marketing tactics, and supporting their community. The set of information types we found often addressed multiple needs, such as viewer age addressing content and community needs.

Table 4.3: Key Information Types across Areas of Analytics Needs

Content Production	Marketing Strategies	Community Management
Viewer Age	Viewer Income	Viewer Age
Viewer Timezone	Viewer Timezone	Platform-level Viewer History
Viewer Location	Viewer Location	
Shared Interest with Streamer	Viewer Stream Interest	
Content-specific Feedback	Viewer Referral Source	
	Platform-specific Trends	
	Platform-level Category Saturation	
	Platform-level Time Saturation	

4.4.1 Content Production

Live streaming content production encompasses many things such as the main content, the technical features (whether the stream has high resolution or a crisp camera), and the personality and conversations carried by the streamer. Our interviewees have noted that they are lacking information that can support and improve this area. They noted viewer demographics and shared interest as information types that can help address this space. Through our interviews, streamers noted that viewers' shared interests serve as conversation starters that allow streamers to spark interactions with community members. Personalized interactions are an important aspect of live streaming. They fulfill a social need from the viewer and streamers' perspective. However, current interaction practices are limited because there is a lack of information for streamers to initialize these conversations. Several interviewees noted that having this shared interest is helpful in establishing intimate relationships and interactions. For example, one participant talked about how a shared interest in a similar game such as Super Smash Bros or the genre of retro games helps him start conversations with his viewers.

“So if they join and they’re interested in Smash [game], that’s helpful. If they join in and they’re interested in retro games, that’s helpful. Helps me establish conversation pieces with them. And it would be a good way to find shared crossover audiences I hadn’t anticipated” (s1p1).

Similarly, another interviewee mentioned that shared interests in the game of Half Life, or the genre of shooters, or esports in general enables them to have a dialogue with the audience. For live streaming, a large part of their content is their personality, with a large emphasis on conversations. “If I knew that you’re playing half life and love shooters and love esports. Those are things that I can pop off like, ‘which games do you like? which teams do you like? and so on‘” (s1p5).

When streamers are aware of their shared interests with their viewers, they will utilize that information to interact and constantly engage their viewers with their content. It is a way for streamers to fill in the empty air, but also shifting the conversation away from themselves and the gameplay and towards their community.

Similarly, streamers also want to be able to tailor their content not just individually, but to a subset of their viewers. Different viewers can be attracted to a channel for different reasons, such as the streamer’s music, personality, or gameplay. Through our interviews, streamers identified that viewer demographic information such as viewer age-range, timezone, and location will enable them to tailor their content. In particular, age-range enables streamers to broadcast age-appropriate content, whether that means narrowing their content to a family friendly community or to a mature community. One of our interviewees only streams family-friendly content and also manages a team of family-friendly streamers. For them, family-friendly means “avoid using profanity both on-stream and in chats, avoid engaging in vulgar or explicit discussions, all while promoting general positivity and good vibes.” This streamer and their community value creating content that is open to a younger audience and their family.

Moreover, viewers' location and timezone information enables streamers to target their content based on language or regional preferences. For example, s1p10 noted that their East Coast friends have tuned in to their Sunday streams and have attracted more European viewers to watch their weekday streams because "it's a very good time for them to be watching then." In this instance, our interviewee noted that different streaming times have attracted different audiences based on their location. In a different instance, s1p6 noted that his viewers have been predominantly international recently, and his Latin American viewers have preferred interacting with him in both Spanish and English. Being able to know content preferences of viewers' timezone and location enables streamers to tailor specific gameplay or persona to their audiences.

In our exploration of Discord servers, we also found that streamers ask for content-specific feedback from their community. An example includes s1p16 sharing designs of potential subscriber badges and asking for his community to vote on a design and give specific feedback. Other questions include opinions on adding a specific overlay, or game suggestions for content and viewer engagement. However, it is worth noting that this is not a practical way to interact with community members live, given the already cognitively overwhelming ecosystem streamers have during a stream.

4.4.2 Marketing Strategies

Another area that our interviewees noted struggling in was the lack of information to support their marketing strategies. Marketing strategies refers to identifying information within and outside of their streaming platform that enables them measure and optimize their return on investment. We found that several information types address this need such as platform-specific trends (i.e. top games on Mixer), viewer referral source, viewer stream interest, and viewer demographics including income, timezone, and location.

While stream analytics offer some data around where viewers are coming from, this data is limited within the platform and streamers are unable to identify the efficacy of their other social media efforts. Streamers often promote their streams on Twitter, Facebook, and Discord; however, there is no way for them to see how much those promotions have translated into actual viewership. This information would enable them to allocate resources appropriately, whether they should increase advertisement on a specific channel or whether they should give up on a different channel. One of our interviewees shared a current limitation of internal analytics:

"Where [did] these people [viewers] came from? Did they click a Discord link? If so, from what server? Probably would be hard to get that info but it would be very nice to have" (s1p6).

Additionally, streamers want to be able to compare their stream content and performance against other channels to help inform their marketing strategies. However, there is little information available to them to make these assessments. Specifically, they noted that the lack of information around category and time saturation prevents some streamers from achieving their maximum viewership potential, and also limits them from potential stream collaborations. Category saturation informs streamers about categories that are populated with the most viewers and streamers, which can allow streamers to strategize around the content that they are about to broadcast. Similarly, time saturation refers to the distribution of content production and consumption on the platform for a given time, which can inform a streamer's broadcast schedule and optimal time to promote their content on social media. While streamers already receive plenty of information during their broadcast, they still lack integral information about their viewers outside of broadcast. The lack of platform level information is not only detrimental to the streamers' potential but also to the streamers' community.

"Am I streaming at an effective time? Am I streaming where people can actually see me or am I streaming too late or too early? Am I playing the game that people tend to like watching me play or not?" (s1p14)

Finally, similar to how viewer demographics of timezone and location allows streamers to tailor their live broadcasted content, viewer demographics also enable streamers to send target marketing notifications to different subsets of viewers. As one our interviewees mentioned, "It would be nice to send out like targeted notifications to people. Because I don't always just want to spam everyone that I'm playing a game because then they'll just unfollow and then they won't get notified the next time I play a game that they actually care about" (s1p12).

In this instance, the streamer noted that spamming notifications to everybody can lead to losing community members, thus being able to target subsets of audiences is more advantageous from a marketing perspective.

Streamers have identified a set of needs that can help them make decisions around optimal resource allocation regarding promotions, and to help them maximize return on investment of their streams.

4.4.3 Community Management

Community building and management is a key skill in being a successful streamer [143]. This was reflected in our findings, when our interviewees identified several information types related to community building. First, streamers identified that viewers' history or prior behavior and viewers' age are useful information types that can support community management.

"A general community idea of upvoting people for being helpful in chat, or [information] that this person has participated in polls in this chat X amount of time. I think that it could be really cool to not just have bits, which are entirely money based, but like citizen scores" (s1p10).

In this instance, the streamer s1p10 was asked about their opinions on having more information regarding a user's prior behavior. They are describing the need for information around a user's history to have an indicator of their potential to contribute within a community. Similarly, streamers also take note of viewers who often donate of gift subscriptions to a channel because of how well they foster growth within that community.

We also found that streamers asked questions about their community on their Discord servers. One of our interviewees asked about their community's opinion on potential platform transitions, given that Mixer was shutting down. Additionally, streamers also use this space to post about applications for stream moderators, who are community members that ensure that chat is behaving according to community norms.

Another key theme related to community is the topic of safety, with regard to having younger viewers. Streamers are concerned in being able to foster a safe space for kids in their channel, such as being wary of toxic or not safe for work (NSFW) messages. This also allows streamers to help shape moderation practices and community norms within their channel. One streamer in particular notes,

"If I knew for example that every one of my viewers was like 13 maximum, in terms of age, I will not swear on stream anymore. I'll be a bit nicer and would probably not swing ban hammers as quickly" (s1p9).

Here the streamer is noting that knowing viewers' ages enables him to cater his actions and also cater his moderation practices so as not to push away this group viewers. In a sense, this enables him to craft his community space to cater to his community's actions and attitudes. Similarly, streamers are also interested in having a better understanding of their viewers' prior behavior in other channels. While most streamers welcome any new viewers to their channel, it is not unusual to attract negative viewers, or "trolls". Knowing viewers' prior history can equip streamers and their moderators to be prepared with deleting messages or immediately banning that member from their community. As our interviewees noted:

"Their [viewers'] history on a banned list, like knowing if they're banned from a channel and what their ban is for, because sometimes you don't want toxic viewers. But if that viewer is like really good at hosting or donating or following. That's good to know too" (s1p16).

"Okay, this guy's been banned 45 from other people's channels that would be really useful for me to be aware of that. Okay, this guy is being nice to my chat right now there's a possibility there's ulterior motives, right? need to keep an eye on them" (s1p18).

4.5 Additional Insights

Across these analytics needs, we describe a couple of high-level insights that persists through streamer's content, marketing, and community needs.

4.5.1 The Current Lack of Predictive and Prescriptive Analytics

Through our analyses, we noted that current analytics generally focus on providing descriptive data. These platforms offer similar and repetitive time series visualizations for various statistics. However, data analytics can be more than just descriptive, as suggested by business analytics that have found success in applying these in their systems and applications [162, 80]. Our interviewees also noted the value and potential for predictive and prescriptive analytics across their needs for content production, marketing strategies, and community growth. For example:

"Getting an idea of when my audience tends to be on Twitch would be helpful" (s1ps15). "It would very useful if there was analytics on predictive patterns ... and have a tool stating like 'around this time people usually start leaving the stream' to enable us to figure out a way to change things to somehow keep people involved" (s1p12).

P5 reported wanting information about viewer behaviors to help him figure out a future stream schedule that could maximize viewership. Similarly, s1p12 wants information around viewer behavior to be able to update his content to keep viewers interested and engaged during a stream. In both scenarios, predictive analytics can help. Having predictions of viewer behaviors before and during their streams can enable advertising at the optimal time, and changing contents appropriately.

"Things like what games caused you to earn the most viewers versus the amount of viewers who are returning per stream. Those kind of things I'm looking for because it tells me where and what things I'm doing right and wrong for my channel. Being able to evaluate your moves like it was a chess board can allow you greater success while only guessing can get you to success but only on a whim" (s1p14).

S1p14 is hinting at the desire for prescriptive analytics that can help him inform his content and marketing strategies to achieve greater success as a streamer. In particular, he is hoping for analytics to provide actionable insights that is grounded in his historical data.

4.5.2 The Desire for Qualitative Feedback

We found that streamers value feedback from their community. However, there are challenges with the receipt, storage and organization of feedback because of how live streaming platforms are designed. While streamers have tried to mitigate this by using external communication tools, there is valuable feedback that is shared and lost during the broadcast. Current analytics fall short on capturing this type of insight.

Our participant shares his thoughts on being able to provide feedback to other streamers. As a streamer and a viewer, he finds value in being able to share his opinion about the current stream content. This could then inform both the streamer's future content production and also marketing strategies, by being able to target and identify groups of viewers who prefer one content over another, and to help inform promotion strategies.

"Let's say I tune in to a stream I frequent, and I'm not interested in the game they're playing. If I could submit a feedback about why I'm choosing not to watch, that would be interesting" (s1p13).

Others also just enjoy hearing about how their streams have affected their viewers. This provides positive reinforcement for their current efforts.

"I have some viewers that literally, they sit there and they lurk. And then they come on and they say something like, I was having one of the worst days and I found your stream by accident. I'm so happy that I came here because it made me feel better" (s1p15).

But dealing with this data is not easy. Aside from the fact that it is hard to capture, not all feedback is constructive. This introduces a challenge regarding the balance between different types of feedback received from the community.

"What will qualify that person to give feedback in the first place? Are they a streamer? Do they know what they're doing? What are their credentials to give that type of feedback?"

(s1p15)

4.6 Discussion

Unlike traditional streaming services, a critical part of live streaming is the real time interaction between the streamers and viewers. This means that like other similar online communities, having user participation is extremely important. And like these communities, growing a successful stream is hard [108]. Thus, in this paper, we sought to understand how streamers may utilize insights about their viewers to improve their streams. We present our findings from our analyses of existing live streaming analytics and interviews with 18 live game streamers. Using a grounded approach in our data analyses, we describe the ecology of tools being employed before, during, and post streaming.

However, while these tools are being used, we also found that streamers have multiple unmet needs from current analytics. Perhaps the best way to characterize the problem is that existing analytics are performance centric. Our analyses of existing analytics offered by Twitch and Mixer shows that they focus on key streaming metrics of views, followers, and revenues – in some ways, metrics that are most critical for assessing success based on the platforms' definition of success. However, while these types of information are used and useful, they fall short in providing streamers real actionable insights to help them improve. For analytics to really help, they need to help explain what factors can result in changes to these performance metrics.

Based on our data, we classify the needs of streamers into three key categories: to help them improve on their stream content, to help them improve their marketing efforts, and to help them build up their communities. In terms of content needs, streamers expressed desires to gain more insights about their viewers (e.g. demographics and shared interests) so they may better tailor and personalize the stream content. Both in terms of tailoring what they say during streams, as well as what content (i.e. games) to stream. In terms of marketing needs, streamers discussed needing to know how their viewers arrived at their streams so they can better track the efficacy of their marketing efforts. They also wish to gain more insights about how they compare to similar streams to develop their marketing strategies.

Finally, our interviewees talked about the need for additional insights about their stream community. This both includes information to help them increase community members' engagement and sense of belonging, but also to ensure the safety of their communities to their viewers.

In addition to advancing our overall understanding of live streaming, our findings also contribute to the research on data analytics. Perhaps most critically, our findings further highlight the need for human-centered design in developing analytics [32]. Through our study with users, we demonstrated that we can gain a better understanding of when, how, and why they use analytics. This can then ensure the value of these tools to users.

Prior work has found that effective socialization and participation of newcomers has been an inherent challenge in social systems [134], and our work contributes to research on supporting community building on attracting participation in these social systems. The findings of our work further demonstrates the challenges in these areas through the problems we identified in community management and growth of live streamers. Then, we outlined recommendations to help live streamers manage and attract further participation within their respective communities in our design implication section below.

4.6.1 Design Implications

Most immediately, our findings call for additional analytics to support video game streamers' needs relating to content, marketing, and community building. Some of this information may be fairly easily implementable. Information such as timezone and location of the viewers could be inferred through the users' IP address. Though not 100% accurate, it could at least provide some preliminary demographic insights. Streaming platforms should also be able to provide some more data about referrals so streamers can track where their audiences are coming from (external to their platform) or even where viewers go after the stream.

There are also opportunities to develop and utilize inference models about viewers. Based on viewers' behavioral patterns, streaming platforms may provide insights on how viewers' engagement changes during streams, allowing streamers to explore how changing their content or how community-level factors affect viewers' engagement. This also relates to our findings about developing prescriptive and predictive analytics. With these inference models, the analytics can do more than just show users what is going on, but actually highlight opportunities to improve and make suggestions.

But as we noted in our findings, not all valuable insights need to be in the form of quantitative data. Streamers do see value in qualitative feedback. However, most of qualitative feedback exchange occurs outside the streaming platform and outside of broadcast times. Not only is it hard for streamers to receive qualitative feedback during broadcast, but it is also hard for them to store and recall feedback amongst all the interactions and messages during their stream. A potential solution is to be able to extract and store helpful and impactful messages during a stream, and be able to present it to the streamer during or after their stream to help their streams.

But this last point also highlights the importance of considering the optimal time and optimal way of presenting this information to streamers. Not all of the data should be shown to the streamers at all times. For instance, individual viewer demographic information really enables streamers to have an intimate conversation with their viewers, but may not always be helpful to streamers for an after-stream summary. On the other hand, while referral source could be a useful thing to know during a stream, it is most useful to a streamer outside of stream to help them prepare strategies and techniques to grow their community. In addition, even if the same data is useful before, during and after streams, there are significant design considerations to be made in order to meet the attentional demands of the streamer.

4.6.2 Limitations

While Twitch and Mixer are considered large streaming platforms for video game streamers, this study did not include the experiences and practices of streamers from Facebook Gaming and Youtube Gaming, both of which are competitive and growing platforms in the industry. While we found significant results regarding video game streamers analytical needs, they may not necessarily translate to streamers on other platforms such as Facebook and Youtube, given that they may provide some of the missing analytics mentioned here and that they provide more utility to their users outside of live streaming.

4.7 Conclusion

This study makes contributions to the live streaming literature by providing a view into how streamers utilize and gather information about their performance and their community. Extending prior work on the experiences of live streamers, we outline the uses and limitations of current analytics tools of streaming platforms, which allows us to capture the set of information needs of this community. Our findings allow us to develop some insights around usage and potential of analytics, and implications for developing human-centered analytics.

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Chapter 5

FOSTERING CONSTRUCTIVE FEEDBACK EXCHANGE IN LIVE STREAM COMMUNITIES (RQ2)

This second study looks at how streamers can effectively solicit and act on feedback from their communities in ways that are more constructive, timely and actionable. Building on insights from the first study, this research explores the design and development of a conversational agent to support real-time feedback exchange.

5.1 Introduction & Related Work

Feedback is a cornerstone of improvement in many domains, from education to professional development [77, 154, 187]. In live-streaming contexts, audience feedback can help streamers refine content strategies, improve engagement techniques, and align their streams with viewer preferences [178]. Despite its potential value, feedback in these settings is often difficult to solicit and act on effectively. Streamers face challenges knowing when and how to ask for feedback, worry about receiving vague or negative responses, and struggle to synthesize large volumes of unstructured input into actionable insights.

These barriers are compounded by the emotional and social risks inherent in public feedback-seeking. Research in organizational and social psychology shows that requesting feedback can trigger self-presentation concerns, ego threat, and vulnerability [19, 20]. For streamers, who perform live and depend on audience perception for social and financial support, these risks are heightened. The fear of judgment or appearing unskilled may discourage creators from asking for input, even when they desire it, leading to feedback that is infrequently sought, inconsistently provided, and often underutilized.

Existing channels for feedback collection, such as live chat, comments, or platform analytics, tend to exacerbate these challenges. Feedback through these means is typically unstructured, sporadic, or overly general, and rarely captures the nuance of a streamer's creative goals, performance style, or evolving identity [127]. Furthermore, these tools often fail to surface feedback in ways that streamers can interpret and apply without significant cognitive and emotional effort. Together, these limitations point to a need for systems that reduce the social friction of feedback-seeking while supporting deeper, more constructive forms of audience input.

To address these challenges, we designed and developed a system to support feedback exchange between live streamers and viewers. This system facilitates constructive feedback by guiding viewers through structured prompts and summarizing their responses into actionable insights displayed on a dashboard. By reducing the cognitive burden on streamers and making feedback more interpretable and socially low-risk, the system aims to support both content improvement and community engagement. This work builds on the idea that feedback systems are not only technical mechanisms, but also social infrastructures that shape how creators perceive, evaluate, and act upon audience input.

Our work makes three key contributions:

1. A Deployable Feedback System: We present a conversational agent tailored to the unique needs of live streamers. The system enables creators to solicit, organize, and synthesize qualitative feedback efficiently.

2. Empirical Insights into Feedback Dynamics: Through a mixed-methods study involving streamers and viewers (including newcomers), we provide empirical data on how structured feedback mechanisms influence community engagement and content improvement.

3. Design Recommendations for Feedback Tools: Based on our findings, we offer actionable recommendations for designing AI-driven tools that support constructive feedback exchange in live-streaming contexts.

By addressing key gaps in existing tools and feedback practices, this study contributes to the broader literature on active feedback-seeking behaviors in digital spaces while advancing the design of AI-supported systems for community-centered content creation. Our findings have implications not only for live streaming but also for other domains where creators rely on audience input to shape their work.

5.1.1 Feedback in Interactive and Creative Contexts

Feedback plays a critical role in the iterative process of creative work, enabling creators to reflect, revise, and refine their ideas. In digital environments, especially those that facilitate interaction among diverse and distributed participants, new models of feedback exchange have emerged. Recent research highlights various strategies and system designs that enhance the usefulness, specificity, and emotional appropriateness of feedback in creative and interactive contexts.

One key theme across the literature is the importance of anonymity and structure in improving the quality of crowdsourced feedback. In a study exploring the effect of anonymity on pitch feedback, anonymous contributors offered significantly more specific praise and criticism, which recipients rated as more useful than feedback from identified users [84]. The removal of personal identity cues appeared to encourage more candid and constructive commentary, possibly by reducing social inhibitions or perceived risk.

Complementing this, scaffolding, defined as guiding individuals through a sequence of subtasks that build toward a complex goal [149], has been shown to improve both the quality and efficiency of crowd-generated feedback almost nearing the levels of expert feedback. In Critiki, a platform developed for gathering feedback on crowdfunding projects, structured prompts led paid crowdworkers to deliver more specific and actionable design critiques [69]. Questions that asked workers to highlight both valuable contributions and suggested improvements were particularly effective in eliciting high-quality responses.

Systems like CrowdCrit further demonstrate the value of structuring and aggregating crowd input [123]. While individual crowdworker feedback might vary in expertise or insight, aggregated critiques were found to approximate expert-level feedback in both content and usefulness. Notably, designers reported that they perceived the feedback as helpful and even adjusted their work in response, highlighting the practical impact of well-structured crowd critiques.

Beyond structural techniques, interactive guidance tools have also proven useful in enhancing feedback from novice reviewers. In one study, features such as adaptive suggestions and reusable guidance templates helped reviewers articulate their thoughts more clearly and constructively [137]. Feedback generated through these tools met the criteria of being "specific, actionable, and justifiable," which the authors identified as hallmarks of high-quality creative feedback.

However, the quality of feedback is not solely dependent on structure and interactivity, it is also deeply rooted in relational dynamics. A study of online fanfiction communities revealed that writers highly valued feedback from individuals with whom they had authentic, ongoing relationships [46]. These connections fostered trust, contextual understanding, and emotional support, which in turn facilitated more balanced and effective critique. Persistent relationships enabled feedback providers to align their comments with the creator's goals and prior work, reinforcing a sense of shared investment and credibility.

Taken together, these studies underscore the multifaceted nature of effective feedback in creative digital contexts. Anonymity and scaffolding can enhance objectivity and clarity, interactive tools can guide novice reviewers, and relational continuity can foster trust and emotional resilience Future systems aiming to support creative collaboration should consider integrating these dimensions, structural support, technological guidance, and social connection, to better serve the evolving needs of creators.

The nature and quality of feedback are also shaped by the platforms themselves. Platform infrastructures not only determine how feedback is given, but also what kinds of feedback are encouraged and discouraged. Additionally, platform culture also influences shared norms, values, and behavioral expectations. So, it is important to study the efficacy of feedback mechanisms in tandem with the affordances and social dynamics of the platforms that mediate them.

5.1.2 Audience Engagement and Viewer-Streamer Dynamics

Audience engagement in digital environments increasingly spans from intentional community-building strategies in institutional media to emergent, platform-mediated practices in creator-driven spaces. Across this spectrum, creators and producers navigate different forms of participation, feedback, and audience relations, all shaped by the technological and social affordances of their respective platforms.

In public service media, such as Flemish current affairs television, producers play an active role in fostering engagement. Audience participation is not incidental but strategically cultivated through immersive, interactive, and para-interactive practices [171]. These are supported by production roles that go beyond content delivery (as curator, facilitator, and observer) demonstrating how engagement can be carefully designed to strengthen community around shared information or civic goals. This top-down model offers a contrast to more decentralized approaches in creator-centered platforms.

At the platform level, the dynamics between content creators and the systems that govern content distribution, monetization, and visibility are increasingly fraught. Platforms like YouTube and Twitch impose algorithmic controls that shape audience reach and feedback visibility, creating a tension between platform control and creator autonomy [29]. Creators must balance their expressive goals with platform metrics, and audience management, often adapting their practices to appease both machines and viewers. These dynamics highlight how engagement is always mediated by larger infrastructures of visibility and power.

Within this landscape, Twitch exemplifies a participatory model where audience engagement is central to the medium. Ethnographic research positions Twitch streams as "third places", informal, social hubs where communities emerge around shared content and identity [75]. These spaces foster a co-creative culture in which streamers and viewers jointly shape the experience of the stream. Engagement on Twitch is deeply embedded in real-time interaction, chat dynamics, and communal rituals, illustrating how live mixed-media environments support fluid, socially driven participation.

On algorithmically driven platforms like TikTok, audience engagement often hinges on creators' ability to strategically manage affect and connection. Research shows that influencers deploy a blend of charisma, content quality, and relational strategies to cultivate likes, shares, and ultimately, brand impact [181]. Engagement here is as much about emotional performance and identity bonding as it is about content strategy. This reflects a broader trend in which creators become entrepreneurial figures, optimizing not just content but their own persona in alignment with platform dynamics.

Together, these cases reveal that audience engagement is not monolithic, it is strategically curated, algorithmically constrained, and socially co-constructed, depending on the platform context and the roles assumed by both creators and audiences.

5.1.3 Designing Feedback Tools for Content Creators

As creative expression increasingly takes place within digital and algorithmically mediated spaces, feedback has evolved into both a community-building mechanism and a computational challenge. Contemporary research into feedback design reflects this duality, on one hand, platforms and communities shape norms through interface cues and participatory culture; on the other, advanced AI systems are being built to simulate, interpret, and augment feedback in real time.

Feedback in creative communities often functions less as critique and more as social scaffolding, a way to shape norms, motivate contribution, and lower the barrier to participation. Mosaic exemplifies this model by fostering a community where artists share works-in-progress rather than finished products[102]. The platform encourages reflective and constructive peer feedback, shifting the focus from outcome to process. This culture of openness reduces performance anxiety and encourages iterative creativity, showing how platform design can nurture developmental feedback loops. On the more systemic end, the Feedback Shaping approach models how creators respond to different forms of engagement [175]. By predicting feedback sensitivity and incorporating those predictions into feed-ranking algorithms, this method helps rebalance platform incentives, supporting not only content performance, but creator longevity and well-being. This highlights the need to consider creators as users with their own feedback needs, not just producers for audience consumption.

Similarly, features like YouTube's creator heart play a subtle yet powerful role in guiding comment section dynamics [47]. By marking certain comments as "hearted," creators can signal approval, incentivize positive engagement, and curate the tone of discourse. This feedback signal strengthens community cohesion and reinforces desirable audience behaviors. Together, these systems demonstrate that platform and community-level feedback tools are not merely additive; they're normative, shaping how creators and audiences understand value, interaction, and participation.

Recent advances in large language models (LLMs) and multimodal AI have introduced new possibilities for interactive, anticipatory, and automated feedback systems that can operate at scale and in real time. Proxona transforms static comment data into structured, multidimensional audience personas [48]. By distilling traits from audience feedback and clustering them into interactive profiles, Proxona allows creators to engage in simulated conversations with representative audience segments. This design turns feedback into a creative resource, supporting ideation, content refinement, and audience empathy. SimTube expands this vision by generating simulated audience comments before a video is even released [86]. By integrating multimodal data from video content and persona modeling, it provides creators with contextual, diverse feedback scenarios that can guide pre-publication decisions. Its customizability and simulation of varied demographic perspectives enable creators to anticipate how different audiences might react to their work.

While these systems offer creators simulated perspectives and audience insight, they primarily operate in a static or anticipatory context. In this work, we explore how feedback can support creators in a dynamic, high-pressured environments of live streaming. Live stream creators must adapt rapidly, often without the benefit of structured and reflective feedback mechanisms. To address this gap, we built Streamfeed, to embed constructive and structured feedback into the live streaming workflow. By combining conversational guidance, feedback structuring, and synthesis tools, it supports streamers in continuously engaging with their audience perspectives.

5.2 Research Gap and Questions

Despite a growing body of work on feedback mechanisms in creative and collaborative contexts, current systems fall short in addressing the unique temporal, emotional, and relational dynamics of live streaming. While prior research has advanced techniques for feedback structuring (e.g., scaffolding, anonymity) and simulation (e.g., persona modeling), these systems often operate outside of real-time, socially charged environments where creators must perform and adapt simultaneously. Moreover, few studies have examined how interactive feedback systems might influence community participation, content evolution, and streamer well-being during live performance.

This leaves a critical gap at the intersection of online communities, creativity support tools, and platform-mediated labor: How can we design real-time feedback systems that are socially attuned, cognitively lightweight, and meaningfully integrated into live digital performance workflows?

To address this gap, we present Streamfeed, a novel interactive feedback system tailored to the needs of live streamers. This research makes a system contribution to HCI by designing, implementing, and evaluating a working prototype that operates in real-time and within the sociotechnical constraints of streaming platforms. Through empirical deployment and qualitative inquiry, we examine how such a system can mediate streamer-viewer interactions, support reflective content practices, and manage feedback without overloading the performer.

We explore the following research questions: **RQ1:** How do streamers perceive the value and relevance of structured feedback from Streamfeed? **RQ2:** In what ways does Streamfeed integrate into and shape streamers' ongoing content practices, decision-making, and community-building efforts? **RQ3:** What tensions or opportunities arise in engaging feedback from both regular and newcomer viewers?

5.3 *Streamfeed Development*

5.3.1 Design Rationale

The design of Streamfeed is grounded in recurring themes identified across related work: the importance of structured feedback, the relational and affective dimensions of audience interaction, and the influence of platform-specific dynamics on engagement. Our goal was to translate these findings into a real-time system that could offer constructive, usable feedback to live streamers, whose work is inherently fast-paced, high-pressure, and socially mediated.

We chose a chatbot interface because it supports guided, conversational feedback, a format shown to reduce cognitive load and improve clarity among novice reviewers [69]. Structured prompts and interactive scaffolding have been shown to elicit more useful and emotionally appropriate feedback than static forms such as surveys or open-ended text fields. This informed our decision to embed real-time follow-up logic into the chatbot's design, allowing it to clarify vague comments and redirect inappropriate inputs.

To ensure relevance to the streaming context, we adopted a feedback framework centered on "strengths and improvements," drawing from best practices in performance and creative critique [13]. This format provides streamers with both affirmation and actionable advice, key factors in fostering reflection and resilience. Feedback is further organized into three categories: content production, community management, and marketing strategy [127], which reflect the core dimensions of streamer success.

5.3.2 Conversational Agent Design

To address the needs surfaced in prior work and our formative study, we developed a conversational agent that guides viewers through the process of giving constructive feedback. The chatbot is deployed during live streams via a shared link, allowing viewers to provide input asynchronously and at their own pace.

To ensure feedback was high-quality and actionable, we employed prompt engineering strategies centered on clarity, constraint, and adaptivity. The chatbot followed a structured conversational prompt designed to elicit responses across three targeted domains: **marketing**

strategies, **content production**, and **community management**. Viewers were asked one question at a time, with each response acknowledged before moving to the next. Input quality was assessed in real time using heuristics such as minimum character length, presence of vague or overly negative language, and relevance. Unclear or off-topic responses (e.g., *"okay", "boring"*) triggered follow-up requests for clarification or rephrasing such as that seen in Figure 5.1. The system aimed to collect **at least one strength and one area for improvement per category** before concluding a session.

The conversational agent uses a structured feedback framework focused on streamers' strengths and areas for improvement [13]. These prompts encourage reflection and specificity while avoiding overly critical or unstructured responses. Feedback is collected across three predefined categories: content production, community management, and marketing strategy [127]. These domains were selected based on prior work and confirmed through our survey as top areas of concern for streamers.

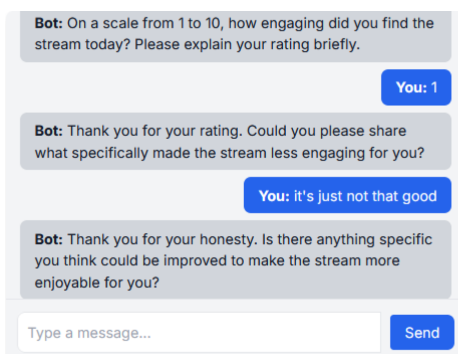

Figure 5.1: Screenshot of a streamfeed's chatbot interaction in which a user rates a live stream poorly and provides minimal qualitative input, prompting the system to request more detailed feedback for potential improvements in engagement.

Unlike static forms or unstructured comment boxes, the chatbot actively monitors the quality of user responses. If a viewer gives vague input, e.g., "the stream was okay", the chatbot follows up with clarifying questions like, "Can you describe a specific moment that stood out to you?" This adaptive follow-up ensures feedback meets the standard of being actionable, specific, and justifiable [137]. Inappropriate or off-topic responses are gently redirected or filtered out, maintaining relevance and emotional safety for both parties.

After responses are collected, the chatbot synthesizes them into concise summaries. This reduces the burden on streamers to sift through raw input by surfacing key patterns and representative quotes. Summaries are generated using a second prompt that instructs the language model to extract insights across five thematic categories, embedding relevant user quotes in each. This process runs server-side via a large language model (LLM) API, which returns a structured JSON object. Each category summary is designed to be at least two sentences long, ensuring clarity, depth, and direct usability within the streamer dashboard.

5.3.3 Dashboard Design

The dashboard (Figure 5.2) is designed to give streamers a clear and accessible overview of viewer feedback. At the top, a concise "tl;dr" section presents a summary of viewer count, key motivations for watching the stream, and actionable suggestions for improvement, structured around the strengths-and-improvements framework [13]. This allows streamers to quickly grasp the most important insights at a glance.

Below this, the dashboard offers a more detailed breakdown of feedback across three categories: content production, community management, and marketing strategy [127]. Each category includes a brief synthesized summary along with two representative viewer quotes drawn from chatbot interactions.

The design follows the 'inverted pyramid' approach, originally developed in journalism [146]. This method, adapted in interface design, prioritizes the most relevant information first, improving retrieval and comprehension [97].

5.3.4 System Development

The system consisted of two main components: a chatbot interface and a dashboard for presenting the data. Streamers shared a unique chatbot link (/chat/¡username¿) with their audience, who interacted with the chatbot in real time. These interactions were captured and stored in a PostgreSQL database. The dashboard, accessible via a tokenized URL

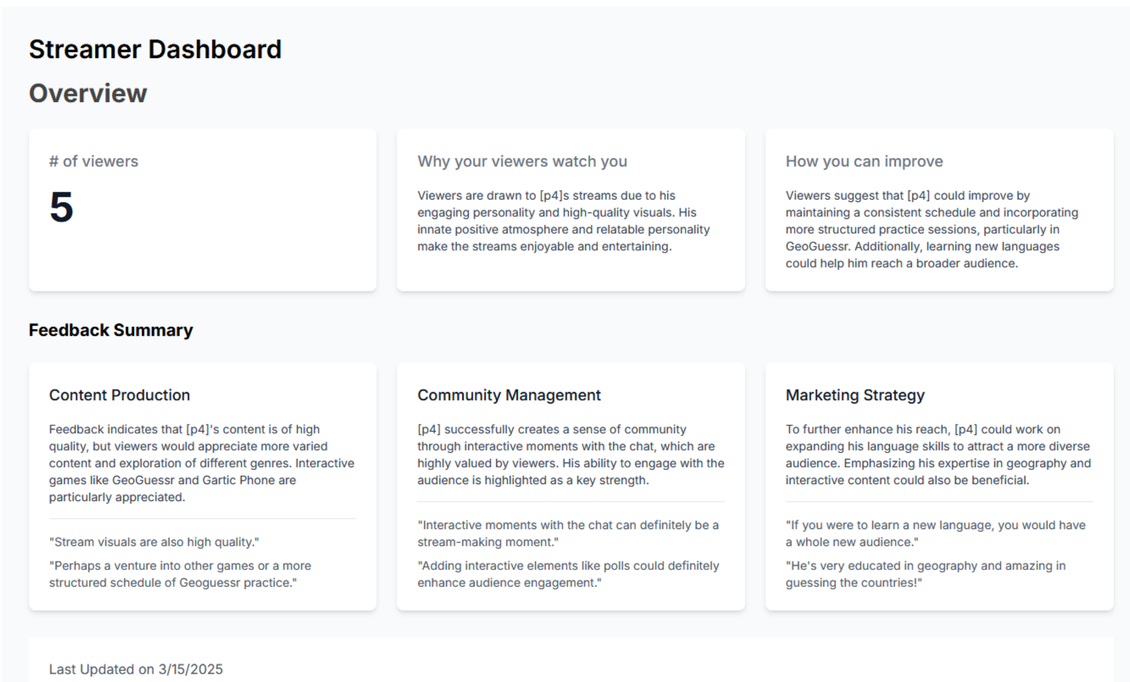

Figure 5.2: Streamer Dashboard for participant [s2p4], displaying a summary of viewer engagement and qualitative feedback. The dashboard highlights a viewer count of 5, reasons viewers enjoy the stream (e.g., personality and visuals), suggestions for improvement (e.g., consistent schedule, language learning), and categorized feedback on content production, community management, and marketing strategy. Each section includes quotes and insights drawn from viewer comments.

(/chat/?token=¡unique_token¿), displayed a summary of viewer interactions. It was initially populated with data upon the first visit after engagement and was subsequently updated manually on a weekly basis by the lead researcher. The front end of the system was developed using React, while the backend leveraged Node.js and Express for routing and API handling. The system diagram is presented in Figure 5.3.

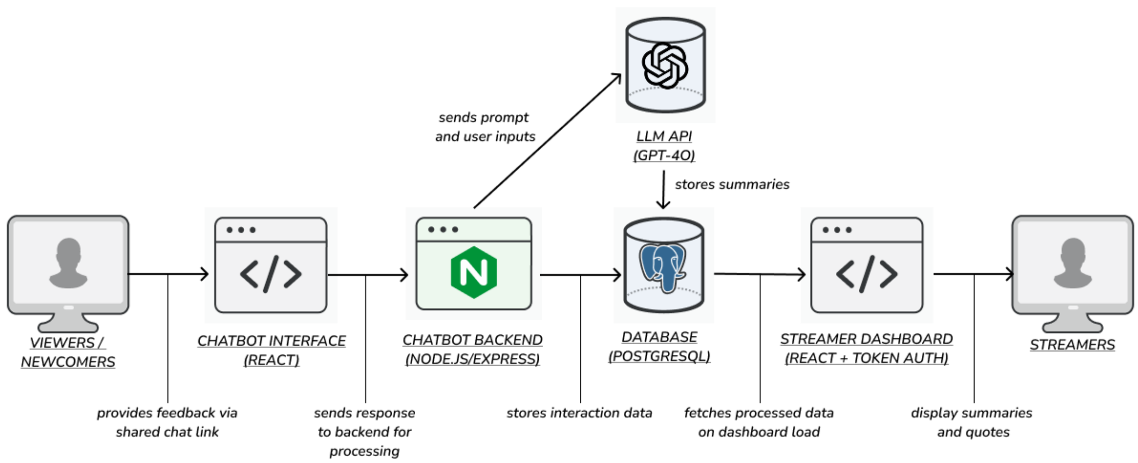

Figure 5.3: System architecture of the StreamFeed platform. Viewers provide feedback through a React-based chatbot interface during live streams. Inputs are processed by a Node.js/Express backend, which interacts with a PostgreSQL database and a GPT-4 API for both adaptive prompting and summarization. Summarized feedback is then displayed to streamers via a secure dashboard interface.

5.4 Methodology

5.4.1 Study Overview

This study aimed to evaluate the usability, challenges, and benefits of a chatbot based feedback system designed for streamers. The primary objective was to determine whether the system could provide streamers with new and relevant constructive feedback to improve their content and stream planning. To achieve this, we recruited streamers to promote usage of the chatbot with their viewers during, and after their live streams. These interactions generated feedback that was filtered, aggregated, and summarized in a dashboard for streamers to review. The study consisted of three phases: onboarding, active use of the system during live streams, and a follow-up evaluation.

5.4.2 Participants

This usability study consisted of 11 streamers (Table 5.1)recruited through social media platforms and personal networks. Eligibility criteria required participants to have prior experience in live streaming, and must have streamed the week prior the onboarding call. The streamers represented diverse content focuses, including gaming, art, and just chatting, with audience sizes ranging from 5 to 100 viewers. Most participants were based in North America. Our participants also had a range of streaming experience, three of whom were Partnered on Twitch, which means they get a bigger portion of the revenue from ads, subscriptions and bits in contrast to an Affiliate streamer [3]. Streamers received a $50 gift card as compensation for their time and contributions, while newcomers participated voluntarily as part of their involvement in the research group.

Table 5.1: Participant Demographics of Study 2

Participant ID (PID)	Location	Followers	Streamer Status	Average Viewer (past 30 days)	Hours Streamed (past 30 days)
s2p1	Sweden	3,145	Affiliate	18	86
s2p2	USA	49,676	Partner	82	133
s2p3	USA	106	Affiliate	3	21
s2p4	Canada	304	Affiliate	4	21
s2p5	USA	1,448	Affiliate	18	249
s2p6	Mexico	19,046	Partner	69	173
s2p7	USA	144	Affiliate	1	4
s2p8	Australia	14,123	Partner	88	127
s2p9	USA	7,395	Affiliate	55	120
s2p10	USA	456	Affiliate	1	49
s2p11	Philippines	166	Affiliate	9	86

In addition to feedback from existing community members, we conducted a focused case study involving a group of eight newcomers (Table 5.2) recruited from a university research group. These individuals were familiar with live streaming, either as viewers or former content creators, but had no prior relationship with the participating streamers. Their role was to provide fresh, outsider perspectives by engaging with streams and submitting feedback through the same chatbot interface used by regular viewers.

Table 5.2: Newcomer Demographics

Newcomer ID	Age Range	Streamer Status	Stream Engagement Frequency	Preferred Stream Genre
s2n1	25-34	Yes, Affiliate	Daily	Games
s2n2	25-34	No	Monthly	Events
s2n3	18-24	Yes, Affiliate	Daily	Games
s2n4	25-34	Yes, Partner	Daily	Games
s2n5	18-24	No	Rarely	Games
s2n6	25-34	No	Rarely	Games
s2n7	18-24	No	Rarely	Games
s2n8	25-34	No	Daily	Games
s2n9	25-34	No	Daily	Games

5.4.3 Study Phases

The study consisted of three phases: onboarding, system use, and evaluation phase described below.

Onboarding Phase

Each streamer began their participation with an onboarding call designed to introduce them to the study's purpose and methodology. During this call, researchers explained that the goal of the study was to evaluate how effectively the chatbot and dashboard could help streamers gather constructive feedback from viewers in a way that was both easy to use and actionable. Researchers demonstrated the tool by sharing their screen, showing how the chatbot collected viewer feedback and how this information was summarized in an accessible dashboard. Researchers asked the participating streamers to share the link to their community through various channels, such as through their chat or Discord servers.

To ensure meaningful engagement and summarizations, they were encouraged to aim for at least five viewers to interact with the chatbot before their follow-up evaluation call. Additionally, streamers were asked to complete a baseline survey reflecting on their current experiences with feedback prior to using the tool.

System Engagement

After onboarding, streamers incorporated the chatbot into their live streams by sharing its link with viewers. Viewers could engage with this tool during or outside of their streamer's stream. The chatbot prompted viewers with questions about content, community, and marketing, per the design guidelines described in section 5.3. These interactions generated feedback that was aggregated into the streamer's dashboard for review. In addition to the community members, the newcomer research group evaluated the same live streamers during their weekly meetings and provided feedback through the same chatbot interface. These two sources allowed for a quick comparison between feedback from current community members and perspectives from potential newcomers.

Evaluation Phase

Once five unique viewers had engaged with a respective streamer's chatbot, the streamer was invited to participate in a follow-up evaluation call that lasted around 30–40 minutes. The purpose of this evaluation call was to gather qualitative insights about their experience with the tool, including its usability, impact on content planning, and perceived value. Researchers began by asking general questions about what participants liked most about the tool, any challenges they encountered, and whether they faced technical issues during its use. Streamers were then guided through a review of their dashboard via screen sharing to discuss how they had used, or planned to use, the feedback generated by viewers.

The evaluation also explored differences between community-generated feedback and newcomer-generated feedback in terms of constructiveness, detail, or actionability. Streamers were asked about specific suggestions that stood out or surprised them and whether newcomer perspectives offered fresh insights not mentioned by existing community members. Finally, participants were invited to provide suggestions for improving the tool's features or functionality and reflect on its potential long-term value for streamers.

5.4.4 Newcomer Feedback Protocol

Assessing live streamers from the perspective of newcomers serves as an exploratory approach to understanding how feedback from individuals with varying degrees of familiarity, especially newcomers versus established community members, can yield distinct and valuable insights [75, 106]. This framing is informed by literature in education and organizational studies, where the role, identity, and relational positioning of the feedback-giver (e.g., peer, teacher, or manager) are shown to significantly shape both the content and reception of feedback [100, 21, 135]. While the live streaming context differs from traditional learning or workplace environments, this study offers a novel lens to examine how different types of contributors assess stream quality and streamer presence, potentially informing both platform design and community management practices.

We chose to focus on newcomers specifically because growth in streaming is heavily dependent on first-time impressions [75]. A streamer's ability to attract and retain new viewers often hinges on how quickly and clearly their content communicates its value. Thus, understanding how new viewers interpret and evaluate streams can offer streamers actionable insights into potential barriers to growth that might go unnoticed by long-time community members.

To ensure structured and comprehensive evaluations, the newcomers followed a set of heuristics developed by members of the resaerch group, who were simultaneously the newcomers. These heuristics guided their review across multiple dimensions of the streaming experience. Newcomers began by watching two to three recent stream clips, skimming full-length recordings, and, when scheduling allowed, observing the participants' streams live. They also reviewed each streamer's About and Schedule pages to evaluate how clearly the streamer's brand, routine, and value proposition were communicated. Additionally, they examined past broadcasts and community elements, such as chat rules, follower counts, and subscriber benefits, to gauge consistency and community accessibility. This structured approach allowed newcomers to provide feedback that complemented the more organic input from existing community members, highlighting areas of improvement that may not be visible to long-time viewers.

5.4.5 Data Analysis

Quantitative Measures and Analysis

We collected quantitative data through two main sources: (1) pre- and post-study surveys administered to streamers, and (2) chatbot engagement metrics derived from viewer interactions.

The surveys included a mix of Likert-scale items and multiple-choice questions focused on streamers' perceptions of feedback quality, clarity, and usefulness. To assess changes in perception before and after using Streamfeed, we conducted paired t-tests on key survey items [52]. A significance threshold of $p < 0.05$ was used to identify meaningful differences.

Chatbot engagement was measured using platform-side logging of message activity. We tracked metrics such as number of unique participants, message counts per session, and conversational drop-offs. These metrics helped us evaluate how viewers engaged with the feedback system during live streams.

Qualitative Coding and Thematic Analysis

Interviews were recorded and then transcribed using Otter.ai. The first author cleaned typographical errors and mistranscriptions in all transcripts before storing them for analysis. Three members of the research group were involved in the qualitative coding process described below.

The team employed a grounded theory approach to qualitative coding [40]. The process began with a collaborative coding session on one interview transcript, which facilitated the emergence of initial themes and informed the development of a preliminary codebook. Each coder was then assigned three additional interviews to independently code. At subsequent meetings, the team discussed discrepancies and updated the codebook to reflect emerging themes and refinements. This iterative process continued until the final codebook was established and all interview transcripts were fully coded. To assess consistency across coders, we calculated inter-rater reliability using Fleiss's Kappa, achieving a score of 0.855, indicating near-perfect agreement.

The final codebook included the following top-level codes:

- **Ease of Use**: Reflections on how intuitively the tool functioned for both streamers and viewers.

- **Feature Desires**: Suggestions and requests for improving Streamfeed's accessibility, design, data presentation, and cross-platform functionality.

- **Feedback Characteristics**: Perceptions of the quality, novelty, clarity, and actionability of the feedback provided by viewers and presented in the system.

- **Newcomer Perspectives**: Streamer reactions to feedback from newcomers, including impressions of its freshness, criticality, or perceived limitations.

- **Newcomer vs. Community Feedback**: Comparisons drawn by streamers between feedback from established community members and that from outsiders.

- **Platform and Technical Considerations**: Observations about the platform constraints (e.g., Twitch, YouTube) and technical or UX limitations of Streamfeed.

- **Tool Integration**: Descriptions of how streamers incorporated Streamfeed into their streaming setup or routines (e.g., sharing links, Discord usage).

- **Viewer-Centered Improvements**: Feedback focused on enhancing the viewer experience or enabling underrepresented voices (e.g., lurkers).

These categories informed the thematic organization of the qualitative findings presented in Section 5.6.

5.5 Quantitative Findings: Viewer and Tool Engagement

This section presents quantitative findings from the survey responses as well as tool engagement by viewers.

5.5.1 Survey Findings

The survey results reveal diverse patterns in feedback frequency and sources for live streamers. Regarding frequency, a majority of respondents (7 out of 11) reported that they "rarely receive feedback when I stream," while a smaller group (4 out of 11) stated they "receive feedback most of the time when I stream." Feedback sources varied, with viewers being the most common, cited by 10 of 11 participants. Analytics tools, such as built-in Twitch analytics, were the second most common source, mentioned by 7 respondents.

The content of feedback ranged from specific suggestions to general improvements. Several streamers reported viewers suggesting games to play, with one mentioning, "I have received suggestions for games to play" (s2p1). Another streamer received advice to expand their content "and expand to Youtube at least for short form videos"(s2p2). Stream improvements were also common, with one participant noting a "viewer recently asked if [they] could add certain rewards for viewers/chat experience" (s2p4).

To evaluate the impact of structured feedback from Streamfeed, we conducted a comparative analysis across two rounds of survey responses (one before using the tool, and another after). As shown in Figure 5.4, average scores improved across all assessed categories in the second round, where feedback was based on the Streamfeed platform. Notably, statistically significant improvements found in "provides clear steps for improving streams" ($p=0.014$) and "helps me improve with my community" ($p=0.026$). While others only showed positive trends, overall these results support a positive impact of the design of Streamfeed between viewers and streamers.

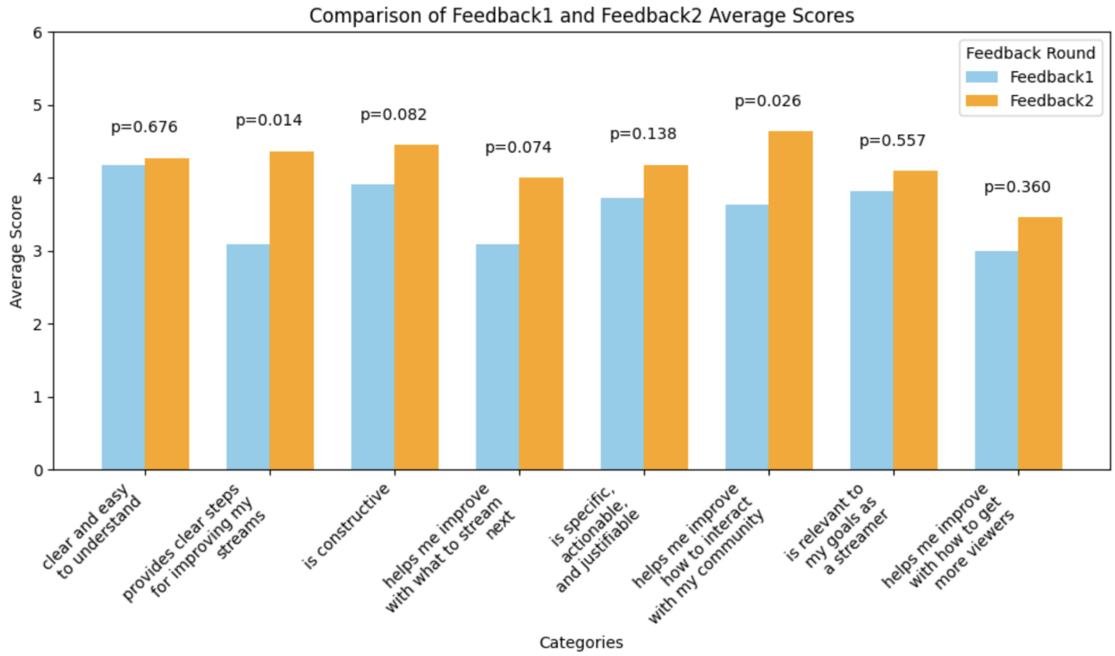

Figure 5.4: Comparison of average scores across two rounds of feedback, showing improvements in clarity, constructiveness, and relevance of viewer feedback after using Streamfeed.

5.5.2 Viewer and Chatbot Engagement Metrics

The study included 11 streamers and 161 viewers. Viewer engagement with the chatbot (Table 5.3 varied across streams, ranging from 5 to 26 active participants per stream. To measure sustained engagement, we filtered for meaningful interactions by excluding conversations with fewer than 10 total messages (combined from both viewers and the chatbot). Analysis revealed 25 viewer drop-offs across all 11 streamer sessions, with a total of 89 message drop-offs observed throughout the study.

5.6 Qualitative Findings: Streamer Reflections on Streamfeed

In this section, we highlight some qualitative insights that arose from the conversations during the usability studies.

Table 5.3: Chatbot Engagement Statistics

PID	Viewer Engagement Metrics			Message Activity Metrics		
	Original Count	Filtered Count	Drop-Offs	Original Count	Filtered Count	Drop-Offs
s2p1	7	5	2	80	72	8
s2p2	22	21	1	390	385	15
s2p3	5	5	0	84	84	0
s2p4	5	5	0	56	56	0
s2p5	20	16	4	242	228	14
s2p6	22	15	7	230	216	14
s2p7	6	5	1	60	56	4
s2p8	23	23	0	330	330	0
s2p9	26	19	7	425	401	24
s2p10	19	14	2	210	200	10
s2p11	6	6	0	110	110	0

5.6.1 Perceived Value of Streamfeed

Streamfeed was widely perceived as highly accessible and user-friendly by both streamers and viewers. During the onboarding process, the researcher guided streamers through the initial setup, which included screen sharing, entering a preferred display name, and accessing their personal dashboard and chatbot link for viewer engagement. While streamers did not complete the setup independently, they found navigating the dashboard and sharing relevant links to be straightforward and uncomplicated. Participants consistently emphasized the simplicity of the process. As one streamer explained, "I think it was very simple because people didn't have to do anything, like, there's no sign up required, so you can directly, just put what you think... So there's no sign up, you can be there anonymously and just tell what you think" (s2p9). A viewer echoed this sentiment, noting, "Like, it's very easy to kind of interact with. It's like, I feel like it's in a format where people intuitively know how to use it" (s2p8). Overall, the lack of required registration and the intuitive design were identified as key factors contributing to Streamfeed's ease of use for both streamers and viewers.

5.6.2 Integration into Streamer Practices

Streamers used a variety of methods to share the Streamfeed feedback link and encourage viewer participation. Many integrated the link into their Discord servers, as one participant explained, “It was mainly on my stream. I did put in my Discord as well” (s2p9). Within the stream chat, several streamers pinned the feedback link to ensure it remained visible, with one noting, “I also pinned it in my chat. So it was always on top of the chat that, like, if you want to provide feedback, here it is” (s2p1).

To further promote engagement, some streamers created custom chat commands or automated reminders. For example, one streamer described, “I kind of made a command in my stream title, and was actually like having some time to encourage people to do it” (s2p6). Another participant implemented a NightBot command that would periodically remind viewers about the feedback opportunity: “I made a NightBot command with the link for the survey pin that when my stream was live, and just brought it up every now and again, just to say, hey, we have a pin message. If you can provide some feedback for the stream, we would greatly appreciate it” (s2p5).

In addition to these digital methods, streamers also encouraged feedback verbally during their broadcasts. One participant shared, “And then throughout the stream, I would just ask people if they had time, and they felt like they’re up to it, if they would mind leaving some feedback. Good and bad” (s2p2). Another described directly urging individual viewers to participate: “I just, like, urged individual viewers, like, hey, fill out the entire... fill out the stream feed link thing, yeah, and they, some of them were, some of them didn’t do it, of course, which makes sense. But like, and some of them did, of course. Five of them did at least” (s2p3).

Some streamers also placed the feedback link in the panel below their stream as seen in Figure 5.5, ensuring it was always accessible to viewers. Overall, these combined strategies,using Discord, chat features, verbal encouragement, and persistent panel placement, demonstrate the range of approaches streamers adopted to promote feedback and engage their audiences

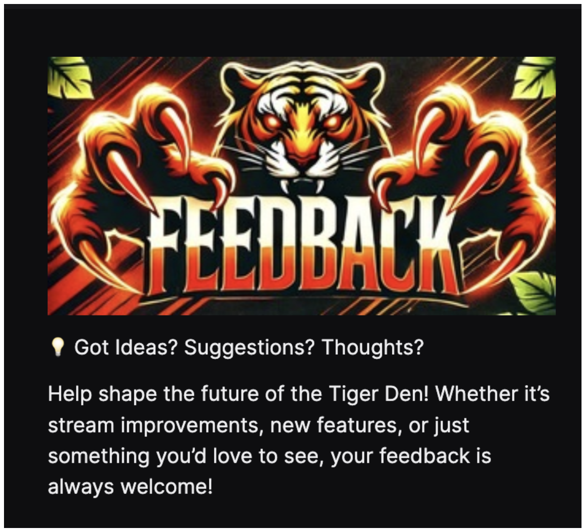

Figure 5.5: Participant's call-to-action graphic encouraging viewer feedback in the Tiger Den, which redirects to their personal chatbot. This image invites participants to share ideas for stream improvements, new features, or general suggestions, reinforcing a collaborative and interactive streaming environment.

5.6.3 Novelty and Constructiveness of Feedback

The tool enabled streamers to receive feedback they hadn't encountered before, which tended to fall into two categories: novel insights they had never considered, and affirmations of ideas they had previously contemplated but not yet acted on. As one streamer explained, "I liked the feedback. I think there was some actually really insightful feedback in there. It was just kind of highlighting what I'd already kind of self-assessed. But I do think a streamer that isn't as self-aware, it can be very valuable, um, like, incredibly valuable" (s2p8).

The feedback was not only reflective but also actionable. Several streamers implemented suggestions they received between onboarding and their evaluation call. For example, one participant shared, "I did notice somebody had mentioned, you know, raiding other people at the end of the stream. So I did start implementing that and trying to find other people to, you know, send the stream to... that is easily fixable. And I just started doing that and implementing that" (s2p5).

However, not all feedback was adopted. In some cases, streamers opted not to act on suggestions due to the additional labor required. One streamer received requests to create a Discord server and stream schedule but resisted, stating, "I could, technically, because they asked me to make a Discord server and to have a stream schedule. I'm like, No, I'm not doing that" (s2p3). Even when not implemented, the feedback was considered meaningful. Streamers appreciated the structure of the feedback interface, noting that the categorization and inclusion of direct quotes made it easier to process. The categories captured a broad range of concerns relevant to streamers, while the concise summaries made the information digestible. The quotes lent a sense of credibility and specificity, and despite the platform's anonymity, some streamers felt they could identify which viewers had submitted certain comments.

Importantly, the anonymous nature of the feedback was seen as a key enabler of honesty and transparency. One participant noted, "I think people were honest there. So I think I like that. Because usually people are a little bit like, too damn scared if they want to say something" (s2p9). Another echoed this, saying, "Some people aren't going to just outright say what they would like to see, so I think this provides some anonymity for them to be able to give feedback without feeling like they're going to be targeted... I thought it was very interesting to see what their feedback said" (s2p5). Overall, the platform provided a space for streamers to receive valuable, honest, and sometimes challenging feedback in a format that was both accessible and actionable.

5.6.4 Reactions to Newcomer Feedback

An important aspect of this work involved exploring the value of feedback from different viewer groups, particularly newcomers. Streamers' responses to newcomer feedback varied, reflecting a balance between appreciation for fresh perspectives and skepticism about contextual understanding.

Many participants found that feedback from new viewers brought fresh insights and critical observations that existing community members might overlook. One streamer noted, "It's interesting to see their aspect of things, since they haven't been around... they're not necessarily familiar with how the stream goes. So it is interesting to see from a fresh person's aspect of things" (s2p5). Newcomers were able to highlight elements of the stream that stood out,both positively and negatively, based on their initial impressions, which some streamers found useful in evaluating their first-time viewer experience.

However, this freshness also came with limitations. Streamers raised concerns about the validity and context of newcomer feedback, particularly when it was unclear how engaged these viewers had been. As one participant reflected, "I would be interested to know how much engagement in chat they did" (s2p5), suggesting that the depth of interaction might impact the reliability of their feedback. This lack of context led some streamers to deprioritize newcomer feedback in comparison to insights from long-term community members. As one participant explained, "It's informative, it's not useless, but it's not going to influence what my next stream is" (s2p8). Others emphasized that while feedback from newcomers held value, it was often the community feedback that carried more weight due to viewers' deeper familiarity with the stream and its evolution over time. "The community is a little bit more specific... because they don't know me, obviously they don't have context, they're just making an impression" (s2p8).

In some cases, language and cultural barriers further limited the usefulness of newcomer feedback. For example, one Spanish-speaking streamer shared that many newcomers were non-Spanish speakers, which led to a disconnect in understanding the content: "It was kind of awkward... that would be a big barrier for them to overcome the content and just actually enjoy it" (s2p6).

Still, several participants recognized the complementary roles of both groups, newcomers and established community members. One streamer described this balance by saying, "I give value to both groups kind of the same way, because you want newcomers, of course, but you also want to nurture the community you have. So those two are very, very valuable for me" (s2p4). Another added that feedback from both groups tended to align, albeit in different forms: "It also seems to pretty much mimic what I've seen from my own community's feedback as well" (s2p1).

Together, these perspectives highlight the layered value of newcomer feedback: it is often fresh, sometimes critical, occasionally lacking context, but ultimately one piece of a broader feedback ecosystem that streamers must navigate and interpret.

5.7 Discussion

Existing feedback systems available to live streamers tend to prioritize analytics and numeric performance metrics or offer raw comment streams with minimal structure. These approaches often fail to capture the breadth of roles that streamers inhabit, not only as entertainers but also as community managers, curators, and entrepreneurs. As such, current tools inadequately support the multi-dimensional labor that underpins live streaming. Our findings suggest a need to reconceptualize feedback systems not merely as mechanisms for audience metrics, but as sociotechnical tools that scaffold streamers' reflection, community engagement, and long-term development.

5.7.1 Customizable Feedback and Streamer Agency

Participants' articulated desires for more data, customization, and content specificity underscore not only the perceived limitations of the current system but also point toward concrete design opportunities. For instance, many streamers sought greater control over how feedback is organized and surfaced. One participant envisioned a configurable interface: "There could be more preferences, like some sort of drop down menu, like, what do you want to be displayed in this feedback summary? Choose three at a time" (s2p3). Another requested more granular feedback categories: "Maybe there could be like another specific section that could talk about more specific things than the inner feedback" (s2p3). This preference reflects a broader insight that one-size-fits-all design rarely suffice for diverse social contexts.

In Ackerman's work on the socio-technical gap, they argue that rigid technical systems often fail to accomodate the evolving practices of users, necessitating adaptation and tailoring by those users [11]. The streamers in our study wanted this agency to configure feedback in ways that aligned with their content and community norms, and enabling such customization is a form of empowerment. Recent research also shows that creators frequently seek or even build unique tools when official platforms fall short of community-specific needs. Cai et al. discusses how Twitch streamers commonly rely on third-party extensions and bots to implement personalized functionality that the platform does not natively support [35]. Our findings echo the notion that flexibility and tailorability are key design considerations for feedback systems in collaborative environments. Streamers are not only content creators, but also community leaders and curators of experiences. Giving granular control of feedback mechanisms can increase their sense of ownership and trust in the system. In summary, designs that support customization and appropriation of feedback systems better align with streamers' on-the-group realities, reaffirming long-standing calls for user-control and tailorability in social computing tools.

5.7.2 Contextualizing Feedback: Anonynimity and the Need for Context

A key theme that emerged was the importance of context in interpreting audience feedback. Comments lacking sufficient context, such as anonymous suggestions, were often difficult to understand or act upon. While anonymity can encourage more candid responses by reducing fear of repercussions, it also removes identity cues and interaction history that help receivers assess credibility and intent [168, 26]. In the case of Streamfeed, this tradeoff proved beneficial for both streamers and viewers, given the inherent power dynamics at play. Viewers typically want to be liked or acknowledged by streamers, which can discourage them from offering honest or critical feedback [128]. Streamfeed then enables viewers to provide candid feedback without consequences in how their streamer may treat them in the future.

However, streamers repeatedly emphasized that feedback alone is not enough, it must be grounded in context. Temporal markers (e.g., when a message was sent), content-specific details (e.g., the game or segment being streamed), and situational nuances were seen as essential for meaningful interpretation. As one participant explained, "I would be interested to know... what game was the streamer playing at the time? Because it depends on the game... it's hard to engage with chat" (s2p5).

This desire for deeper context highlights the often-invisible interpretive work streamers perform to make feedback actionable. While the tool provided summaries and excerpts, participants wanted richer detail and more quotes to better understand viewer sentiment. As one participant noted, "It'd be nice to have a bit more of, like, more quotes... because it gives you only two quotes" (s2p8).

These insights underscore the value of feedback systems that go beyond surface-level summaries, tools that situate feedback in its original context and offer a degree of identity accountability (while respecting user privacy) may better support streamers in making sense of audience responses.

5.7.3 Newcomer Feedback vs Community Norms

We found notable tensions between feedback from newcomers and that from established community members. Streamers often viewed feedback from long-time viewers or moderators as more informed and in line with the channel's norms, whereas feedback from brand-new viewers (while sometimes fresh and insightful) could also conflict with or ignore those norms. This dynamic reflects a classic challenge in online communities: integrating newcomers while preserving community culture.

Newcomers bring new ideas and energy, but they may also lack understanding of the community's history and standards, leading to friction [106]. Kraut and Resnick describe how newcomers, "in their ignorance, may act in ways that offend other group members or undercut the smooth functioning of the group" [106]. In the context of stream communities, a newcomer's well-intentioned suggestion (e.g., to change the stream format or game) might be received poorly if it disregards established practices that veteran viewers value. Prior research has documented severe consequences when communities handle newcomer contributions poorly. Halfaker et al. studied Wikipedia and showed that a surge of hostile reverts to good-faith newbie edits led to a decline in newcomer retention, ultimately stagnating the community's growth [74]. In our study, streamers did not outright "revert" newcomer feedback, but they did express a need to filter or contextualize it. Some streamers noted that long-term community members had earned trust over time, so their feedback carried more weight, whereas first-time commenters' ideas might be taken with a grain of salt. This is consistent with observations by Hamilton et al. that successful Twitch communities often have regulars and moderators who informally tutor newcomers in the channel's norms, helping integrate them into the social fabric [75].

Ideally, communities strive to be welcoming – moderators and veteran viewers frequently greet and guide new viewers to make the stream inviting [75]. Our findings suggest that when it comes to feedback, however, streamers perform a delicate balancing act between openness and skepticism. On one hand, they don't want to dismiss potentially valuable outside input; on the other, they rely on their core community to maintain a consistent experience. This tension underscores a broader theme of community moderation and governance: how to handle new voices in a collaborative space.

5.7.4 Expanding the Social Role of Chatbots

In many streaming contexts, chatbots are primarily deployed for automation or moderation tasks. Our findings suggest an alternative role: bots as active participants in the feedback ecosystem. Rather than simply answering queries or enforcing rules, bots could prompt viewers to reflect, share impressions, or provide structured input.

This resonates with emerging research that challenges the notion of bots being mere technical instruments. Seering et al. argue that bots in online communities can fulfill social roles, influencing discussions and community dynamics much like human participants [9]. In live-stream settings, popular chatbots greet newcomers, enforce channel rules, and engage users with mini-games, effectively integrating into the community's social fabric [9]. Our findings add qualitative evidence that creators perceive these bots as participants: for example, a streamer might say "the bot helped keep the chat civil during feedback time," crediting it much as they would a human moderator. This perception aligns with the concept of chatbots as community members – an idea explored by Seering and colleagues, who envision multi-party chatbot designs that behave as full-fledged community actors (e.g., a "Social Organizer" bot that introduces newcomers, or a "Clown" bot that entertains users) [156].

In our study, streamers' comfort with Streamfeed's bot as a co-moderator indicates that bots can be accepted as legitimate actors in creator communities, provided they are designed to respect community norms and augment (rather than override) human judgment. This has implications for platform governance and creator labor: bots might shoulder some of the work of gathering and triaging feedback, but they need to do so in a way that is transparent and accountable. Overall, recognizing bots as participatory agents means designing them not just for efficiency, but for social compatibility – ensuring they earn user trust, embody the community's values, and can smoothly integrate into the ongoing social interactions of the stream

5.7.5 Reframing Online Feedback Exchange

This work contributes to social computing research by extending how online feedback exchange is conceptualized in real-time, socially embedded environments. Traditional models often frame feedback as static, asynchronous commentary, oriented around performance metrics or structured review cycles. In contrast, Streamfeed surfaces feedback as an *interactive, situated, and socially negotiated process*, tightly coupled to the live dynamics of content production and audience engagement.

By embedding feedback solicitation into ongoing live streams and leveraging chatbots to prompt structured reflection, our system enables a more participatory model of feedback exchange. Our approach shifts the locus of control from platform-centric metrics to community-grounded dialogue. Furthermore, the ability to distinguish between feedback from core and casual audiences complicates assumptions of feedback homogeneity, emphasizing that feedback is always filtered through social position, platform affordances, and performer–audience relationships.

In doing so, we argue that online feedback should be understood not merely as information transfer, but as a form of *relational infrastructure*, supporting creators' navigation of identity, labor, and growth in public digital spaces. Future feedback systems, particularly in online communities, should be designed to reflect this complexity: supporting nuance, context-awareness, and the interpretive practices that make feedback meaningful.

5.7.6 Design Implications

Finally, we outline several design implications from our findings to inform future tools and platforms to support community-centered feedback.

1. **Support Customization and Flexibility:** Feedback systems should allow creators to tailor the tool to their needs. This empowers streamers to integrate the system organically in their workflow and community norms.

2. **Embed Context in Feedback:** Design mechanisms to attach contextual data to viewer comments. Providing context will help streamers interpret and prioritize feedback more accurately, reducing ambiguity and miscommunication.

3. **Newcomer Onboarding and Norm Education:** To address tensions between regulars and newcomers, feedback tools can incorporate features to educate newcomers about community norms before or as they give feedback.

4. **Bots as Collaborative Agents:** Leverage bots to assist with feedback moderation and engagement but design them as transparent collaborators.

Our discussion emphasizes that designing for live streamer communities require balancing flexibility with guidance: empowering creators to shape their feedback process, while embedding safeguards and supports that draw from prior social computing research.

5.8 Future Work and Limitations

Our work could be expanded to other creative domains such as art live streams, educational content, and more. Additionally, scaling the system to accommodate larger communities would enable broader insights and a more robust evaluation. Improving integration with host platforms could also improve engagement, as asking users to go to an external site may hinder engagement. Finally, a longitudinal study could provide additional insights on how the tool affects creator-audience dynamics over time, including changes in engagement and content development.

We acknowledge the limitations of this work such as its limited scope, focusing on a single platform, Twitch. Other live streaming platforms like Youtube or TikTok have distinct interaction models that would require additional analyses. From a technical standpoint, the current implementation faces challenges common to language models, such as potential hallucinations or rigid adherence to prompt templates [82]. These issues may affect quality and relevance of the summaries and future iterations should address such limitations through fine-tuning the model or human-in-the-loop mechanisms [173].

5.9 Conclusion

This work introduces Streamfeed, a real-time feedback system that reimagines the role of conversational agents in live streaming—not as moderators or content responders, but as facilitators of reflection, interpretation, and dialogue. Through the design, deployment, and mixed-methods evaluation of Streamfeed with 11 streamers and 166 viewers, this research makes a system-level contribution to HCI by demonstrating how feedback tools can be embedded meaningfully into live, high-pressure performance contexts.

Our findings show that such systems can surface actionable and nuanced viewer insights, while also revealing underlying tensions between community maintenance and audience growth. Streamfeed supported streamers in affirming or discovering new perspectives on their content, while also making visible the interpretive labor involved in making feedback usable and timely.

These contributions point to a broader need for context-aware, segment-sensitive feedback systems that support the evolving roles of creators—not just as performers, but as moderators, sensemakers, and community stewards. Looking forward, we argue for reimagining feedback not as a performance metric, but as a shared, situated, and co-creative practice, embedded in the rhythms of digital labor and live interaction.

Chapter 6

REVISITING CHAT TO DEEPEN UNDERSTANDING IN LIVE STREAM COMMUNITIES (RQ3)

This final study explores how streamers can revisit and interpret chat data after a broadcast to deepen their understanding of audience feedback and engagement. Building on challenges identified in previous studies, this work investigates the design of post-hoc tools that help streamers make sense of fast-paced context-rich interactions.

6.1 Introduction & Related Work

Prior work highlights the emotional labor involved in streaming, particularly around managing community dynamics and maintaining on-camera presence [71, 191, 150]. While existing moderation tools can flag or remove overtly harmful content in real-time, they often fail to account for the subtleties of context-dependent language (such as sarcasm, banter, or in-group slang) common in many streaming cultures. As a result, streamers are frequently left to process emotionally charged or ambiguous feedback on their own, sometimes days after a stream ends.

Similarly, streamers face challenges in understanding their audiences at scale [59]. Standard analytics tools emphasize surface-level metrics like view counts or chat frequency, offering little insight into who participated, what they valued, or how different audience segments responded [127]. This lack of interpretive support makes it difficult for streamers to reflect meaningfully on their community or make informed decisions about content direction and moderation practices.

This paper presents a unified study exploring how sociotechnical systems can support streamers in post-stream reflection. We developed PostChat to examine two design concepts:

- A chat message-level reframing tool that helps streamers revisit and reinterpret ambiguous or negative comments.
- A persona-based analytics system that clusters viewers into composite audience profiles to increase audience familiarity and reflect on overall community engagement

Both concepts were explored with the same set of participants, allowing us to compare reflection practices at different levels of granularity, individual message interpretation versus high-level audience understanding. In this paper, we seek to answer: "**How can we design systems to support streamers' post-stream reflection across different levels of granularity, from individual messages to audience-wide engagement analysis?**"

By investigating both conceptual and functional prototypes, we offer a layered view of how post-stream reflection can be supported through design. Through the design and evaluation of these tools, we contribute a system-level perspective on how reflection can be supported across different layers of feedback. Our findings have implications for the development of socio-computational tools that mitigate emotional burdens and enrich community understanding in live content creation.

We begin with a consideration of literature on live streaming and feedback exchange. Following this, we offer a description of the design and development of the system and tools presented in this work. Then, we describe the methodology for conducting our usability tests and analyses of the prototypes. Finally, we show the findings and then highlight some insights in the discussion section.

6.1.1 Audience Analytics and Viewer Understanding

Recent scholarship highlights the importance of audience analytics in shaping creators' strategies and self-perceptions. The previous chapter and other studies show that streamers use real-time metrics and chat interactions to gauge viewer preferences, adapt content, and foster community engagement [164]. However, analytics often provide only a partial picture, leading to potential misinterpretations of audience intent and satisfaction.

Content creators actively use analytics to adapt their content strategies in response to audience behaviors and platform algorithms. Creators often experience tension between algorithmic demands and genuine audience engagement, regularity versus audience autonomy, and analytics versus decision-making autonomy [90]. Prior work has shown that these are some strategies that enable creative control over their content while also optimizing for platform and algorithmic distribution.

One popular approach has been sentiment analysis for content adaptation. Sentiment analysis has allowed creators to gauge audience reactions to their content and inform content optimization strategies, which can be used for tailoring future content to audience preference [148]. This broadly applies to content creators in general, such as YouTube videos and social media posts. For example, platform analytics tools like YouTube Studio provide metrics on view counts, watch time, and demographic data to support content decisions; similarly, Twitch offers these same metrics and a suggestions page to help streamers with scheduling and recommended categories for future planning. However, these analytics have shown to be limited for live streamers themselves, which often requires creators to utilize external analytics tools [121].

For live streamers, engagement metrics are often referred to as the currency of success for those hoping to grow and resonate with their community [43]. The technical features of social media platforms also facilitate the formation of dynamic and networked communities, not just within streamer-viewer relationships but also between streamers and between viewers. Many content creators often try to understand the way recommendation algorithms work so they can "work the system" to potentially increase their visibility and profit [126, 125, 90, 98, 53].

While analytics offer valuable insights, they also introduce new forms of labor and emotional investment for creators, as explored in the following section.

6.1.2 Labor in Live Streaming

Live streaming blurs the boundaries between work and play, demanding both emotional and physical labor from creators. Streamers face constant pressure to perform, manage their communities, and maintain an authentic presence, which can often lead to burnout or emotional exhaustion [150, 161]. The visibility of this labor is frequently underestimated, as creators must navigate complex expectations from both platforms and audiences alike.

Live streaming requires creators to engage in intensive emotional labor beyond just appearing on camera. Streamers often have to be constantly "on," friendly, or witty, while also staying in character for hours at a time [133, 191]. This emotional labor manifests through various performances required of creators, such as being friendly to viewers, soliciting donations and subscriptions, and more [191, 34]. Emotional labor is critical as streamers need to express the right emotions to foster viewers' active attitudes and behaviors in communication and transactions [199]. This requires streamers to display organizationally desired emotions while also actively suppressing others that might negatively affect current, live, and ongoing content [199].

There are also gendered dimensions to emotional labor. For example, female streamers are often expected and labeled to be "nicer" and to intersect with societal expectations of women as attentive and caring [150]. However, this becomes intertwined with sexualized expectations, where viewers expect female streamers to entertain with sexual innuendos and fantasies to maintain streamer-viewer relationships and encourage gift giving, often hiding their personal relationships behind the camera [150].

Prior research has also identified and highlighted hidden labor as a key component of streaming work, including the day-to-day maintenance for potential earnings, responding to collaborations and emails, checking statistics, planning future content, community management, and more to ensure that each stream is well run. These tasks vary across different types of viewers and streamers. For those who are successful, streamers spend many hours adhering to a regular streaming schedule, properly configuring technical aspects, and promoting streams across social media [127, 191].

These labor dynamics are further complicated by the ambiguous and interpretive nature of online interactions, which can heighten uncertainty and stress for both creators and viewers.

6.1.3 Limitations of Existing Moderation and Feedback Tools

Although platforms provide various moderation and feedback tools, research indicates that these systems are often inadequate for addressing the nuanced and evolving challenges of live streaming. Automated moderation can miss context, while manual moderation places additional strain on creators and their communities [157, 36, 119]. Feedback mechanisms may fail to capture the full spectrum of viewer sentiment, limiting creators' ability to respond adaptively.

Recent advances in large language models (LLMs) and multimodal AI have enabled interactive, real-time feedback systems at scale. Proxona leverages static comments to build structured audience personas, allowing creators to simulate conversations with diverse viewer segments and use feedback for ideation and content refinement [48]. SimTube extends this by generating predictive audience responses before a video's release, combining video data with persona modeling to offer creators context-rich, demographically varied feedback scenarios [86]. These tools reframe feedback as a creative asset rather than a reactive metric.

While such systems highlight new possibilities for creator support, they also underscore a critical gap in our understanding of how creators navigate feedback, labor, and moderation in practice. While these systems offer creators simulated perspectives and audience insight, they primarily operate in a static or anticipatory context.

6.2 Research Gap and Question

Despite advances in understanding audience analytics, labor, and moderation in live streaming, there remains a lack of integrated research examining how these elements intersect to shape creators' day-to-day experiences. Specifically, few studies address how the limitations of current tools and the inherent ambiguity of online spaces combine to affect creators' ability to interpret feedback and manage their labor effectively.

While prior work has explored moderation, viewer engagement, and analytics in isolation, there is a need for systems that support post-stream reflection as a situated, emotionally grounded, and layered practice—spanning both granular interpretation of chat messages and high-level analysis of audience behavior.

To address this gap, our research makes a system contribution to HCI by designing, developing, and evaluating two integrated tools—one that helps streamers revisit and reinterpret individual messages, and another that supports audience-wide sense-making through persona-based analytics. Together, these systems explore how interactive tools can support streamers' emotional processing, decision-making, and community understanding after a stream ends.

This work is guided by the following research questions:

- **RQ1**: How might systems support post-stream reinterpretation of ambiguous or emotionally charged chat messages?
- **RQ2**: What types of persona-based analytics best support streamers' understanding of audience dynamics after a stream?
- **RQ3**: How do different reflection tools (message-level vs. audience-level) affect streamers' emotional labor, sense-making, and decision-making?

6.3 PostChat Design and Development

In this section, we describe the details of the iterative design and development of two complementary designs of PostChat, aimed at supporting after-stream reflection for live streamers: a chat message-level analysis and an audience-level persona analysis dashboard. Our approach is grounded in user-centered design principles, developing solutions iteratively and in cooperation with their target users[72].

6.3.1 Chat Message-Level Reflection and Reframing

Existing moderation tools primarily address surface-level disruptions in real-time, but rarely facilitate the deeper interpretive work that streamers undertake after the broadcast. Our design investigates whether streamers value structured message-level reflection, how ambiguous negativity affects them, and what features are most beneficial.

Drawing on the framework from "Navigating Ambiguous Negativity: A Case Study of Twitch.tv Live Chats," we operationalized three tiers of harmful chat behavior: surface-level disruptions (e.g., spam, slurs), relational/dialogic behaviors (e.g., trolling, banter), and meta-discourse/ambiguous negativity (e.g., subtle social tensions or controversial topics) [131]. Representative chat messages were generated across these layers, informed by this typology.

In the diagram below (Figure 6.1, we present a screenshot of the prototype for chat negativity with the following components: On the left side, we start with the metadata of the stream including category, stream date, duration, and number of messages to allow users to easily contextualize which stream is being represented. Below, we show the frequency of chat messages in a bar chart segmented in 5-minute intervals, highlighting segments with colors relating to themes that showed up in the analysis. Finally, there is a scrollable chat transcript that provides the line-by-line chat message history, with respective messages highlighted with the theme color. On the top right, a pop-up tooltip that provides information about this page. Below, are the list of themes as collapsible/expandable sections to get a description of the highlighted negativity themes, some findings related to the chat, and associated recommendations. This is repeated for the other themes found in this chat history.

For this part of the prototype, we simply designed a static HTML page utilizing sample data. Given that different streamers may experience varying degrees of "ambiguous negativity" from little to none, we presented them with this synthetic page to get their feedback across these three themes.

6.3.2 Audience-Level Reflection with Persona-Based Analytics

While Twitch offers a real-time chat for a continuous stream of audience feedback, this data is often noisy, overwhelming, and difficult to interpret. These platforms also provide basic quantitative metrics (i.e. viewer count, chat messages), they offer little support for understanding composition, communication styles, and motivations of the audience. Prior research has emphasized the emotional and attentional demands of sustaining live engage-

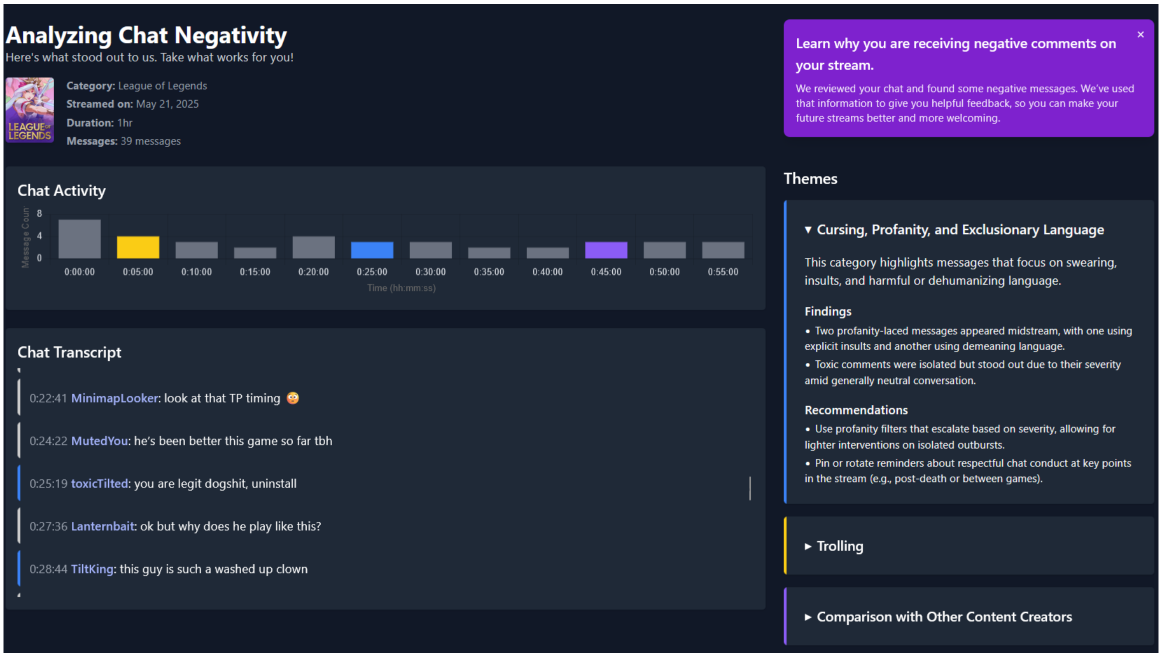

Figure 6.1: Screenshot of Prototype Analyzing Chat Negativity

ment, yet tools for post-hoc reflection on audience behavior and community dynamics remain limited.

Building on systems like Proxona [48] and SimTube [85], which transformed raw feedback into persona-based insights, we also explroe how persona-based analytics can support deeper reflection for streamers. By abstracting chat into composite audience profiles, this approach surfaces patterns in tone, recurring themes, and styles of interaction.

A Chain-of-Thought (CoT) prompt guides the model through interpretable steps: identifying patterns, assigning labels, selecting representative quotes, and describing behavioral themes [182]. We adopted a grounded typology-based coding framework, following categories from Schuck [155], to classify each chat message into one of three recurring viewer personas:

- System Alterers (SA): Messages attempting to influence or direct the streamer (e.g., advice, critique).

- Financial Sponsors (FS): Messages referencing financial support mechanisms (e.g., subscriptions, donations).
- Social Players (SP): Messages engaging in playful, interactive, or socially bonding behaviors (e.g., emote spam, memes).

All chat messages were included via forced classification to ensure comprehensive representation.

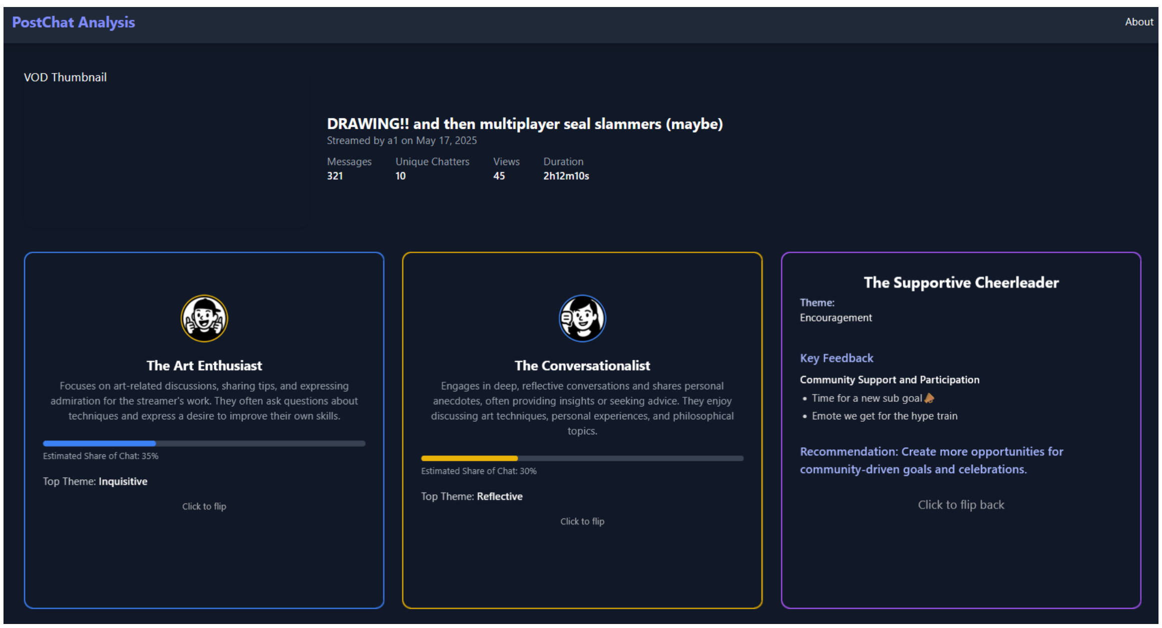

Figure 6.2: Viewer Persona Prototype Tailored to Streamers Using Twitch VODs

To support audience-level reflection, we developed a prompt-based inference pipeline leveraging GPT-4o via the OpenAI API [87]. Chat logs were segmented into batches of 200 messages, with each batch analyzed independently to maintain granularity and scalability. For each batch, we employed structured prompting to guide the model in inferring approximately three distinct viewer personas. Each persona profile (Figure 6.2) included a concise descriptive label, a summary description, an estimated proportion of messages, and dominant communicative theme (such as encouragement or critique). When users click the card, the profile also includes representative quotes pulled from chat accompanied by actionable feedback for streamers.

To ensure interpretability and reduce redundancy, similar persona profiles were aggregated and merged using Levenshtein-based fuzzy matching on both name similarity and behavioral traits [99]. This process allowed us to surface the most salient and distinct personas for each stream, supporting nuanced audience insights. Importantly, all model prompts included strict constraints to minimize hallucination and speculation, ensuring that all generated insights were directly traceable to the underlying chat data [196].

From a technical perspective, the system was configured with a temperature setting of 0.6 and a maximum token limit of 3000 per prompt. Outputs from the language model were validated against a predefined JSON schema to ensure structural consistency and facilitate downstream processing. Finally, the resulting personas were visualized in an interactive dashboard, with each persona represented as a card displaying sentiment bars on the front and qualitative summaries on the back. This design enabled streamers to quickly assess the emotional landscape and communicative dynamics of their audience, supporting reflective practice and informed community management.

Both prototypes were developed iteratively, beginning with low-fidelity wireframes created via Figma and advancing to interactive prototypes using Python and Flask. This process enabled rapid exploration of the design space, early user feedback, and refinement of core interaction flows [165].

6.4 Methodology

6.4.1 Study Overview

This study employed remote usability testing sessions to investigate how streamers reflect on and manage their post-stream activities, audience dynamics, and interactions with chat data. We used personalized audience persona pages and a message-level prototype to evaluate participants' perceptions of these tools and gather feedback on their potential utility.

6.4.2 Participants

We had recruited 11 participants (Table 6.1 recruited through through a combination of personal networks, public Discord servers, and relevant organizations. All recruitment activities were conducted with appropriate permissions, including moderator approval when necessary. Eligibility criteria required participants to have at least 2 publicly available recent VODs (video on demand) for generating their personalized audience personas, and have streamed recently before their scheduled session. The streamers represented a range of content including gaming, art and just chatting, with followers ranging from 109 to 7633. Participants were recruited globally with six from USA, four from Asia and one from Australia. We also required our participants to be at least Twitch Affiliates, the minimum level at which creators can earn revenue on the platform, as a signal that they were serious about streaming [3]. This study was approved by the Institutional Review Board (IRB) at the authors' university.

Table 6.1: Participant Demographics of Study 3

Participant ID (PID)	Location	Followers	Streamer Status	Average Viewer (past 30 days)	Hours Streamed (past 30 days)
s3p1	USA	109	Affiliate	2	11
s3p2	USA	1580	Affiliate	8	48
s3p3	Philippines	230	Affiliate	8	82
s3p4	USA	3569	Affiliate	3	25
s3p5	USA	5205	Affiliate	12	28
s3p6	India	7576	Affiliate	56	122
s3p7	USA	1685	Affiliate	17	217
s3p8	India	128	Affiliate	5	25
s3p9	Australia	3133	Affiliate	16	244
s3p10	Indonesia	7633	Partner	46	51
s3p11	USA	143	Affiliate	7	19

6.4.3 Interview Procedure

Each usability testing session followed a semi-structured interview format. Prior to the study sessions, participants were asked to share links to two of their previous and recent Twitch VODs (videos on demand), enabling the research team to generate personalized audience personas ahead of each interview. Participants were first asked about their typical post-stream workflows and the ways in which they currently analyze their stream content. Next, we introduced the personalized audience-level personas generated from their own Twitch data and invited participants to reflect on the personas' effectiveness in helping them understand their audiences. In the final stage of the session, we presented a prototype that visualized individual chat messages using synthetic data, focusing on potential applications for identifying negativity and supporting content analysis. Participants were asked to provide feedback on the prototype's utility, design, and potential extensions.

6.4.4 Data Analysis

All interviews were recorded and transcribed using Otter.ai. The first author manually reviewed each transcript to correct typographical errors and address any transcription inaccuracies. Transcripts were then shared with the research team for qualitative analysis and coding via Google Sheets and Miro.

We adopted a grounded theory approach to analyze the interview data [39]. The coding process began with a collaborative session on two transcripts, during which the team identified initial themes and drafted a preliminary codebook. In subsequent meetings, team members reconciled coding discrepancies and iteratively refined the codebook to incorporate emerging concepts. This process continued until all transcripts were fully coded. To assess coding consistency, we calculated inter-rater reliability using Cohen's Kappa, achieving a score of 0.83 for a near-perfect agreement.

The final codebook consisted of the following top-level categories:

- **Labor and Practices:**
  - **Post-Stream Work:** Descriptions of tasks participants engage in after a stream,

such as content review, highlight selection, and future planning.

  - **Moderation Approaches:** Strategies employed to manage and moderate chat, whether through delegated moderators or self-moderation techniques.

- **Community and Interaction:**
  - **Audience Understanding:** Insights into how streamers conceptualize their audience and community, including perceptions, expectations, and engagement practices.
  - **Chat Negativity:** Accounts of negative experiences within chat and their perceived impact on community dynamics and streamer well-being.

- **Design and Impact:**
  - **Prototype Applications:** Participant suggestions for practical uses of the prototype, including identifying clippable moments, facilitating retroactive moderation, improving audience insights, and reducing emotional labor.
  - **Feedback:** General impressions of the prototype, including positive responses, critiques of current features, and recommendations for future development.

These thematic categories structure the presentation of our findings in the following section.

6.5 Findings

6.5.1 Post-Stream Routine

After a stream ends, many content creators transition into a second phase of labor, which is often unseen by audiences but is essential to sustaining their channels. This post-stream work includes reviewing chat logs, editing videos for highlights, preparing assets for future streams, and evaluating analytics. These tasks can be emotionally and mentally demanding, especially following the long hours of streaming. Some streamers, such as s3p1, describe delaying this reflection until the next day, allowing space for rest before critically engaging with their performance. “If I want to do any reflections, I do it, like, the next day... I try to, like, see what’s going on and how I can improve,” s3p1 explains.

Reviewing chat logs is often used as a tool to understand audience behavior, particularly in identifying which moments drove engagement, who the new viewers were, and why some chose to stay. s3p1 elaborates: "I'm mostly curious about the new viewers, what their preferences are, and how to keep them engaged without... changing my entire personality." Others, like s3p2 and s3p4, emphasized the importance of recognizing "hype moments" and spikes in interactivity as indicators of successful content. These segments often serve as inspiration for clips, which streamers reuse for promotion or content repurposing on platforms like YouTube.

Streamers take varied approaches to this post-stream routine. While some immediately engage in editing or reviewing their stream (s3p6: "I will just do some editing and stuff"), others prioritize basic self-care, like getting food or going to bed (s3p8: "I just die in bed because I'm so tired"). The transition out of the stream can also include community engagement, such as initiating a Twitch raid to direct their viewers to another streamer, typically someone whose energy matches theirs. As s3p2 notes, this is a way to "take my whole group... to a new stream," extending the social dynamic beyond their own broadcast.

Tools like Twitch's built-in interface and OBS are frequently used during this phase. Some, like s3p1, simply scroll through their video with chat replay visible. Others lean on chatbots or Discord communities for ongoing discussions and feedback, especially when chat during the live stream is difficult to analyze in real time. s3p2, for example, has a designated space in Discord for users to share their favorite chat moments, further facilitating audience understanding.

Not all streamers engage deeply in post-stream analysis. Some, like s3p3, report little interest in re-reading chat: "I don't remember all my conversations." But many others, such as s3p10 and s3p7, make a point of tracking metrics like view count, average viewer time, and even revenue. For them, reviewing chat is part of a broader analytical routine that includes uploading VODs, studying audience behavior, and understanding content performance over time.

Streamers ultimately share a common goal: better understanding their audience. They want to identify what draws viewers in, what makes them stay, and how to engage new followers without losing their authenticity. As s3p1 puts it, "I'd rather have someone come to my stream and want to stay here ... whether they like my conversations or the content I create." Yet the complexity of audience analysis is compounded by language barriers (s3p5: "English is like a second or third language for a lot of them") and varying viewer preferences. Understanding this diversity is crucial, especially for navigating sensitive topics or fostering a more inclusive environment.

6.5.2 Managing Negativity

While live streaming offers a space for community-building and entertainment, it also exposes streamers to real-time negativity that requires emotional resilience and active moderation. Participants described dealing with hurtful, disruptive, or simply confusing comments during their broadcasts. These messages can range from overt insults to unsolicited trauma-dumping. S3p1 recalls banning a viewer who persistently shared personal life issues in a way that disrupted the stream's flow: "Why are you telling me about all your dates... Okay, I'm gonna ban you."

Moderation becomes a critical part of managing this emotional labor. Many streamers rely on Twitch's built-in systems, including banning users, enabling "Slow Mode" to reduce spam, and using chatbots to flag problematic messages. S3p6, for example, notes that enabling Slow Mode helps keep conversations manageable and less overwhelming. Streamers also discuss drawing boundaries around off-topic or overly negative content, even when it's not explicitly targeted. S3p1 reflects on this, saying: "It's not targeted towards you personally... but that should also be regulated."

Moderators, who are trusted community members who help manage chat and enforce community guidelines, play an important role in shielding streamers from harmful content. As s3p3 notes, "I try to catch the message before they read it so it doesn't ruin their mood while they're streaming." The emotional toll of reading hateful messages, especially those related to appearance, identity, or marginalized status, can be intense. S3p11 comments on the particular vulnerability of LGBTQ+ streamers, who may face a disproportionate amount of hate. In response, streamers develop strategies not just to manage toxicity, but to protect their own mental health and emotional equilibrium.

However, banning or publicly addressing negative comments isn't always straightforward. For newer or smaller streamers, such actions can feel too severe or risky, especially when trying to grow an audience. S3p11 reflects on this tension, describing how banning someone can feel like "an extreme move," even when justified. Still, streamers recognize the importance of setting clear boundaries to maintain a healthy, welcoming environment for themselves and their communities.

Despite these challenges, many participants emphasize that negativity is inevitable but manageable. As s3p4 succinctly puts it, "There's negativity everywhere." The key lies in moderation of not only of their chats, but of their own emotional responses. By developing systems to filter harmful content and protect their mental well-being, streamers find ways to sustain themselves in a space that is both highly social and deeply personal.

6.5.3 Chat Message-Level Insights

Message-level analytics offered streamers detailed insights into the live chat experience, enabling both retroactive moderation and the identification of peak moments. These tools supported streamers in managing emotional labor, audience engagement, and content repurposing long after the live stream had ended.

Retroactive Moderation

One major application of message-level analytics was retroactive moderation where streamers could use chat logs and analysis tools to revisit potentially problematic interactions post-stream. This gave streamers more time to make thoughtful decisions, alleviating the pressure to moderate in real time. For instance, s3p1 described relying on memory and pattern recognition to evaluate user behavior: "This person is a regular and they're only saying this to make fun of me... not in bad faith," but added, "If it's a new person and they're suddenly saying that stuff, of course, I'm like, 'Get out of here.'" For larger channels, where hundreds of messages may flood in, tools that filter messages and identify trolling or hate speech were seen as essential. As s3p1 imagined, a feature that flags emotionally charged messages with prompts like "please verify" could assist in decision-making while maintaining nuance and fairness.

Several participants emphasized that such tools are particularly valuable for large or front-page streams, where the volume of interaction often exceeds what a streamer can monitor. S3p7 noted, "This would be more useful for someone who has a huge viewership... so they can have the analysis even post stream." Similarly, s3p10 reflected on using analytics during high-traffic events to identify trolls or flag homophobic messages: "I think maybe I can use it... to report it to Twitch." S3p5 added that these tools might be especially beneficial in communities associated with toxicity, like those surrounding games such as League of Legends.

Streamers also found value in using message-level analytics to assess not just individual comments but patterns of negative behavior across time. S3p4 reflected, "There's no way I let that slide," upon reviewing offensive comments she missed during the stream. S3p11 shared a similar experience, stating, "This tool is telling me... your first 10 messages are just like, 'Get good scrub.' I might have to have a chat with this guy." These retrospective views enabled streamers to distinguish between one-time incidents and sustained negativity, which informed their future moderation strategies.

Participants appreciated how the platform offered more than automated flagging; it provided contextual cues that existing moderation bots might miss. As s3p2 and s3p4 both emphasized, bots alone often fail to catch all violations, especially when the issue is tone or context rather than specific trigger words. S3p4 commented, "It shows a lot more sections and what specifically is being said," highlighting the tool's depth compared to traditional keyword filters. Manual review, guided by such granular analytics, allowed for a more informed and emotionally grounded approach to moderation.

In addition, the platform's recommendations on how to address negative commentary were seen as particularly helpful, especially for newer streamers. S3p3 said, "I didn't know what to do with the dude who's commenting on the streamer's appearance," noting that recommendations and potential warning messages could provide actionable steps during live interactions or after the stream. This functionality not only supported emotional labor but also empowered streamers to handle conflict in more constructive ways.

Even outside of explicit moderation, streamers saw benefits in simply identifying drama or tension in the chat that they might want to avoid or address. As s3p8 put it succinctly, “Some people do like to avoid drama,” and having tools that surface those tensions post-stream can help maintain community harmony.

Peak Moments

Another key use of message-level analytics was the identification of peak moments, sections of the stream where audience engagement spiked. These moments often became the raw material for clips and highlights, enabling streamers to extend the life of their content across platforms like YouTube, TikTok, or Twitter. S3p4 described this practice as a way to “see where I make them talk… I see what hypes someone.” Similarly, s3p6 recounted reviewing a session with unusually high views during a short time window, suggesting it might indicate a particularly engaging segment worth revisiting.

For streamers aiming to grow their audience, understanding what content resonates most was vital. S3p7 noted that seeing where conversations spiked helped them learn “what people are liking,” while s3p11 reflected on how analytics allowed them to “look back and see what content I was doing when the hype was happening.” These moments were not just quantitatively interesting; they were also emotionally meaningful. Streamers like s3p1 expressed enjoyment in revisiting chat logs to re-experience positive moments, saying, “Oh yeah, that conversation did happen. Oh yeah, this person did say that.”

Timestamps and duration data were particularly valued for locating and remembering meaningful interactions. S3p1 mentioned that timestamps acted as emotional and narrative markers: “Even if you cannot get the context of the video itself… you’ll be like, ‘Oh, that was this topic.’” This helped streamers remember key discussions and reactions that might otherwise blur together during long streaming sessions.

For those invested in content repurposing, these tools helped streamline an otherwise time-consuming task. S3p2 commented, “I am always trying to get more clip generation. It is like a major thing that I do,” while s3p8 noted that reviewing gameplay footage with chat helped them find strong moments for highlight reels. S3p4 added that hype trains and memorable chat events often served as anchors for creating compelling video snippets: “If I get, like, a really good clip, I’ll go back to that to find it.”

Participants generally appreciated that the platform offered intelligent recommendations on what to clip, guided by audience behavior. By surfacing moments with high chat activity or emotionally resonant content, these tools reduced the labor of manually searching through hours of footage. As a result, streamers could more effectively connect with their audience across platforms, reinforcing the moments that mattered most during their live broadcasts.

6.5.4 Persona-Level Insights

Persona-based analytics offered a new lens for understanding audience dynamics and planning future content. Participants responded to this feature in two primary ways: as a tool for deepening community understanding and as a resource for content planning.

Community Understanding

Streamers used persona analytics to interpret distinct audience segments and reflect on specific moments of engagement during their streams. Several participants highlighted the value of timestamps associated with persona shifts, which allowed them to detect “pivot points” in audience behavior; transitions where, for instance, a viewer moved from being a passive supporter to an active conversationalist. As s3p1 explained, “When did this persona suddenly become different kinds of personas? … Which sections of the video were mostly this? So which sections of the video are mostly that?”

Others appreciated how persona histories could offer broader context on individual viewers, especially when behaviors suddenly changed. For example, s3p1 envisioned looking back at a long-time viewer’s chat history to understand a sudden trolling episode, noting that “if this user has, like, a history of being like an art enthusiast or a supportive person, then I won’t ban them or something like that." The ability to interpret changes in persona over time helped streamers feel more informed and fair in how they responded to their communities.

Streamers also valued the quantitative summaries provided by the platform. For instance, s3p4 appreciated that the system "tells you exactly how many messages [per persona]," and found it useful for identifying what content resonated, as when they learned how many subscribers engaged during a certain moment: "That means I did something good during that moment."

In addition to behavioral patterns, participants were interested in emotionally significant moments they might have missed live. S3p10 shared that it would be helpful if the system highlighted "a very heartfelt message... because sometimes, honestly, I miss chat or totally forget about them." In this way, persona analytics served not just as a performance metric but also as a way to reconnect with community members and their emotional contributions.

Despite these benefits, some participants expressed discomfort with how negative personas or critical comments were presented. S3p6 described their concern that the platform initially felt like "a page of everything that they hate about you." Both s3p6 and s3p7 suggested prioritizing or filtering for positive messages as a way to maintain streamers' emotional well-being. As s3p1 simply put it, "I would love to see this for the positive comments."

Content Planning

Beyond understanding their audiences, streamers saw persona analytics as a valuable tool for planning future content. Many appreciated the tailored recommendations generated from persona trends, whether encouraging new stream formats, adjusting tone, or responding to specific viewer types. S3p1 described wanting "a whole list of recommendations" based on their chat data and liked suggestions such as "encourage storytelling prompts" or "ask more questions to your chat." For smaller streamers in particular, these suggestions helped spark new content ideas and strategies for community growth.

Streamers also found value in aligning their strengths with their content planning. S3p4 remarked that the tool helped identify what they were "really good at," such as "getting support from [the] community and engaging them to ask questions." S3p3 echoed this need for creative inspiration, stating: "I don't exactly know what to do... this would help in finding out what people would want to do for [a community event]."

Several streamers described using persona data to brainstorm themed segments tailored to specific audience interests. S3p6, for example, appreciated the recommendation to create "a dedicated segment of sharing tips and strategy to enhance [the] player segment," particularly in games like Genshin Impact where viewers are often interested in mechanics. Similarly, s3p11 highlighted more novel ideas, like "use informative overlays or trivia segments," calling them "interesting recommendations."

Incorporating specific chat quotes into the recommendations made them more actionable. S3p4 reflected on a suggestion tied to a viewer's comment: "It shows exactly what they're saying, like, 'Oh, you didn't press R.' Okay, fine. I'll press R next time." These concrete links between viewer feedback and stream content helped participants visualize how to integrate audience preferences directly into their planning.

However, some streamers wanted deeper integration between persona data and the context of their streams. S3p5 suggested that the tool would be more helpful "if it was providing more data," such as the emotional or gameplay context when negative feedback occurred, to better inform future decisions (e.g., avoiding frustrating stream segments).

Overall, participants found persona-based recommendations helpful and often creatively generative. S3p7 summarized the general sentiment: "The recommendations are nice, and it's really good to see that kind of thing." When supported with rich context and actionable insights, persona analytics proved valuable for both reflecting on past streams and envisioning future ones.

6.6 Discussion

This discussion explores how emotional impact and feedback framing within analytics tools shape streamers' content decisions and self-perception. By examining how actionable recommendations enhance content planning, we also consider broader implications for streamer-audience relationships, community management, and the design of future creator-facing platforms.

6.6.1 Emotional Impact and Feedback Framing in Analytics Tools

Participants frequently raised concerns about how feedback, particularly persona-level summaries that foreground negative behaviors or sentiments, might affect their emotional well-being. Several described moments where encountering critiques or "harsh truths" about their audience felt demotivating, especially when presented in bulk, without positive context. This finding highlights a key tension between transparency and morale: while streamers valued knowing when something went wrong, unbalanced feedback, especially in textual or quantified form, risked amplifying stress or self-doubt. This reflects a broader challenge in collaborative tools where honest critique must be moderated to support long-term creative engagement.

Crucially, streamers expressed a desire for tools that would frame feedback more thoughtfully, either by pairing critiques with affirmations, or by allowing users to toggle between emotional "modes" (e.g., focus on support, critique, or general trends). Several participants imagined configurations that allowed them to "ease into" difficult feedback or to receive it only at designated times (e.g., after a stream, not during). This resonates with prior work on affect-aware systems and self-tracking, which show that users often seek to control the timing and tone of self-reflective data to protect emotional well-being [23].

From a design perspective, these insights suggest the need for more flexible framing mechanisms within streamer analytics tools. Features such as sentiment filters, adjustable thresholds for critique visibility, or "positive highlights" modes may support streamers in navigating emotionally charged insights without disengagement or burnout. Importantly, this goes beyond interface aesthetics; it speaks to how feedback systems must attend to the relational and emotional dynamics of creative labor. For collaborative systems in creator communities, feedback is not just data but it is a form of dialogue that must be negotiated with care.

6.6.2 Enhancing Content Planning Through Actionable Recommendations

Streamers repeatedly emphasized the value of analytics that go beyond surface-level summaries to offer actionable, context-specific recommendations. They appreciated suggestions that were grounded in concrete evidence, such as chat excerpts, timestamps, or specific audience responses, which made it easier to connect feedback to content decisions. One participant described this as the difference between "being told your audience got bored" and "being shown the moment they checked out." This kind of actionable granularity allowed for practical reflection and content planning, helping streamers iterate with intention.

Moreover, participants expressed interest in temporal tools, like the ability to track shifts in audience personas across a stream or to isolate moments of change in engagement or sentiment. These desires echo broader findings in creative support systems, where creators seek tools that not only assess past content but also inform future production through meaningful context [127]. Participants viewed analytics not as a static reporting mechanism, but as a collaborative partner in the iterative cycle of planning, performing, and adapting. This reframing positions analytics as an active co-actor in content co-production.

In addition, several streamers highlighted the appeal of adaptive features, such as goal-based suggestions ("how can I improve retention?") or inspiration prompts ("here's a moment your audience loved, can you build on it?"). This points to opportunities for designing recommendation systems that support exploratory creativity rather than optimization alone.

6.6.3 Implications for Streamer-Audience Relationship and Community Management

A central theme across interviews was the desire for analytics that help streamers maintain emotional connection with their audiences. Participants appreciated when the tool surfaced unexpected moments of warmth or support, such as a kind message from a long-time viewer, or a chat segment that rallied behind them during a tough moment. These features reframed analytics from a cold diagnostic tool into a reminder of community presence and shared experience. Such reframing aligns with research on affective computing and participatory systems, where technology acts as a bridge between emotional labor and community stewardship [96].

This emotional scaffolding was not only personally meaningful but seen as critical to the health of the broader community. Participants described how analytics could help them identify emerging group dynamics, such as a new cohort of active users, or the subtle alienation of a previously loyal viewer. Tools that help surface these shifts at the persona level, especially when contextualized through chat content or behavioral timelines, were seen as especially valuable for maintaining long-term community cohesion. Rather than reacting to problems only when they become visible in moderation queues, streamers hoped for tools that could proactively help them steer the social dynamics of their stream.

Beyond affective connection, many participants also envisioned integrating persona analytics into moderation workflows. For example, tools could help flag evolving behavior patterns that signal the need for a check-in, or differentiate between a one-time negative comment and a consistent persona shift. This nuanced understanding supports more equitable and informed moderation. especially in emotionally complex, parasocial environments where streamers often bear the brunt of relational and managerial labor.

6.6.4 Design Implications

Based on these insights, several design implications emerge for developing effective streaming analytics tools. First, it is crucial to balance positive and negative feedback within the interface. Presenting strengths alongside areas for improvement can encourage streamers and reduce the risk of discouragement associated with overly critical views of audience behavior. Second, interfaces should support fluid navigation between persona-level summaries and detailed message-level data. Such integration allows streamers to maintain both broad awareness of audience composition and a nuanced understanding of individual interactions, facilitating more agile and informed decision-making.

Furthermore, recommendations should be explicitly linked to both types of analytics, providing streamers with clear explanations and examples that ground suggestions in their community's actual behavior. This contextualization helps streamers see why certain actions are recommended, increasing the likelihood of adoption. The ability to customize filters and timelines, such as focusing on specific time segments or persona transitions, would enable streamers to tailor their analytics experience to fit their unique content and audience dynamics. Lastly, incorporating emotional and social context into message-level analytics can surface meaningful community moments beyond quantitative metrics, strengthening the bonds between streamers and their viewers.

6.7 Future Work and Limitations

Looking ahead, future research should explore the long-term effects of integrated persona and message-level analytics on streamer behavior, audience development, and community health. Longitudinal studies could reveal how these tools shape content strategies and community engagement over time. Additionally, the development of adaptive feedback systems that tailor the tone, frequency, and type of analytics based on streamer preferences and streaming context may optimize both utility and emotional impact. Expanding analytics across multiple platforms would provide a more holistic picture of audience engagement, accommodating the increasingly multi-platform nature of streaming.

There is also an opportunity to broaden the scope of analytics beyond streamers to include moderators and community members, fostering collaborative community management and shared understanding. Finally, ethical considerations surrounding data collection, persona modeling, and privacy warrant further investigation to ensure transparency and respect for both streamers and viewers. Addressing these areas will be critical to designing analytics tools that are not only powerful and actionable but also ethical and user-centered.

While this study provides valuable insights into the use of persona- and message-level analytics for streamers, several limitations should be acknowledged. First, our participant sample, though diverse in streaming experience and content focus, may not fully represent the broader streaming community, particularly larger-scale or professional streamers whose needs and interactions could differ substantially. Additionally, the qualitative nature of our data relies heavily on self-reported feedback, which may be influenced by individual biases or recall inaccuracies. The prototype tools examined in this study are also limited by their current features and design, and may not yet capture the full spectrum of streamer-audience dynamics or real-time interactions. Furthermore, the study focuses primarily on English-speaking streamers, potentially overlooking cultural and linguistic factors that could influence persona recognition and engagement strategies. Finally, the implications drawn are based on initial user reactions and may require longitudinal studies to assess the long-term impact of these analytics on streamer behavior and community growth.

6.8 Conclusion

This study demonstrates how system-level tools—specifically, message-level reframing and persona-based analytics—can support streamers in making sense of feedback and understanding audience dynamics after a stream. By designing and evaluating PostChat, we contribute a functional prototype that highlights how layered reflection tools can alleviate emotional labor, support more informed content planning, and deepen community engagement. This constitutes a system contribution to HCI, offering both conceptual framing and technical implementation around post-stream reflection practices.

Our findings show that streamers value tools that surface nuanced audience insights and support message reinterpretation, enabling more tailored engagement strategies. At the same time, they caution against designs that foreground negative sentiment without context, which can undermine morale and emotional resilience. Striking a balance between constructive critique and positive reinforcement emerges as a key design principle for future feedback systems.

By integrating context-aware, emotionally sensitive analytics with actionable guidance, platforms can help streamers navigate the complexities of real-time interaction while sustaining their creative and relational work. Future research should extend this work by studying these systems in live contexts and with more diverse creator populations, ultimately informing the next generation of sociotechnical tools that enhance both streamer experience and audience participation.

Chapter 7

CONCLUSIONS & FUTURE WORK

7.1 Conclusion

This dissertation began with a central question: *How can we support feedback exchange between live streamers and their communities?* As live streaming has evolved from a hobbyist medium into a demanding, emotionally layered, and commercially viable practice, streamers are increasingly tasked with interpreting and managing audience input in real time. The need for feedback systems that are timely, contextual, and emotionally attuned is more urgent than ever.

A key contribution of this work is a critical examination of existing feedback exchange frameworks, which tend to be curated, static, and episodic—often designed for discrete moments such as product reviews, academic evaluations, or managerial appraisals. Such models do not fully capture the continuous and situational nature of feedback in live streaming communities, where interaction happens spontaneously and feedback may arise whenever necessary. This continuous exchange resembles the ongoing feedback managers provide to employees throughout their tenure—not just during mid-year or annual reviews—highlighting the importance of flexibility and timing in feedback design.

To investigate this, I conducted three interconnected studies that explore feedback exchange from multiple angles: streamers' existing information practices, proactive strategies for soliciting feedback, and reactive techniques for interpreting audience response post-stream. These studies collectively propose a proactive-reactive feedback framework that recognizes the temporal and emotional complexities of live streaming feedback.

A key insight across these studies is the **multidimensional nature of feedback in live streaming**. Unlike traditional domains where feedback is primarily instrumental (e.g., aimed at improving a product or performance), in live streaming, feedback serves additional functions: it operates as social validation, emotional support, and a signal of community norms. Streamers must interpret this feedback in the moment and retrospectively, often without adequate tools to distinguish between noise and valuable insight. Viewers may perceive their messages as fleeting interactions, but streamers are left to make meaning from these signals under complex social and emotional conditions.

Another cross-cutting theme is the **critical role of timing and framing** in the feedback process. The real-time nature of live streaming makes it difficult for streamers to pause, interpret, or respond to feedback immediately. Conversely, post-stream, there is more opportunity for reflection, but often a lack of structured tools for revisiting or contextualizing past viewer input. These studies demonstrate that feedback needs are both temporal and contextual; they fluctuate across a streamer's lifecycle and their content planning, live performance, and community maintenance activities.

The three studies in this dissertation were intentionally designed to reflect and respond to this temporal spectrum:

- **Study 1** explored the current information ecosystem streamers operate within, highlighting challenges such as fragmented analytics, information overload, and the emotional labor of interpreting feedback in an unstructured environment.

- **Study 2** introduced a *proactive feedback mechanism* through the design and deployment of Streamfeed, a conversational agent that allowed streamers to intentionally seek structured input from their communities. This system emphasized goal-oriented, targeted reflection that extended beyond ephemeral live interaction.

- **Study 3** addressed *reactive feedback*, focusing on how streamers can analyze post-stream chat data to surface themes, sentiments, and overlooked signals. This system allowed streamers to revisit and make sense of audience responses with greater emotional distance and clarity.

Together, these studies 1.1 articulate a design space that foregrounds both proactive and reactive feedback modalities. Unlike feedback systems in other creative domains, such as video commenting or design critique, which are largely asynchronous and episodic, live streaming demands tools that operate across different time frames and emotional intensities. The dual-mode model proposed here positions feedback not only as a functional tool for improving content, but also as a core part of streamers' identity formation, community management, and emotional resilience.

Across these studies, I also explored the potential of Large Language Models (LLMs) to scaffold feedback synthesis. In both the proactive and reactive systems, LLMs were used to generate summaries, extract themes, and support persona-driven reflection. While streamers generally appreciated these affordances, particularly when audience feedback was overwhelming or vague, they also raised important concerns about interpretability, nuance, and agency. These findings underscore the importance of transparency and control in AI-mediated feedback systems, especially when emotional labor is involved.

Finally, this research highlights the diversity of feedback preferences and emotional boundaries among streamers. Some welcomed structured critique and granular data, while others prioritized tone, emotional safety, and autonomy. As streaming platforms and supporting tools increasingly incorporate AI and automation into feedback loops, designers must consider how to preserve empathy, trust, and consent. Feedback systems must not only inform and support, but also respect the complex emotional dynamics that define streamer-viewer relationships.

In sum, this dissertation challenges traditional, static models of feedback exchange by proposing a continuous, proactive-reactive framework tailored to the unique demands of live streaming. By offering empirical insights, design frameworks, and deployed systems, this work expands HCI's understanding of online communities and provides actionable pathways for creating more intentional, respectful, and meaningful feedback systems in dynamic, socially rich environments.

7.2 Contribution

In this section, I highlight the research contributions of this work by directly addressing the research questions introduced in Chapter 1.3.

RQ1: What does the information ecosystem of live streamers look like and how does it shape their content and community relationships?

The first study, an interview-based exploration with streamers across Twitch and Mixer, surfaces a taxonomy of streamers' information needs related to content production, community management, and marketing strategies. It revealed that while platforms provide basic metrics, they often lack tools that help streamers interpret the *why and how* behind these numbers. Moreover, streamers expressed a desire for more qualitatively-driven insights. This study contributes toward our understanding of streamer-centered analytics, or more broadly, content-creator focused analytics, and offers concrete design recommendations.

This is an empirical contribution that deepens our understanding of streamers' information practices. It aligns with HCI's tradition of qualitative fieldwork investigating the lived experiences of technology users and informs future system design for content creators.

RQ2: How can feedback mechanisms be designed to support constructive, timely, and meaningful exchanges within live stream communities?

The second study introduced Streamfeed, a platform featuring a conversational agent that collects viewer feedback via structured prompts and synthesizes it using large language models (LLMs) into a feedback dashboard. Through a mixed-methods evaluation with 11 streamers and 166 viewers, we found that streamers valued Streamfeed's ability to elicit focused, constructive feedback across key domains: content, community, and marketing. The tool helped streamers not only gather input but also interpret it without emotional exhaustion. However, the study surfaced tensions such as tradeoffs between anonymous honesty and accountability, and between encouraging feedback from newcomers versus preserving community norms.

This work contributes both an artifact—the design and deployment of Streamfeed—and empirical insights from its user-centered evaluation. It advances design knowledge for AI-mediated feedback in live stream settings and highlights key tensions that future systems must navigate.

RQ3: How can systems be developed to support streamers in translating and managing information while minimizing physical and emotional labor?

The third study introduces PostChat, which investigates how streamers reflect on feedback after their streams end. We designed and developed two complementary tools: one offering chat message-level reflections highlighting emotional and relational dynamics in chat logs, and another providing persona-based analytics that abstract chat into composite viewer profiles. The study revealed that streamers appreciated tools helping them reframe ambiguous and emotionally charged feedback, and saw value in returning to specific moments in the stream. While the persona system sparked curiosity, streamers often found it annoying or unhelpful, demonstrating that prior work on persona-based summarization may not fully translate to live streaming contexts.

This study contributes to a design space for post-hoc reflection tools and illustrates how LLMs can scaffold emotional and cognitive sense-making. It is both an artifact contribution, in its novel tool design, and an empirical contribution, in its qualitative evaluation. Crucially, it exemplifies how artifact-based studies enable us to build a checklist of what works and what doesn't within a design space, informing future work and researchers. For example, although persona-based summaries have been posited as promising in previous work, our findings challenge this assumption, emphasizing the need to critically evaluate design elements in real-world contexts. This enriches the literature on reflection technologies and emotional labor in creative work.

7.3 Future Work

Live streaming is still a relatively young medium, and streamers are its pioneers. Unlike in other industries, there are few long-term role models or "career arcs" for live streamers to emulate. As such, today's streamers are not just content creators, they are cultural architects, shaping the norms, boundaries, and expectations of what this ecosystem will become. This presents a unique opportunity for researchers to co-create tools, platforms, and social infrastructures that reflect and support the values of these emerging communities.

One important area for future work lies in rethinking AI's relationship with creators. As generative models grow more powerful, it is critical to ask: Are we building AI that supports creators, or that competes with them? Many creators already express anxiety over automated tools that mimic or appropriate their content without credit. Future systems should be built around principles of augmentation, attribution, and creator ownership. For instance, AI could help suggest ideas without replacing originality, or summarize community responses while clearly pointing back to user-generated input.

Another promising direction is in supporting emotional sustainability and labor visibility. Live streaming is not just performative, it is labor-intensive, emotionally vulnerable, and often isolating. There is a growing need for tools that help streamers manage burnout, navigate emotionally ambiguous feedback, and develop healthier boundaries with their communities. Future research might explore sentiment-aware analytics, personalized feedback coaching, or community governance support that helps distribute the emotional load more evenly.

Lastly, the design of future systems should center community co-creation and transparency. Live streaming communities are not passive audiences, they are active co-creators in the content and culture. Feedback tools, moderation systems, and analytic platforms must reflect this reciprocity. Designing with and for these communities means embracing feedback that is situated, social, and evolving, not merely optimizing for metrics or engagement.

In sum, this dissertation contributes foundational insights and design approaches for supporting feedback exchange in live streaming. As this domain continues to grow, it is imperative that we develop systems that not only serve platform goals, but also reflect the creative, emotional, and relational needs of the people who bring these communities to life.

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