The Language of League: Making Sense of Multimodal Meaning in Twitch Live Streams

Dena Elisabeth Arendall

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THE LANGUAGE OF LEAGUE:
MAKING SENSE OF MULTIMODAL MEANING IN TWITCH LIVE STREAMS

by

Dena Elisabeth Arendall

A Dissertation
Submitted in partial fulfilment of the
Requirements for the degree of
Doctor of Philosophy

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Dedication

To my father, Dr. Steven Arendall, who even in absence, reminds me to ‘move forward with purpose’.
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The Language of League:
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by
Dena Elisabeth Arendall
BLS English and Korean Linguistics, The University of Memphis, Memphis TN 2004
MSEd Special Education, University of Wisconsin at Stout, Menomonie, WI 2013
PhD Applied Linguistics, The University of Memphis, Memphis TN 2023

ABSTRACT

Though there has been a good deal of research on digital discourse and online gaming, there has been relatively little research on 1) the social structure of specific groups within the large online gaming community, 2) the multimodal structure of the online gaming live stream, and 3) the impact that these structures have on the final communicative event. One noteworthy component of the social characteristics of online streams is the streamer gender and size of the stream’s audience. In addition, one difference that sets the live stream apart from other online communications is its intense technological complexity. This study then, will examine both of these social and technological characteristics, in an effort to understand how the participants themselves influence language use and how that language use is further impacted by the availability of multiple mediums, each of which houses multiple modes for communication.

The data for this study consists of a corpus of 32,397 messages posted in the public chat area of 12 League of Legends live streamers, collected between July and September of 2019. Once collected, however, there was no prior convention in place for organizing and transcribed the data for analytical purposes. Therefore, this study also examines multiple transcription
protocols and outlines the model developed by Graham and Arendall for an online gaming digital corpus.

For this study, I take an interactional approach to explore the communicative strategies employed by participants in a complex multimedium-based multimodal event. Using quantitative analysis, I examine patterns of communicative strategies as related to streamer gender and stream size (participant population). In addition, I examine the qualitative characteristics of those patterns, as well as the influences that multiple available mediums and modes have on those patterns. The results of this analysis indicate that both social and technological characteristics of the live stream heavily impact the communicative strategies employed by participants and is often tailored to the specific needs of each community, especially where the use of graphic images is concerned. These results have implications for the further study of online gaming, live streams, and visual communications within multimedium-based multimodal events.
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Chapter 1: Introduction

We live in a world where communication is complex, depending on more than just words to express ourselves. Whether talking to a friend over coffee using facial expressions and specific intonation, reading a textbook packed with charts, images, and text, or replying to your friend’s message with a cute cat emoji—whether face to face or across digital space, language is multimodal. Each time we interact with others, we may use sound, images, gestures, or other strategies, to share our thoughts, feelings, and ideas.

Exposures to multimodal texts online occur daily for the majority of the world’s population. There are 5.2 billion daily internet users around the globe—two thirds of all people are online at least once a day (Statista, 2021). These internet users spend, on average, 7 hours per day online, all the while interacting with texts composed using multiple modes of communication (Statista, 2021). One popular way to experience this multimodal composition at its best is on live streaming platforms, such as Twitch.tv or YouTube. Live streaming is the broadcasting of real-time live videos to an online audience—and its popularity is increasing, with over 30% of the world’s population watching live streams on a weekly basis (Statista, 2022). In 2021, world-wide live streaming revenue was 59.14 billion and by 2025 it is expected to top 175 billion (Statista, 2022).

Live streaming affords us the ability to produce and present our own content, to be active participants in what we watch, and to make connections online. Though these connections are not made face-to-face, they are just as authentic, and bring a genuine and personal feel to the vast world at your fingertips. Streamers (i.e., those producing the live streams) may broadcast a number of different content types, from everyday-life type streaming (e.g., grocery shopping, cleaning house, cooking, working out) to playing video games while hanging out in your cow
costume pajamas—and everything in between. Of these, one of the most popular (i.e., most viewed) live stream content types is video game play. There are over 10,000 video games streamed regularly on Twitch (Media & Entertainment, 2019), with these gaming broadcasts accounting for over 80% of all live streams watched by viewers (Santora, 2022).

“You mean they’re sitting online, just watching them play?”

This question has been asked of me multiple times during conversations about this research. Others do not understand that it is much more than just. And the ones just being watched? Tyler ‘Ninja’ Blevins—the most followed professional gamer and streamer of all time—makes approximately $500,000 per month—6 million dollars a year—from his 252,000 paid subscribers alone (i.e., those paying to watch him play). This, however, does not include the other 11 million dollars he earns from product endorsements, merchandise sales, and esports tournaments (Hore, 2021).

Video gaming has transitioned over the last decades, from being the hobby of a few, to a multi-billion-dollar industry that encompasses nearly every corner of the world. In 2016, the video game industry in the U.S. brought in $22 billion and it was estimated that, by 2023, this number will top $250 billion (ESA 2020). To participate in this gaming, nearly every household in the country (80%) owns at least one console on which to play these games (ESA, 2019). In addition, according to the Statistics Portal, as of 2018, 73% of Americans own a desktop or laptop computer and 77% own smartphones. Furthermore, only 10% of American report not using the internet on a daily basis, with 0% of the 18 – 29 age bracket reporting this (Pew Research Center, 2019). While certainly these devices are also used for work and/or school, in an online survey taken by 5,000 Americans online, 90% reported playing games on their phones and 52% on their laptop or desktop computers (Crecente, 2018). Overall, this study found that
approximately 240 million Americans (73%) spend time each day, playing computerized video games online.

With these numbers in mind and with the drastic increase just over the last decade, it is clear that online video gaming is a prominent activity in today’s society and culture. With an increase in prominence comes an increase of influence on culture, and therefore, on language. It is essential to understand more about the online behavior of the users, as it is shaped by, but also indicative of, their activity and behavior offline.

This understanding can then lead to a broader knowledge of how cultural and language practices on-screen can affect off-screen practices, as well. This research attempts to examine language use on a well-known video game streaming platform. In addition, this research looks at how the very nature of the platform, the way that it allows for a convergence of meaning produced via multiple modes, impacts that language use.

This research centers on the idea that people watch people play these video games. And while the platform at hand is a fairly recent development, the idea of having an audience is not. As a matter of fact, video game play is often accompanied by the presence of others and has been throughout the history of gaming. This concept of “onlookers” (Lin and Sun, 2011), in fact, shapes game play. After all, the “digital gaming experience is not limited to what takes place between gamers and screens, or among players who cooperate with and compete against each other” (Lin & Sun, 2011). These interactions between player and audience are complicated at times and constantly changing, but in their 2011 study, Lin and Sun found that the audiences actually “assist in enhancing and expanding game play.”

Video game audiences began decades ago, standing around friends in an arcade, feeding quarter after quarter, cheering each other on. Today, they have evolved into people sitting at
home, all around the world, logging in and watching live streams. The transition from *Pong*—widely recognized as the first ‘video game’—to online streaming has been complex, fast paced, and everchanging, but it is a history that co-evolves alongside the changing presence of audience interaction. Video gaming did not necessarily begin as a spectator sport. It was not until the “golden age of the arcade game” that people, especially the youth population, began crowding around one another, looking over a player’s shoulder, and encouraging or heckling one another (Tekin & Reeves, 2017). The emergence of new technologies, however, has allowed for a new type of spectatorship, one where fans can virtually engage on interactive platforms and view tournaments, competitive game play, tutorials, and even their favorite eSports athlete, at home, playing the game.

These viewers are the single most valuable asset on streaming platforms (Cheung & Huang, 2011). In fact, though not directly controlling the game play, viewers are considered fully active participants (Cheung & Huang 2011), able to impact gamer action and match outcomes. One study found that many gamers often would prefer to watch other gamers compete than to play the game themselves (Kayto et. al., 2018). Just as in ‘traditional’ sports, competitive gamers have professional players and spectators dedicated to them (Edge, 2014). And those spectators watch for many of the same reasons people watch traditional sports matches (Cheung & Huang, 2011). The difference is that these sports take place one—giving access to the majority of the world’s population.

One reason that viewership of eSports has increased exponentially over the past decade is that the streaming platform interfaces allow for easy access to the athletes—the streamers. And not only can matches be watched, but the platforms also afford chat functions as well—a dedicated space within which the core of audience participation takes place, with people all over
the world *just* watching the gamer play. This research examines this audience occupied space—the public chat area of the live stream—and the language used within. In the following chapters of this dissertation, I discuss the relevant literature on the subject, as well as the steps of exploration and analysis of the rich language content contained in the ‘viewing area’ of this increasingly popular sports arena—Twitch.tv.
Chapter 2: Literature Review

As forthcoming sections will show, there is a great deal of relevant linguistic literature applicable within the realm of this research. This chapter is organized into two sections, positioned to outline both the critical concepts needed for a contextual understanding, and to establish and detail a framework for the analysis. In addition, these sections will highlight the gaps in the literature, leaving an opening that this current research intends to fill.

The review of the research begins here, in section 1, with a focus on three contextual topics: digital discourse, multimodality, and online gaming.

1. From Computer Mediated Communications to Digital Discourse

Before discussing the hows and whys of language use online, there must be a clear understanding of its beginnings, of where it has occurred, where it continues to occur, and of how its very presence has shaped the way it is viewed and used. As will be shown in these next sections, from nearly the moment the internet was born, the research surrounding it grew exponentially, with the purpose of understanding how this digital space shaped the communications taking place within.

Over the course of the last three decades, digital interactions have become more widespread, to a nearly universal level, with just over five billion regularly accessing the internet (Statista, 2021). Computers have come a long way since World War II, when the first digital electronic computer was built in the spirit of national defense. By the end of the 1960s, the first groups of network computers were functioning, and the first recorded exchange of emails sent. From then on, people began communicating at an increasing rate via this new technology. While at first it was restricted to the military and government, it then was welcomed into universities and other businesses, and eventually, by the late 1980s and early 1990s, people were able to go
‘online’ right from inside their home. As the number of ‘connected’ people grew, so did the increasing need to communicate via online channels—and with that, the concept of Computer Mediated Communication (CMC) began to emerge. CMC, as defined early on by a pioneer of the field, Susan Herring, is considered to be any “communication that takes place between human beings via the instrumentality of computers” (1996). As the technology has changed, so has the definition, to include other forms of digital media, and as researchers were exposed to and became more familiar with it, questions began to arise about the language of this new digital world.

As this language has changed and adapted to the technology on which it occurs, the terms used to define it have been reexamined and reconstructed, numerous times—with numerous scholars proposing just as many names. In the 1990s, the term *Computer Mediated Communication* was made increasingly popular by Herring. Since then, it has been speculated that perhaps this label is too broad. Some researchers have begun to use terms such as *Electronic Mediated Communication* and *Digital Mediated Communication*—though neither has acquired a standard existence in the linguistics world (Crystal 2011). This “third medium”, as Crystal (2001) calls it, with its properties unlike those of speech and writing, has been given multiple names over the past years, such as: *electronic discourse* (Davis & Brewer, 1997), *electronic language* (Baron, 1998), and *Netspeak* (Crystal 2001; Thurlow, 2001; Abu Salim, 2015; Tejada et. al., 2020; Herring, 2022). The name continued to develop, and ten years after coining the term CMC, Herring (2016) proposed to update the term CMC to CMCMC (*convergent media CMC*), to account for the increased use of multimodal communications in converged media platforms. These platforms, which provided novel content and context to examine, offered previously unseen affordance and often positioned communications as “secondary to other
information or entertainment-related activities” (Herring 2004, 2016). No matter the term a researcher chooses to adopt, however, Crystal (2011) emphasizes that the internet changes language in a way never before experienced—and as the numbers of daily users has exponentially increased, so too has its influence on language. Because technological advancements have allowed for increased flexibility in the way digital communications occur—far beyond the confines of ‘just a computer’—the term digital discourse will be used here to refer to any communication that occurs in an online, digitally mediated environment.¹

**1.1. Waves of Research**

In the mid-1980s, this computerized concept was new, and scholars like Naomi Baron (1984) were still positing that “many people perceive computers (and the use of computers) as alien, intimidating, and a personal threat.” People quickly began to adapt to the technology, and then began to adapt their language as well. These emerging language choices and patterns attracted scholarly attention, and the researchers found ways to adapt their methods to the digital world.

In those early years of CMC research, during the first wave (Androutsopoulos, 2006), most research studies focused on looking at this new digital discourse as a single method of communication, one that had simply transferred over to a different medium (Androutsopoulos, 2006; Herring, 2007). At the time, communication methods online consisted of emails, newsgroups, AOL chats, IRC, and the like—on stand-alone platforms. Much of the early scholarly interest was focused on the intersection of text-only and personal communication, examining such points as whether computers are inadequate and ineffective in personal communication (Daft & Lengel 1984) or if this communication is still possible, considering only

¹ except where original author uses different term
a partial loss of interpersonal cues (Spears & Lea, 1994). At first, the latter stance prevailed; studies such as Rice and Love (1987) and Kiesler (1986) showed that CMC was impersonal, lacking non-verbal cues, and void of social and emotional content. However, in the 1990s, the opposite was found—that CMC wasn’t so “fixed and stark” (Walther 1996). In fact, Reid (1991) and Rice and Love (1987) found that online discussions could be deeply emotional, and that friendships and romance could even be found. This communication across the dimensions, with its exciting nuances, but previously unexperienced lack of direct contact, was determined by some scholars to be both “liberating and limiting” (Walther, 1996).

By the late 1990s, early 2000s, it was becoming more apparent that the internet was changing the very core of human life—communication—and that, Bargh & McKenna, 2004; Anderson & Tracy 2001). This is where the ‘second wave’ of computer-mediated communication research emerged, with more focus on the social contexts of the communication and how the technology at hand has shaped it (Androutsopoulos, 2006). During this time period, internet demographics began to change, with wider access and availability, spreading rapidly to a wide range of users, in many countries around the world. Researchers began to explore topics such as diversity, gender differences, identity, power dynamics, in an effort to understand how this ‘internet’ was shaping users’ social practices (Androutsopoulos 2006; Buchholz 1996; Danet 1998; Tynes et al 2004).

Finally, as Androutsopoulos (2006) posits there is a third wave, an ongoing examination of digital practices, of “linguistic variability”, and of intersections of different media (Herring 2019; Androutsopoulos 2006). One specific area of research concentrates on the significant variations of language that have been shaped by the technology—topics such as linguistic structures and how they play out in communicative roles (Thurlow 2003), the presence of digital
discourse features such as unconventional spelling, punctuations, abbreviations (Crystal, 2001, 2011; Lee, 2002; Abrams, 2003), as well as several studies that investigate the specific characteristics of digital discourse (i.e., initialisms in chat, (Abu Salim, 2013); instant messaging (Tagliamonte & Denis, 2008); unconventional spellings across platforms, (Lyddy et al., 2014); instant messaging amongst college students, (Baron, 2010); and linguistic economy, (Abrams, 2003)). This focus continued, and alongside it, there has also been considerable attention directed toward the pragmatics of digital discourse (Kehoe & Gee, 2012; Bou-Franch & Graces-Conejos Blivitch, 2014; Evans, 2016; Huang et al., 2016; Graham, 2017; Graham & Hardaker, 2017; Xie & Yus, 2018; Yus, 2018). Even as these studies were published, however, technology continued to advance, language continued to adapt, and the internet made itself a necessary tool in our everyday lives. The digital world creates seemingly endless spaces in which to produce limitless discourse. And in each of these spaces, when examining the discourse in context, there are multiple factors to consider, each one allowing for a unique style and method of communication.

1.2. Factors to Consider in CMC

According to Herring (2007), there are specific factors that must be taken into consideration when describing and classifying digital discourse. While there are two groups of causal agents for these factors (i.e., medium factors, social factors), here the focus is on medium factors—those that relate to the technological features of CMC systems. The second set of factors for classification are those related to the contextual situation within which the communication is taking place. While these factors are considered to influence communications in their presence, they are not pertinent to this piece of the conversation and will be addressed
further in the chapter on qualitative analysis, when applicable. The list of medium factors, as establish by Herring (2007) are as follows:

<table>
<thead>
<tr>
<th>medium factor</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>synchronicity</td>
<td>relating to simultaneous user participation</td>
</tr>
<tr>
<td>message transmission</td>
<td>one way (message by message) vs two way (character by character)</td>
</tr>
<tr>
<td>persistence</td>
<td>length of time message remains after sent</td>
</tr>
<tr>
<td>message buffer</td>
<td>restrictions of message length</td>
</tr>
<tr>
<td>channel of communication</td>
<td>comprised of visual modes vs audio modes, or combined</td>
</tr>
<tr>
<td>anonymous messaging</td>
<td>relates to technological affordances, may be used if available, restricted by guidelines of system</td>
</tr>
<tr>
<td>private messaging</td>
<td></td>
</tr>
<tr>
<td>filtering</td>
<td></td>
</tr>
<tr>
<td>quoting</td>
<td></td>
</tr>
<tr>
<td>message format</td>
<td>visual presentation of message (e.g. placement of new message as it appears, from bottom to scroll up)</td>
</tr>
</tbody>
</table>

Herring (2007) emphasizes that this list is open-ended and can be added to or detracted from as necessary. For purposes here, three factors will be discussed as particularly relevant to the current research: **anonymity**, **persistence**, and **synchronicity**.

According to Herring (2013), **anonymity** is a major influence on these online interactions, especially in the gender sub area, where it has been posited to promote gender equality. While anonymity can be practiced by any user, some systems encourage it. For example, there are some CMC modes that require that usernames not be similar to your email address—encouraging interaction through pseudonyms (Danet, 1998). However, there are also sites and platforms that require no verification of identity—allowing for complete concealment. This anonymity, however, may come with a price. Users may find that they encounter more anti-social behaviors, such as hostility, aggression, flaming, and other generally uncivil and impolite behaviors (Herring 2007; Chen et.al. 2009; Shive et.al. 2010). In fact, the anonymity that is provided can protect toxic individuals, making it difficult to determine who is accountable for long strings of aggressive comments by multiple users (Barlinska et.al., 2013; Davis et.al., 2015). This is not to say that anonymity is absolutely negative; on the contrary, users often find a safe haven which promotes freedom of expression and self-disclosure (Jiang et.al., 2011). In addition, Kang et.al. (2013) found multiple emotional benefits to anonymity on the internet, such
as relaxation, comfortableness, positive image building, and a sense of security. Whether positive or negative, the changes that occur within a person’s cognition when “relative levels of privacy and anonymity” are provided are certain to affect their behavior (Graham 2017), and therefore their language practices.

Another technological factor influencing digital discourse is the *persistence* of the message, or as Graham and Hardaker (2017) classify it—*longevity*. This factor related to how long a message stays visible after being sent, or how long it is retrievable. Examples of messages with low persistence are those in chat rooms—as these messages disappear once participants log out or once they scroll off screen (barring a deliberate saving of messages). Emails, on the other hand, have a high persistency, due to their remaining on the server indefinitely—or at least until deleted by the user—allowing for multiple re-reads. This level of message persistence is important because it can change how interlocutors form messages and also because it can heighten “metalinguistic awareness” (Herring 1999). For example, in a low persistency mode, participants are more likely to put less thought into and send shorter messages, since the other participant has very little time to read the message; whereas in high persistency modes, participants are more likely to reflect on and alter their messages before sending (Herring 2007, 2008; Georgeakopoulos 2011).

The final factor discussed here is *synchronicity*—which describes whether the communication is in real-time or delayed. Real-time, or *synchronous* systems, such as instant messaging, video conferencing, charts, Multi-User Domains (MUDs) and MUD Object Oriented (MOO), require both the sender and receiver to be logged on at the same time. Asynchronous systems (i.e., email, discussion forums, list servers), on the other hand, do not have this requirement and therefore, allow for a lag in time of minutes, hours, days, or even longer,
between the initial message and response. Synchronicity is an important factor to consider, as this can dictate other important aspects of language, such as turn taking. For example, in synchronous communications, exchanges often occur rapidly, with each interlocutor having short turns that contribute to a conversation occurring in real time. Whereas, in asynchronous communications, the turns are longer, as are contributions, with the interactions being drawn out over an indefinite period of time (Androutsopoulos, 2011).

2. Multimodal Perspectives

As indicated above, there are multiple technological factors that should be considered when examining communications online. Another such consideration that is becoming increasingly more prominent in current research is the multimodal nature of digital discourse. In the moment of a communicative event, there are an incredible number of interactions at play. And as the technology continues to advance, this fundamental component of the digital world must be considered. The increases in bandwidth availability and technological capability allowed for more complex interactions to occur and scholars began to assert that if digital discourse research was going to move forward, a thorough understanding of this multiplex multimodal structure was necessary (Thurlow & Mroczek, 2011; Herring & Androutsopoulos, 2015; Adami, 2016).

2.1. Defining Multimodality

Multimodality, in its broadest sense, is a way to describe communicative events which use varying combinations of modes to construct meaning (Bateman 2019). Though it is often discussed conceptually as ‘new media’, this multimodal expression of discourse is not a new phenomenon (Bateman, 2019). In fact, Bateman (2019) emphasizes that “multimodality needs to
be seen as always having been the norm.” This research focus is quickly growing in linguistics and centers on the development of theories and tools with which to approach the ever-changing technologies, while still considering the multiple media and modes that converge in any communicative event. There are four basic assumptions to consider in this research on multimodality:

- *all communication is multimodal*
- *analysis of language alone is not enough to determine meaning*
- *each mode delivers different characteristics based on materiality and histories—these shape together to fulfill a communicative need*
- *modes work together, each with its own role, to make meaning* (Jewitt 2013, 2014)

To fully grasp the multimodal nature of digital discourse, however, means being able to conceptualize the idea of ‘mode’. While generally understood as a means of representing meaning (Norris, 2004), scholars have not been able to reach a consensus on the specifications of just what a ‘mode’ entails. Bateman (2019), in examining the challenges that multimodality holds for researchers, lays out numerous definitions from different scholars, some detailed below—though he adds that this does not make the picture any clearer:

- “the use of two or more of the five senses” (Granstrom et. Al. 2002)
- “image, writing, gesture, gaze, speech, posture” (Jewitt 2014)
- “the work of culture in shaping material for representation” (Jewitt & Kress, 2003)
- “a socially shaped and culturally given resource for meaning making” (Kress 2010)

With a wide array of possible meanings for the term ‘mode’, it is difficult to characterize its presence—but this characterization is important in the development of methodologies for empirical investigation. Forceville (2006) expressed early on that it is “impossible to give . . . a satisfactory definition”, and this still is the case.
For purposes in this research, I refer to ‘mode’ as a *way in which meaning making devices (i.e., semiotic resources) are presented for communication*, while always being mindful of any potential contribution to the meaning making. This definition, however, still provides no specification on what is to be considered as a mode. Jewitt et. al. (2016), suggests that perhaps many resources could be considered as a mode—gesture, gaze, writing all seem plausible, she posits, but what about color? layout? facial expressions or posture? actions? And as she explains further, not only do different scholars postulate multiple answers—sometimes there is difference within the same publication (Jewitt et. al, 2016).

### 2.2. Working Together

Given that multimodality is prime research territory currently, Bateman (2019) explains that this is when a guiding method or theory would be useful—the lack of consensus, however, has left researchers needing to be flexible and make their own defining methodological decisions. In line with this flexibility and in considering the work of Gee (2014) and Herring (2019), for purposes here, I consider the following as modes within their own right: *linguistic (textual), graphic (visual), and auditory (sound)*. In addition, I consider a fourth mode, a *mechanic or elemental* mode. This last mode, which will be discussed further in forthcoming sections, considers how digitally embedded mechanics, rules, and codes act as a semiotic resource which contributes to the overall meaning.

Understanding the *modes* at play—both individually and in relation to each other—in the contexts surrounding digital discourse is key in determining the depth of communicative events. We have an understanding, Bateman (2019) points out, of how specific forms of expression operate within the digital realm—what we need now, he elaborates, is also to see how these forms and meaning function collectively, creating a “unified activit[y] of communication.” It is
imperative, however, to remember that while multiple modes do work together within communicative events, they do so with “different by complementary information” (Collentine, 2009). Kress and Van Leeuwen (1996) emphasize this idea by explaining that multimodality is not about an “alternative means of representing the same thing,” but rather about the interactivity in creation of a combined meaning. A full grasp of this combined meaning, in its entirety, is especially important in environments where there are multiple modes intertwining. These modes, which are used for various language and social purposes, work together, in a complex structure (such as an online platform), to convey meaning to others. These platforms can be intensely interactive, with multiple conversations occurring across different modes, and via different media.

As explained by Herring (2015), Interactive Multimodal Platforms, or IMPs, are interfaces that allow the user to comment on a website via multiple channels—text plus at least one other mode, such as audio, video, or graphic. One of the first IMPs was YouTube, where a viewer could asynchronously comment, either via text or by producing a video response. Facebook is another example, but only since the addition of the video chat system. Twitter, however, is not, as it is a text-based Web 2.0 site—at least for now (Herring, 2015).

Studies show that within IMPs, there is a clear influence of mode on the communicative choices a participant makes when communicating. Research indicates, for example, that users tend to be more self-conscious (e.g., withholding information) in video chat than in text chat (Herring, 2009, 2013). In addition, Sindoni (2014) found that when examining emotions in the two separate modes (i.e., textual, graphic) of the Tumblr application, there are more positive

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2 Web 2.0 is a term used to refer to the transition of the internet as a one-way, static form of communication to a more interacting, engaging, and dynamic environment—one in which users were able to create and share content, rather than just view it.
emotions expressed through GIFs than in the text-based chat, where more negative expressions were found (Herring 2013, 2015; Sindoni 2014).

Because digital discourse has intertwined characteristics of both spoken and written language it “exists on a continuum between the context-dependent interaction of oral conversation and the contextually abstract composition of regular text” (Foertsch, 1995). In other words, digital discourse takes on specific characteristics of face-to-face (f-t-f) communication, such as immediacy, transience, or lack of editing/planning, and combines them with characteristics of written language, e.g., lack of visual cues, lack of physical presence, and the written mode (Georgakopolou 2011). The interactions of these characteristics “should not be treated as a dichotomy, but as a continuum of numerous overlapping and intersecting cases” (Georgakopolou 2011).

2.3. Multimodality in Live Streaming

It is this overlap, along with advances in technology and an increase in bandwidth, that has allowed for the interactive incorporation of video and audio streaming in online platforms (Herring, 2004). Though this made audio and video platforms more popular, initially they were not generally used for communicative purposes (Kibby & Costello 2001). In fact, according to Herring in 2004, “CMC has yet to embrace its full multimedi um potential.” Nearly twenty years later, however, technology has continued to evolve, and one multimodal space that is become more popular daily is that of online gaming. As Graham (2019) recognized in her research on conflict in digital communications, “online gaming provides a rich representation of Jewitt’s (2013) multimodal ensembles.” As online gaming continues to become increasingly more popular, scholars such as Ensslin (2012) have examined the social interactive qualities of online gaming. In fact, the simple act of broadcasting the live stream implies a certain level of
spectatorship and interaction—a key property in multiple online gaming studies (Cheung & Huang, 2011; Smith et al., 2015; Payne et al., 2017; Flores-Saviaga et al., 2020).

With the increase in popularity of multiplex platforms like Twitch.tv, where multiple media and modes are incorporated into a single digital space, a trend has occurred in the last decade which recognized digital gaming and video game live streaming for its multimodal properties and affordances. Much of this research, according to Wildfleuer and Stamenkovic (2022), attempts to apply what is known about digital discourse to the multimodal context of the live stream (Aarseth, 2014; Ensslin, 21012; Ensslin & Balteri, 2019; Gee, 2014; Stamenkovic et al., 2017). To undertake a multimodal analysis of video game live streaming would entail an examination of how the interplay of the multiple semiotic modes worked to create meaning within the context (Wildfleuer & Stamenkovic, 2022). This type of analysis on the Twitch platform could be used to account for numerous features, such as participatory aspects (Consalvo, 2017; Guichon & Cohen, 2016; Smith et al., 2015), roles and functions within the stream (Wildfleuer & Stamenkovic, 2020), emoji or emoticon use (Graham, 2019; Grosz et al., 2021, Knight, 2019), or coherence in stream (Juul, 2002; Bucher, 2011; Ford et al., 2017; Smith et al., 2013).

The intersection of research on digital discourse where it relates to online gaming is worth a thorough examination, from every perspective—as Gee (2015) explains both language and games can illuminate “how we think about language” and “how we think about and live in the world.” While each of these previously mentioned studies provides a needed perspective to the field, covering a great number of topics, what is lacking is research focused on the multimodal nature of video game live streaming, specifically where it relates to the medium specific discourse used within. Through an exploration of a converged media multimodal
dataset, I seek to fill this gap, partially through use of Herring (2007) faceted classification scheme. Furthermore, in an effort to examine how the demographic variations within the participant population of the live stream affects the multimodal interplays, I operationalize a ‘toolkit’ created by Herring (2004), to examine how participation patterns within the stream are indicative of changes in structural and meaning elements of the language use.

3. Discourse Analysis

Discourse Analysis, hereafter DA, can be a difficult term to specifically define, as it is more clearly identified as an overarching approach, used in many fields. Researchers in each of these fields, and sometimes within the same field, will put the DA approach into action with different sets of assumptions, but with the same goal—the understanding of the specific given communicative event, set within its societal and situational context.

Stubbs (1983) defines DA as “the linguistic analysis of naturally occurring connected speech or written discourse.” He further develops this by explaining that DA is the study of 1) language above sentence level, 2) language in social context, and 3) language that occurs in interaction among interlocutors. Taylor (2013) suggests that DA “refers to a research approach in which language material, such as talk or written text, and sometimes other material altogether, is examined as evidence of phenomena beyond the individual person.” Gee, in keeping his definition simple, explains that language is not just for saying, but for being and doing, as well (1999, 2015). DA includes a solid consideration of the entirety of the communicative event: time, place, environment, situation, and participant. According to Johnstone (2018), this ‘entire picture’ concept is behind calling what linguists do a ‘discourse analysis, as opposed to ‘language analysis, as the former recognizes an analysis beyond the words, an analysis that considers more than just language within a vacuum.
Even the term *discourse* itself can be difficult to define, especially in the dynamic state of online communications. For the purposes of this writing, I define the term *discourse* as *any production of text (written, spoken, or gestural) that is intended to communicate information, meaning, or knowledge. Discourse Analysis*, then includes *any approach used to analyze or deconstruct a communicative event in all its pieces, in relation to simultaneously occurring events and while considering the context within which the discourse occurs.* Above all, it is important to remember that in order to give language meaning, its surroundings must be considered, as well.

An important component of considering the context of any given *discourse* is recognizing the changes that occur when language crosses *media.* Given the available technology, and the pervasive nature of the internet—with a global penetration rate of 59%, and a North American penetration rate of 92% (Statista 2021)—it is logical to assume that most of these internet users some form of *discourse* in a digital environment on a regular and consistent basis. In the digitally mediated world, the DA approach may be used to “view online behavior through the lens of language, and its interpretations are grounded in observations about language use” (Herring 2004).

4. Computer Mediated Discourse Analysis

Even with this applicability, however, the intensity and speediness with which some online communications were occurring—producing rapid fire style, simultaneous communicative events, within the same *mode,* but also across *modes*—made it necessary to adapt DA into a new methodological approach—one that was capable of examining the specificities and multi-faceted peculiarities of those communications. The *Computer Mediated Discourse Analysis* (CMDA) approach was specifically developed by combining methods from various disciplines
and applying them in current contexts, in an effort to both recognize and analyze the characteristic features of digital discourse. Continually developed since the mid-90s, CMDA can be applied across phenomena from micro-level processes and choices to macro-level coherence, community, gender or identity (Herring 2004). In the process of adapting the original DA approach to include this idea of digital discourse, three basic theoretical assumptions were set in place with regards to CMDA:

- that discourse occurs in recurrent patterns
- that speakers make choices in conversations (both cognitively and socially)
- that “computer mediated discourse may be, but is not inevitably, shaped by the technological features of computer mediated communication systems” (Herring 2004)

These first two assumptions are generally recognized by DA, with two goals of the approach being to identify and analyze the recurrent patterns, and to examine the cognitive and social choices in conversation, providing insight into both the linguistic and non-linguistic phenomena (Herring 2004). The third assumption specifically pertains to CMDA and is applied in such a way that it is used to then help explain conversational choices and recurrent patterns. This last statement, then, is one of the primary focuses of this research—how the technological characteristics of particular communities affect the recurrent patterns and conversational choices of the digital discourse used within.

Herring emphasizes that CMDA should not be viewed (or used) as a single theoretical or methodological approach, in which the researcher might use a definitive, prescribed method of analysis. Instead, Herring (2004), describes CMDA as a “toolkit”, and as a “set of theoretical lenses” which can be used, via various strategies and tools, to make both make observations and interpret empirical results. This particular ‘toolkit’ is focused on examining discourse within four language domain groupings: structure, meaning, interaction management, and social
phenomena (Herring 2004, 2019). Each of these domains has its own unique concerns, representations of language, and preferred methodological approaches, as seen in Table 1. While not all inclusive, this chart serves as a demonstration of possible purposes and uses of the CMDA ‘toolkit’.

Table 1

<table>
<thead>
<tr>
<th>Language Domain</th>
<th>Concerns</th>
<th>Representations</th>
<th>Methodological Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure</td>
<td>formality, efficiency, characteristics of genre, complexity</td>
<td>typography, orthography, morphology, syntax</td>
<td>Descriptive Linguistics, Text Analysis, Corpus Analysis</td>
</tr>
<tr>
<td>Meaning</td>
<td>intended meaning, intended accomplishments</td>
<td>denotation/connotation, speech acts, exchanges</td>
<td>Semantics, Pragmatics</td>
</tr>
<tr>
<td>Interaction Management</td>
<td>interactivity, timing, coherence, development of topic, repair</td>
<td>turns, sequences, exchanges, threads</td>
<td>Conversation Analysis</td>
</tr>
<tr>
<td>Social Phenomena</td>
<td>social dynamics, power plays, identity, community formation</td>
<td>status expression, conflict negotiation, face management, play activity</td>
<td>Interactional Sociolinguistics, Critical Discourse Analysis, Ethnography of Communication</td>
</tr>
</tbody>
</table>

While the methodological approaches listed above may have been originally intended to examine face-to-face communication, when they are applied to the analysis of digital discourse, the interactive textual features should be at the center of focus (Herring 2004, 2019). In addition to the domains listed above, there is an analysis domain that focuses not on specific formations of language, but rather on counting the instances of those formations (see Table 2). This domain, participation, is associated with providing quantitative evidence of language use and patterns (Herring 2004, 2010).

Table 2

<table>
<thead>
<tr>
<th>Language Domain</th>
<th>Concerns</th>
<th>Representations</th>
<th>Methodological Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participation</td>
<td>number of messages, speed of message/response, message length</td>
<td>power, influence, engagement, hierarchical roles</td>
<td>Statistical Analysis</td>
</tr>
</tbody>
</table>
4.1. Multimodality in CMDA.

In 2008, a special edition of *Language@Internet* was produced. In their Introduction, Androutsopoulos and Beißwenger (2008) explain that this special edition, entitled *Data and Methods in Computer Mediated Discourse Analysis*, emphasizes a need to go “beyond the screen” and look at research beyond the log files. A portion of the research in this issue focused on extending Herring’s (2004) CMDA framework, due to the increasing levels of multimodality in CMC. Multiple scholars contributed to this edition, applying new paradigms to the CMDA concept (Androutsopoulos and Beißwenger 2008). These studies were completed across multiple CMC venues, focusing on personal ads (van Compernelle, 2008), Instant Messaging Platforms (Marcoccia, et al. 2008), Internet Relay Chat (Siebenhaar, 2008), and various online communities (Nishimura, 2008; Stommel, 2008; Androutsopoulos, 2008). According to Herring (2019), however, this research and these transitional suggestions still focused on the “behind the scenes” production of CMC text, rather than on the actual complete interactive characteristics of multimodal CMC.

Since 2008, there has been continued interest in research on multimodal CMC, such as those using Conversation Analysis (Jenks and Firth, 2013; Pasquandre 2011), social semiotics (Sindoni 2014), interaction analysis (Shih 2014), or Interactional Sociolinguistics (West 2013). Over the last ten years, some researchers (Androutsopoulos 2011; Jones 2014; Thurlow & Mroczek 2011), have produced critical perspectives on the subject, with other researchers suggesting possible re-works of the paradigm, or at least, expansions. Garcia et. al. 2019, for example, proposed suggestions for how settings are defined and how observations are made, taking a more ethnographic approach to the analysis of digital discourse. Herring (2019), however, argues that “these are healthy developments that indicate the CMDA is an active area
of scholarship” (p. 10). Indeed, as the years have progressed, there have been multiple uses of the CMDA paradigm to include researchers such as Darics 2010, Kushin and Kitchener 2009, and Sabater 2017. Furthermore, because there are multiple components and tools associated with the CMDA paradigm, there are studies that make use of specific tools, but do not report as such. For example, Asprey and Tag (2019) make use of Herring’s faceted classification scheme, which, while not a fundamental component of CMDA, contributed toward the paradigm. In addition, researchers also at times use specific components of the paradigm, such as Nemer’s 2017 use the CDMA ‘coding and counting’ scheme for a Speech Act analysis of Tweets of famous people.

Herring, of course, has also continued her part in maintaining a dynamic approach to the paradigm; in 2013, a fifth language domain was added—*multimodal communication*—to the CMDA ‘toolkit’. This level, which can be seen in Table 3, is a level addition to Table 1, above.

Table 3

<table>
<thead>
<tr>
<th>Language Domain</th>
<th>Concerns</th>
<th>Representations</th>
<th>Methodological Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multimodal Communication</td>
<td>effects of mode</td>
<td>mode choice</td>
<td>Social Semiotics</td>
</tr>
<tr>
<td></td>
<td>cross-mode coherence</td>
<td>positionality</td>
<td>Context Analysis, Visual</td>
</tr>
<tr>
<td></td>
<td>reference management</td>
<td>directionality, deixis</td>
<td></td>
</tr>
<tr>
<td></td>
<td>graphical units</td>
<td>animation</td>
<td></td>
</tr>
<tr>
<td></td>
<td>media coactivity</td>
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</table>

Herring (2019) has since reworked this multimodal level, allowing separation of audio, visual, and graphic components and taking into consideration, IMPs and other increasingly complex multimodal platforms.

Due to the dynamic nature of the ‘online world’, there is a constant and consistent lag between the current *digital discourse* trends and any research which addresses those trends. This is important to acknowledge because it is almost always the case, then, that while the same frameworks and methodological approaches are still being used, they must be constantly...
reshaped and adjusted in order to make them applicable to current technologies. CMDA itself is being challenged, to expand both methodologically and theoretically (Androutsopoulos, 2008; Beißwenger, 2008; Weininger & Shield, 2004; Yus, 2010).

Susan Herring, the developer of this paradigm, sees this not as a question of validity, but as a challenge to evolve. She points out in Herring (2019) that “multimodal CMC . . . has several characteristics that are arguably shared by all modes of CMC.” If this is taken into consideration, then each mode on a multimodal platform is still available for analysis in terms of structure, meaning, interactional patterns, etc. If then, the core of CMDA analysis is still usable, it should still be viewed as a relevant paradigm in its current state—whether the context is a traditional email server or a complex communicative platform.

5. Difficulties in Multimodal Research

The multimodal nature of digitally composed texts often creates significant difficulties for researchers attempting to organize their data for analysis. For a complex communicative event to be wholly understood, everything pertinent to its meaning must be collected and then organized in a manner which allows for future analysis. Despite the fact, however, that multimodal communication is all around us, there is still much to be learned—especially where it related to complex digital communications. As will be discussed further in the next chapter, there are multiple issues which arise in both the design and implementation of research and analysis in multimodality, such as complexity and variability of data (Zhang & Liu, 2015; Recktenwald, 2017), subjectivity/interpretation (Bezemer & Jewitt, 2017; Knight & Thompson, 2018; Machin, 2019; Larkin, 2021), and technical challenges (Kipp, 2014; Sloetjes, 2016; Bateman & Wildfeuer, 2018; Jetka, 2018; O’Halloran, 2019). many more traditionally developed frameworks rely on “segmentation and compartmentalization,’’ it is difficult to use these to
examine how “ensembles” work together as an entire productive unit (Bateman, et.al., 2017; Jewitt, 2009, 2011). And because the combinations encountered are not predictable more standardized tools are needed that will provide support in any direction (Bateman, et.al, 2017; Kipp, 2014; Kress, 2017; Bezemer, 2018, Norris, 2018; Adami & Ciliberti, 2021).

As is evident from the entirety of this chapter, the research in the area of online interaction and communication is vast and covers decades of changes in technology. The research has evolved alongside technologies that have led to the current use of online streaming platforms as a global means of communication. But the methods have not caught up to the undeniable hold these platforms have taken on society.

Acknowledging the gap in literature at the juncture of digital discourse, multimodality, and online gaming, this current research takes an interactional approach to explore the linguistic features of an intense multimodal communicative event and seeks to answer the following:

**RQ1:** How can the data from a converged media multimodal platform be organized to allow for analysis?

**RQ2:** What communicative strategies are employed by participants in a multimedium-based multimodal event (i.e., the Twitch.tv live stream)?

**RQ2a:** How do streamer gender and stream size impact the strategies chosen?

**RQ2b:** How does the availability of multiple mediums and semiotic modes impact this language use?

Using both quantitative and qualitative methods of analyses, this mixed-methods study promotes an understanding of digital discourse, and of how it is helping to shape, but is also shaped by, the context within which it is occurring.
Chapter 3: Methodology

In seeking to answer the research questions put forth in Chapter 2, I developed a study which could examine language use in a converged media, multimodal context. The methodology for this study is separated into two chapters, for clarity and ease of understanding. Over the course of these chapters, the multiple steps and tiers of dataset preparation are explained, in detail, beginning with an orientation of the social and technical context of the online gaming world within which this study is occurs. In the current chapter, the data collection process, research design, and brief analysis plan are detailed to provide the reader an in-depth understanding of the situational context, as well as the procedures that were followed.

The overarching drive for this research is the ways in which the multimodality of live streaming creates meaning, and how these meanings help to construct communities. Current digital platforms allow for an interconnectivity that incorporates numerous elements into a single entity. In this research, I examine multiple examples of this entity—the live stream—both for its individual media and modes, and in its entirety. In these next sections, I lay out the procedures for collection of the data that will serve as the core of this research.

1. Venue of Collection

1.1. About Twitch.tv

The venue of collection for this research is the online streaming platform, Twitch.tv (hereafter, Twitch). This platform was initially for users to stream their real lives, in real time. Twitch, which has been primarily used to live stream video game play, has grown exponentially since its conception in 2011. As seen in Figure 1, concurrent viewership (i.e., the number of people viewing content on Twitch at the same time) has increased from 100,000 to just under 3,000,000 over the course of the last decade.
On the Twitch platform, each user has their own digital space—a channel from which they are able to broadcast their stream. Also depicted in Figure 3 (upper line) is the growth of these channels over the past decade. The streamers on these active channels (i.e., those which have been streamed from in the last month) produce 90% of streamed content across all platforms (e.g., YouTube, Facebook Gaming), with 30 million users per day watching. With this ever-increasing growth and popularity, Twitch continues to be the top video game live streaming platform in the world.

1.2. Twitch Streams

Twitch streams have an extremely populous synchronous chat system that operates within a complex environment. These aspects of the platform have created linguistic phenomena that are “unlike any other internet specific way of communicating” (Olejniczak, 2015), as all participants have had to adapt to new rules and social practices of communication. There are a number of different roles within this participant population, as seen in Table 4.
Table 4

Twitch Stream Participants

<table>
<thead>
<tr>
<th>participant type</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer</td>
<td>user who is broadcasting the live stream</td>
</tr>
<tr>
<td>viewer</td>
<td>user who is currently viewing a stream</td>
</tr>
<tr>
<td>participant</td>
<td>viewer who is interacting within the chat feature</td>
</tr>
<tr>
<td>follower</td>
<td>user who chooses to receive updates and notifications from/about chosen streamer</td>
</tr>
<tr>
<td>subscriber</td>
<td>users who pay to support a streamer, often gaining them access to personalized emotes, games, or other items designated by the streamer</td>
</tr>
<tr>
<td>moderator</td>
<td>users designated by the streamer to help regulate chat behavior, using the Twitch Terms of Service (ToS) and streamer's personal chat rules; these users are able to remove participant posts (or participants) via specified commands</td>
</tr>
<tr>
<td>autobot</td>
<td>automated, preprogrammed feature used to moderate, provide alerts, or give interactive information</td>
</tr>
</tbody>
</table>

Live streams on the Twitch have a similar screen layout that, while housing intricate details, complex data, and often intense game play is, at its core, simple (Figure 2).

Figure 2

Twitch Live Stream, Core Layout
And while each streamer can change settings and alter some elements of their individual stream layout, the basic layout remains the same. Within this layout, as labeled in Figure 3, are four basic components: the public chat, the streamer’s video feed, the streamed content, and current stream(er)/channel contextual information.

Figure 3
Labeled Components of Twitch Live Stream, Core Layout

In Figure 4, the two purple highlighted areas are stream(er)/channel information. In the upper of the two are the streamer’s name, status, and to the far right, various interactive buttons, such as ‘follow’ and ‘subscribe.’
In the lower of the two informational areas, the streamer has selected a stream name (i.e., *Please riot, bless me with talented and positive teammates*), which can be changed throughout game if the streamer desires. In addition, there are three tag types which are located in this stream information area, as seen in Figure 5.
There are three of these tag types, as seen in Table 9, which are used to make a stream more easily discoverable via the search and browse features on Twitch.

Table 9

<table>
<thead>
<tr>
<th>Stream Information Tag, Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>tag type</strong></td>
</tr>
<tr>
<td>category tags</td>
</tr>
<tr>
<td>descriptive tags</td>
</tr>
<tr>
<td>stream tags</td>
</tr>
</tbody>
</table>

Next, the blue box in Figure 6 outlines the *public chat area* of the live stream screen. This feature creates a space in which users can interact and engage with the stream, the streamer, or the streamed content. Communication in this chat occurs via text and images—there are no options, as of yet, to participate in the chat via voice or video.
During a live stream, the screen area for the *streamed content* (e.g., video game play, watching tv, cooking ‘just chatting’) is shared with viewers and is where the main activity of the streamer is taking place. This area is the largest part of the screen (Figure 7, outlined in red) and is typically overlaid with the *streamer’s video feed* (depicted in green, Figure 8).
Figure 7
Basic Layout, Streamed Activity Space

Figure 8
Basic Layout, Streamer’s Webcam Overlay
In addition to these components, there is one more that may appear depending on the chosen streamed content. For example, in League of Legends game play, there is a player chat overlaid onto the game (Figure 9). This is where the players are able to communicate with each other in game. These players—2 teams of 5 players each—communicate in text via this chat and are also able to communicate via voice.

Figure 9
Basic Layout, League of Legends Specific, Player Chat

It is important to note here that these components detailed above (i.e., stream(er) context information, public chat, streamer’s video feed, streamed content, player chat) are not fixed in their placement on screen. The streamer is able to customize what viewers see and how the screen is positioned and presented. The exception to this is the public chat, which is locked in its place to the right of the screen by Twitch.

The nature of the live stream requires an understanding that it must be viewed, both in its entirety, but also in its systematically separated components. This separation of the basic screen
components provides a foundation upon which the affordances and constraints of each element can be examined—allowing the further identification of the individual modalities and modes which connect and intertwine in this complex communicative event.

1.2. About League of Legends

When broadcasting on Twitch, there are numerous ‘activities’ which can be the focus of the stream. To control the variables within the data, I chose to focus on a single activity for this study—League of Legends game play. This game was chosen primarily due to my familiarity with the content, as well as the game’s immense popularity. Since League’s conception in 2009, monthly active user numbers (see Figure 10) have increased from 100,000 players to nearly 110,000,000—consistently positioning it as the world’s most popular video game since 2013.

Figure 10
League of Legends Monthly Users, in millions

League of Legends is a Multiplayer Online Battle Arena game, or MOBA for short, which is a subgenre of video games that stems from the Real Time Strategy genre, in which players play simultaneously (as opposed to turn-by-turn progression), working together to strategize and achieve the game’s objective (in League of Legends, to capture the enemy team’s
Each game session in League begins with the players choosing a champion (avatar) alternatively by team (2 teams, 5 players each). Once selections are complete, gameplay commences and players navigate their champions to a pre-determined area, subsequently attacking enemy minions (AI controlled enemy bots), damaging enemy structures, and eventually attempting to destroy the enemy team’s homebase structure, claiming a victory. The game is fast paced, with action unfolding as it is live streamed. This creates a complex environment—with the game play, user interactions, and streamer presence combining to create a single, multiplex communicative event.

2. **Population Selection**

To choose the specific streamers whose live broadcasts would serve as the data for this study, I first examined a list of the top 250 *League of Legends* streamers in a three-month period from July to September 2019. These streamers were first divided into two gender-based groups.³ I then examined the streamer metrics for each League player on the site *Twitchtracker*. These websites provide analytical tools that may be used to provide insight into such information as, but not limited to, a streamer’s viewership, growth, or streaming schedule. In reviewing each streamer’s page (see Figure 11), I focused on average viewership—all males with viewership over 7,500 were excluded, given the lack of female streamers meeting this threshold.

³ Gender categories were assigned based on streamer-assigned labels, outward binary appearance, pronoun use, and other gender references. Three streamers who did not fit the binary profile were not included in this study.
To further narrow the selection, I then examined the streamers’ broadcasting regularity and consistency of League play within streaming sessions:

1. *the streamer consistently broadcasts at least four times per week*
2. *the streamer consistently streams on the North American server*\(^4\) and in English
3. *the streamer consistently plays League of Legends for majority of broadcast time*

Finally, from a pool of seven females and twenty-nine males, a division was made at one thousand average viewership count. Three each males and females were chosen from below this threshold and three each from above this threshold. As seen in Table 5, there were twelve streamers chosen in all, with an equal number of males vs females and of small stream population vs large stream population.

Table 5
*Streamer Selection for Data Collection, Listed Alphabetically*

---
\(^4\) The Twitch network consists of numerous servers around the world in various regions. When a streamer goes live, they are able to select a server—typically one that is geographically the closest to them, allowing for solid quality and stability (i.e., lowers the amount of buffering or other lagging issues).
Once the streamer population was narrowed and selected, the live streams were collected through a screen recording capture process. To begin, over the course of a month-long period, two stream sessions per streamer were recorded—twenty-four in all—from start to finish.

### 3. Collection Process

A typical stream session (i.e., live stream) lasts, on average, just over 5.5 hours, with a normal range of 4 to 9 hours (twitch metrics), and according to a popular gaming forum, many streamers regularly aim for an average of two games per hour of a short stream, and less for a longer stream (reddit), where there is an expected level of viewer interaction and engagement. No matter the number of games played in each live stream, the pragmatic function of the stream during the initial and final games is similar amongst streamers. The initial portion of a session tends to be greeting heavy and often contains a great deal of ‘game talk’ and ‘catching up’, with the streamers verbalizing their game play plans for the day and generalities about life since their last live stream. The last portion of the session, on the other hand, serves an opposite purpose—with the streamer beginning a signing off process, which entails both personal messages, as well as game play recap. Therefore, to limit content variability where possible, I
chose to pull two individual game play segments from each of the twenty-four recordings, based on the following criteria:

1. streamer was in active League of Legends game play (i.e., not between games)
2. streamer was not in first or last active game of stream

The live stream data were collected via a screen capture of the live broadcast. The live stream was positioned to play on the right side of the computer screen while Chatty, an external program detailed below, ran simultaneously, aligned to the left of the screen (Figure 12).

Figure 12
Layout for Recording of Live Stream

Created by a gamer unaffiliated with Twitch.tv, the Chatty software displays posts in real time and contains extra information, such as autobot-deleted messages and ban times—information unavailable to viewers of the public chat. Chatty was connected to the appropriate streamer and recorded alongside each individual live stream. The screen capture software FonePaw was used to record the computer screen as the stream was broadcast live, in HD (4K) resolution. This ensured that all screen elements were easily visible.
At completion of data collection, there were forty-eight individual game play segments, totaling over twenty-two hours of recorded live streams, with each segment ranging in length from 10.88 minutes to 46.43 minutes (depending on length of match). It is the language contained within these recordings that would serve as the dataset for this research.

3.1. Ethical Considerations of Collection

In all research regarding human subjects, it is imperative that care and caution is taken in protecting the privacy of the individual(s) being examined. Broadcasting live video game play complicates this somewhat, as it is time-prohibitive, if not impossible, to identify and contact each streamer and/or viewer. The Office of Human Research Protocol (OHRP) has taken advancements in CMC into account, and as of January 2019, there are new regulations, which my research complies with, specifying a human subject as “a living individual about whom an investigator obtains info or biospecimens through intervention or interaction with the individual, and uses, studies or analyzes the information or biospecimen; or obtains, uses, studies, analyzes, or generates identifiable private information or identifiable biospecimens.”

While there was no intervention or direct interaction with any individuals present in the streams, ethical issues may arise from the recording of (possibly) private information. Again, according to OHRP Regulations (2019), private information is considered to be data produced which the individual can “reasonably expect” is not being recorded or made accessible to the public. In this case, however, it is the individuals themselves who are recording the stream, with the intention of live streaming and later posting the feed to an internationally known website (making it public themselves). Therefore, there is no reasonable expectation of privacy by the streamer. Regarding the public chat members, they, too, are aware that the chat is being live streamed, recorded, and subsequently posted. As such, there is no reasonable expectation of
privacy from that group, either. With this in mind, ethical issues stand at a minimum in this research, with the only possibility being cases where a streamer may verbally give identifying information about other streamers. While this information is included in the corpus of data for context, it will not be used in any published analysis without first redacting identifying information.

4. Analysis Plan

In order to examine the multiplex phenomenon of video game live streaming, recordings of multiple League of Legends live streamed game play segments were collected from the Twitch.tv platform. These streams provided a clear “depiction of nearly constant, rapid fire, cross-modal communications” (see Rozenbaum et. al. 2016). To appropriately attend to the fast-paced, chaotic nature of this data, a tool was needed that would allow for complex input, but still provide an easily viewed, analysis ready output that could serve as the dataset for this research.

To examine this data at its most intricate points and to create a path that allows for a deeper understanding of the impact that multimodality has on the language use within this environment, I apply a mixed methods approach. First, a quantitative analysis will identify and describe specific language use, followed by a qualitative analysis that attempts to position that language use as a means of displaying the necessity of attending to its multimodal nature.

In this chapter, I have laid out the methodological procedures for the identification and collection of numerous multimodal live streams. Once collected, however, there was no prior convention in place for organizing the data for analytical purposes. In the next chapter, I outline the transcription model developed by Graham and Arendall for an online gaming digital corpus project.
Chapter 4: Organizing Multimedium-based Multimodal Data

Picture this: You log into Twitch.tv to view your favorite streamer, who is just about to ‘go live’.6 As you navigate into their stream, the streamer’s voice is loud and clear through your speakers. You hear the music in the background, the clicking of the streamer’s keyboard, and the chatter of champions preparing for battle. ‘Minions are spawning,’ the game announces.

The graphics are incredible—the vibrant colors, the bright lights swooshing across the screen, and the quick-paced movements of champions vying for the upper hand. The game clock ticks away, scores are rising, and the points change rapidly on your screen. You can feel your heart racing as you watch each moving, waiting for what will come next.

The chat is a constant stream of messages, with users sharing tips, telling jokes, or immersed in their own conversations. One user makes a donation, triggering an alert dancing across the screen. The streamer is still in the game, thanking the user and shooting a spell simultaneously.

As the game comes to a close, the music becomes livelier, and excitement builds in the chat. When the victory is finally sealed, the chat erupts in a congratulatory ‘roar’. As you log off, you send one last message—‘good game’.

At any moment during a Twitch.tv broadcast, there are numerous concurrent communications taking place. Intense scenarios, like the one above, are commonplace, with multiple components working in unison to produce a single entity. As seen in Figure 13, in the moment depicted, there are multiple simultaneous occurrences:

---

6 Streamer has logged on and is about to broadcast in real time
Given the complexity of this data, producing a transcript of the live stream was challenging. The desired transcript template would need to accommodate the inclusion of multiple concurrent occurrences, in an organized manner, and separated into units of analysis. In addition, it would need to allow for cross-referencing and synchronization of multiple temporal structures. Numerous issues were encountered during the development of this template, concerning components such as temporal alignment, content separation, and inclusion parameters. The processes and decisions made in reference to this design, as well as the difficulties encountered, are laid out in the remaining sections of this chapter.

1. Multimodality of the Live Stream

Before delving into a conversation about multimodal communications within a converged media environment, there must be an understanding of specific terms and how they fit together. As previously mentioned, defining terms related to multimodality is problematic at best.

1.1. Terms to Know

**medium**  
the ‘housing’ of the technological inscription, allows the meaning of the semiotic representation to be accessed; access is shaped by structural affordances

**mode**  
semiotic representation of a meaning making device; may be expressed in a variety of ways—text, image, sound, etc.; each mode must function in a manner that is experiential, logical, social, and textually coherent

**multimodal**  
refers to communicative events which are made meaningful via multiple modes of representation

**multimedium**  
refers to communicative events which have semiotic representations ‘housed’ within more than one medium

1.2. Identifying Modes

Traditionally, there have been five *semiotic modes*: textual, visual, audio, gestural, and spatial (New London Group, 1996). The focus here, however, will be on the *textual*, *visual*, and *auditory* modes. This is not to imply that the *gestural* and *spatial* modes should be disregarded; instead, they are discussed, when necessary, as subsets of the *visual* mode.

As discussed in Chapter 2, defining and identifying a *mode* is difficult and there is little consensus across researchers (Jewitt, 2009; O’Halloran, 2004; Kress & van Leeuwen, 2001; Jewitt, 2001; Halliday, 1987; Kress, 1997). One agreed upon characteristic, however, is that modes may differ by community. As Kress et. al (2000) explains,

“...the question of whether X is a mode or not is a question specific to a particular community. As laypersons we may regard visual image to be a mode,
while a professional photographer will say the photography has rules and practices, elements, and materiality quite different from that of painting and that the two are distinct modes.”

With this in mind, and in building on the work of Jewitt (2009b), Kress (1993), and Kress & van Leeuwen (2001), I consider three primary criteria for identifying a mode:

- **must be able to convey content that expresses meaning**
- **must have its’ own set of conventions and established rules for use**
- **its presence is required for overall meaning (i.e., its removal would change the meaning of the multimodal artifact as a whole)**

While potentially not the case for all live streamed content, in the case of video game play, specific elements of the game convey meaning through establishment of elements such as game objectives, reactive consequences, or actions of embedded characters. This meaning is conveyed through specific coding protocol and the meaning supplied to the whole is required for understanding. Therefore, with these above criteria met, I suggest the **mechanic** mode here, representing meaning made through embedded codes and rules of the game.

### 1.3. Accessing the Meaning via Mediums

It is important to note here that *modes* are *representations of meaning*—the meaning itself is not accessible without some form of technological inscription. The ‘housing’ of this technological inscription, then, is a **medium**. A textbook, for example, is a **medium** which houses the use of the **textual** and **visual modes**, and in the case of a digital textbook, the **auditory mode**, as well. It is through a **medium** that semiotic representations (i.e., **modes**) are accessed, as depicted in Figure 14.
Any given medium will consist of a grouping of modes which has been combined in a manner best suited for its affordances, as well as a structure and specific set of rules. Adapted from several researchers (e.g., Kress & Van Leeuwen, 2001; Palacios and Noci, 2007; Herring, 2007; Guichon & Cohen, 2016; Graham & Hardaker, 2017), four characteristics were identified as able to distinguish each medium from another: modal combination, expectation of interactivity, participation structure, and temporal parameters (Figure 15).

Figure 15
Distinguishing Characteristics of a Medium

<table>
<thead>
<tr>
<th>modal combination</th>
<th>interactivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>any combination of modes which is best suited for the affordances of the medium</td>
<td>Who can post? View? Edit? Controlled by? Programmed by?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>participation</th>
<th>temporality</th>
</tr>
</thead>
</table>
As discussed in Chapter 3, there are four main components to the League of Legends live stream: public chat, streamed content (game play), streamer’s video feed, and player chat.

Figure 16
Distinguishing Media Characteristics of a Video Game Live Stream

As illustrated in Figure 16, these four components are individually distinct from one another based on the characteristics of a medium noted above.

2. Breaking Down the Live Stream

Prior to beginning a transcription or organization of complex data, obtaining a complete picture of the environment is necessary. It is not uncommon, when dealing with multimodal and/or multimedium-based data, for difficulties to arise during any stage of collection or analysis. As Bateman, et. al. (2017) explains, many of these difficulties can be pre-identified—and therefore possibly avoided—by “systematically decomposing the particular ‘places’ where multimodal meaning making is going on ‘within’ the overall situation or entity”. There are multiple ways this can be accomplished, depending upon the final unit of analysis. In an attempt to gain a better understanding of the individual happenings within the larger picture, I will:

1) decompose the live stream as a whole, along with each medium present

2) complete a modal inventory for each medium present
In the next section of this chapter, I detail this medium decomposition (i.e., examination of how these mediums and modes work together in practice) and modal inventory (i.e., identification of available modes and modalities within each medium). In addition, I examine possibilities for medium directionality (i.e., where communications are being directed) and cross-medium communications (i.e., communications which are produced within the confines of one medium but received via its place in another). By breaking each medium into constituent parts, we gain a better understanding of the various components, both in the context of the game and within relation to each other. In addition, a detailed breakdown helps to identify data and ensure all modes are included in any subsequent transcription and/or analysis.

2.1. Public Chat Medium

The public chat, highlighted in Figure 17, acts as the space of communication for the participants in the live stream. The chat window is always present and positioned to the right side of the screen, making it a prominent focal point for viewers. The speed with which the chat scrolls is dependent on the number of messages posted. It is likely that streams with larger viewership will have more messages, therefore making the scroll faster than it would be for a stream with lower viewership (and therefore lower number of messages).
As seen in Figure 18, the **public chat medium** allows for two modes of communication—the *textual* and *visual*. The *textual mode* performs a great deal of semiotic work in this medium. It is employed to represent the message content itself and is the primary method of communication between participants. The *visual mode*, which varies by stream, allows for representation and emphasis of content (e.g., through capitalization), as well as for emphasizing a participant’s presence (e.g., through chosen username color).
There are some resources which, while typographic and associated with the *textual* mode, also have a *visual* representation through which paralinguistic information is conveyed. Participant names are presented in a consistent visual pattern, using colors and boldface, creating a theme which carries throughout the chat.

2.2. *Streamed Content Medium*

In the center of the live stream screen, occupying the greatest amount of space, is the *streamed content*—here, where League of Legends is played (Figure 19).

Figure 19
*Live Stream Display, Streamed Content Medium*
With this content strategically located in the middle of the screen, it is positioned as the dominant element, the “nucleus of the information” (van Leeuwen & Kress, 2006). This medium acts as a ‘background’, a space onto which overlays can be placed. The amount of streamed content visible to viewers is dependent upon the size and placement of these other components.

Housed within this medium, as seen in Figure 20, are four available modes: textual, visual, auditory, and mechanic. The visual mode uses both static and dynamic images to create meaning. During League of Legends game play, the majority of the streamed content area shows constant movement. In addition, there are static images which depict various champion and team statistics such as health status, possession, or damage. Though the visual mode may appear as most prominent, it is the mechanic mode which performs the greatest amount of semiotic work.

The mechanic mode is used to represent meaning making devices housed within the game design itself. Meaning is made through triggered actions and player control, or through time-based game progression of the game. What is particularly noteworthy about this mode is that it requires the assistance of another mode to be fully realized. For example, without the visual
mode to display the champion movement and game element progression, the information conveyed is unattainable for processing. The reverse is true in some cases, as well—without the mechanic mode, the visual mode would have champions performing random movements with no purpose attached—no linear progression, no game endpoint, and no controlled movements. Furthermore, some manifestations of the textual mode (e.g., scores, numeric tallies, in-game pop up text) and of the auditory mode (e.g., game announcements, sound effects) also become unattainable without the mechanic mode. In other words, if the game element is removed, the text, images, and sounds associated with that game play no longer have purpose or meaning.

2.3. Player Chat Medium

Overlaid onto the gameplay area is the player chat (Figure 21). This chat, a feature specific to League of Legends, can be moved within the confines of the gameplay space and is preprogrammed to disappear when dormant for ten seconds and reappear when a new message is posted.

Figure 21
Live Stream Display, Player Chat Medium
As seen in Figure 22, the *player chat medium* houses three available modes: the *textual*, *visual*, and *mechanic*. The *mechanic mode* operates here as it did in the streamed content medium, relying on the assistance of the *textual* and *visual modes* for the meaning to be fully realized.

Figure 22  
*Media Decomposition & Modal Inventory Representation, Player Chat Medium*

The *player chat* is used not just to provide a place for team communication, but also as a place for some game features to be broadcast to both allies and enemies. The *textual* and *visual modes* each have their own affordances to attend to. There are not settings to change the typeface of the chat messages, but the placement of the chat on the screen can be partially altered (i.e., moved within the allotted space). There are some subtle visual representations of paralinguistic information such as red/blue distinction for team membership, boldface for emphasis of information, and color indication for categorization.
2.4. *Video Feed Medium*

Finally, there is the streamer’s video feed—an adjustable picture-in-picture frame of the streamer’s webcam view, which can be size adjusted and positioned anywhere on the content screen (Figure 23).

Figure 23
*Live Stream Display, Video Feed Medium*

![Figure 23](image)

This is the space in which the streamer depicts themselves. The variability in multimodal resources allows for streamers to customize the way they depict themselves, as well as their environment. Figure 31 shows the camera feed of a live streamer, while Figure 24(a) shows a streamer portrayed by an avatar and Figure 24(b) shows a streamer who chose to remove this component altogether.
No matter which depiction is chosen, its position on the screen is wholly customizable.

The video feed medium houses three modes, as seen in Figure 25. The visual mode is used to represent meaning through images—both static and dynamic—as well as through spatial design (e.g., background environment, placement of information on streamed screen) and gestural manifestations of streamer non-verbal language. The textual mode represents meaning via text, assisted by the visual mode, while the acoustic mode represents meaning through the streamer’s speech.
In addition to the display inside of the physical video feed frame, are the participant triggered overlays used to announce subscriptions and donations. These alerts are streamer controlled and appear at various locations on screen. No matter their position on screen, they are associated with the video feed medium because they are communications from the speaker. These pop-up notifications are typically superimposed over the streamed content area and are made meaningful via the concurrent use of the textual and visual modes, and in some cases, the auditory mode.

In this medium, the primary mode used by the streamer is verbal speech, though there are a total of three modes at work. The work that each mode performs is viewer-dependent in this medium. For any given viewing session, there are choices that viewers can make to 1) view and listen to the stream in its entirety, 2) access audio only, or 3) access video only—though this is rarely used (oneesports.gg, 2021).

2.5. Visualizing the Whole

The media decomposition and modal inventory provide a more transparent picture of the affordances of each medium, as well as the modes available in each. In addition, they allow a
more detailed understanding of the various ways in which different modes of communication are used to convey meaning. Collectively, this breakdown shows how individual components work together to produce the live stream. This is visualization is depicted in Figure 26 below.

Figure 26
*Media & Modal Composition of the League of Legends Live Stream*

Breaking down the constituent parts of each medium was important because the distinctions helped us to determine what should be transcribed and coded.

3. Corpus Development & Compilation

The dataset for this dissertation was collected as part of a larger corpus project. This online gaming corpus is actively being compiled under the direction of, and in collaboration with, Dr. Sage Graham. We created a working model of the multimodal transcript early in the
research process and have adapted it to accommodate emerging multimodal considerations and challenges.

3.1. Building a Multimodal Corpus

A multimodal corpus can be defined, at its core, as an “annotated collected of coordinated content” (Foster & Oberland, 2007). While the live stream must be considered and viewed in its entirety by its’ viewers, for analyses purposes the individual pieces of coordinated content must be separated into smaller ‘chunks’, allowing for a thorough micro-level examination.

The building of a multimodal corpus leaves an incredible amount of room for variation (Hiipala 2015), and so the choices made in this current development are only one set of numerous possibilities. In some cases, researchers use a multimodal annotation tool, such as ANVIL (Annotation of Video and Language) or ELAN (Eudico Linguistic Annotation) (Kipp 2014; Sloetjes 2016). While certainly equipped to handle multimodal annotation, many of these programs create concerns which work against the building of this corpus:

- many tools require transcript alignment to the primary video file, creating difficulties in aligning multiple temporal structures
- annotation allows for only single tag labels, preventing multiple tags on a single tier, thus eliminating the ability to notate more complicated phenomena which may be relevant to multiple tiers
- lacking the ability to perform user defined search criteria useful in mass identification of common features for automatic annotation
- with real-time data that is highly complex, fast-paced, and interactive, it is difficult to manually annotate multiple modalities, often becoming time-prohibitive (Law et. al., 2019; Pires et. al., 2018)
• live stream game data may require annotation of data that is specialized, such as game progression or champion action—annotation that may not be possible with traditional models, or AI (Johnson et. al., 2020)

While different multimodal annotation tools may lack only certain features, transfer between them is technically difficult and at times requires duplicate effort. Therefore, the possibility of exploiting each tool for its desired features is removed. Furthermore, the separation of the converged media and decomposition of modal qualities is important to the core of this research, and these programs do not allow for manipulation of the transcript layout by user. These above-mentioned challenges leave the multitude of multimodal annotation tools currently unworkable for this research. With this in mind, a unique model would be needed for transcribing this live stream data. Recktenwald (2017) created a transcription process for some Twitch stream features, working towards a usable analysis tool. The problems with this model for use in this analysis are:

• it groups multiple aspects of speech in a single column, lacking the ability to easily allocate added space for multiple coding schemes

• uses the recording time stamp as the anchor point for interactional connections—thus creating the possibility of improper synchronization across users

Due to the lack of readily available and/or acceptable tool, both a novel design and technique for compilation and coding was necessary. There were two primary challenges in creating a corpus template: 1) how to organize multifaceted information which is often produced via multiple co-occurring events with overlapping participants, and 2) how to synchronize multiple timestamps recorded differently across mediums.

3.2. Content Separation
There were multiple possibilities for content separation, such as by speaker/writer, medium, mode, or on a timeline. Separation by medium was not useful, because at any given moment there may be multiple events occurring within the same medium. In the streamer’s video feed medium, for example, the streamer may laugh at the same moment a donation alert appears. Considering separation by mode brought about two issues: 1) it is possible for meaning to be realized through multiple modalities within a single mode, and 2) different mediums may house similar modes, creating the possibility of unintended cross-over. Separation by smaller unit, however, was unnecessary as most events occur within a single mode. Therefore, we chose to attend to each mode individually in the corpus, grouped by medium and further separated when needed by manifestation of the mode.

3.3. Designing a Template

A column based tabular format (i.e., a spreadsheet) was chosen for the transcription template, with time progression on the vertical axis and content separation along the horizontal axis. This format would be particularly useful here because, as Bezemer and Mavers (2011) point out, “this provides an impression of how the meanings made unfold synchronously and diachronically, and how they map onto each other.” A final template was created which, as previously mentioned, would account individually for each medium. Within each of these groupings, as seen in Figure 27, data is separated by mode, with added space for contextual information if needed.
Figure 27

*Media Groupings of Columns*

These separations create the headings for the corpus template, with each grouping housing the data contained within the live stream medium, as seen in Figure 35, above:

- **Public chat** houses space for transcription of both the textual and visual modes, as well as space for contextual user information
- **Streamer’s video feed** houses spaces for recording of the textual, visual, and auditory modes, including both the gestural and spatial elements of the visual mode
- **Streamed content (game play)** houses space for all four modes (i.e., textual, visual, auditory, and mechanic), as well as for contextual scoring information
- **Player chat** houses space for the textual, visual, and mechanic modes, as well as for contextual user information

### 3.4. Synchronizing Concurrent Sequences

With numerous interactions occurring simultaneously, often in rapid succession, and three timelines concurrently progressing, a procedure was needed that would maintain the temporal integrity of the data. This synchronization allows for a visualization of the temporal relationship between occurrences. In addition, it would create an alignment of modes, allowing researchers to create a timeline of overlap and/or switching. As seen in Figure 28, there were two core temporal structures that would need alignment:
• **Chatty Time Stamp**: imported automatically by the Chatty software, corresponds to streamer’s local time, appears on each line of data

• **Game Clock**: indicates elapsed game play time, manually recorded approximately every thirty seconds

Figure 28
*Multiple Temporal Structures*

Each of these timestamps was included in the template, but these were reference points for the convenience of the researcher.

### 3.5. Alignment of Data in Corpus

Throughout this research, determining a procedure for synchronization of the data across all media has proven to be problematic. With numerous interactions occurring simultaneously or in rapid succession, a procedure was needed to maintain the integrity of the progressive timeline. After attempting other solutions, we decided to use the public chat messages themselves as the primary reference point. Because this message is automatically imported and time stamped by
the *Chatty* software, it creates a concrete point on which to anchor the other mediums and modes. Creating this anchor point allows for a single point with which all concurrent communicative events can be aligned. The following protocol was followed for each entry into the corpus: at the moment a give message appears in the Public Chat, all simultaneous communications are recorded horizontally on the spreadsheet, under the appropriate heading.

In the example below (Figure 29) there are seven events occurring simultaneously, each of which must be transcribed.

Figure 29
Concurrent Events Example

The anchor message—depicted in Figure 30—is located within corpus, and each event is transcribed into the corresponding column, aligned horizontally. Once this procedure in completed, all seven events are aligned, at the same moment in time, just as they occur within the live stream, itself.

Figure 30
Concurrent Event Alignment
Note that all data transcribed is aligned in this same manner, unless otherwise noted. In the next section, the details of the transcription process itself are discussed.

### 4. Transcription Processes & Protocols

#### 4.1. Public Chat

In *Public Chat*, there were three components of the *textual mode* (i.e., Chatty timestamp, username, message) which were automatically imported into the corpus (Figure X). This data was placed to the far left of the template, positioning the remaining data to reference back to the alignment point.

#### 4.2. Video Feed

In this grouping, there were four components to be transcribed: streamer’s speech (*auditory mode*), environmental layout (*visual-spatial mode*), streamer’s non-verbal actions (*visual-gestural mode*), and pre-coded (by streamer) AI announcements (*textual, visual, and auditory modes*).

Streamer speech was transcribed and aligned as detailed previously. At times, however, a single utterance spanned multiple messages. In these cases, the utterance was separated and aligned across consecutive messages (Figure 30), while maintaining temporal integrity.

Figure 30
Alignment: Speech that occurs across multiple messages

In instances where another voice could be heard—out of camera view—in conversation with the streamer, the speech was included using the same protocol, but with brackets surrounds, is an indication of speaker:

[stpeach husband] how long are you gonna stream?

Environmental layout descriptions were noted at the beginning and revised throughout as elements changed. For example, we might note that unmade bed visible, piled with numerous Kirby plushies and later add cat walks through room, jumps in streamer’s lap. Descriptions of the streamer’s non-verbal language were consistently entered in the appropriate space, with entries including items such as: sips drink through straw, leans forward to pick up dropped paper, or ‘flips off’ in off camera direction.

In the Video Feed grouping, the AI/Bot notices are created and controlled by the streamer. While they differ somewhat between streamers, generally, these are messages concerning subscription alerts, donation amounts, current song, today’s top donation, streamer’s
most recent follower, etc. The text often appears alongside a visual, and a short description of the graphic appears below the transcription of text (Figures 31 and 32).

Figure 31
Streamer-controlled AutoBot Announcement Screen Location

Figure 32
Transcription Protocol: Streamer-controlled AutoBot Announcements

4.3. Game Play (Streamed Content)

Within the Game Play grouping, there are spaces for the transcription of game progression entries (visual and auditory), scoring changes (textual), and game-embedded AI/Bot notices (textual, auditory, visual). The textual components of the AI notifications consist primarily of pop-up announcements and score changes. Unlike the AI announcements that occur
within the *Video Feed* that are streamer-coded, in-game announcements are an embedded function of the game. For example, the first announcement upon starting in the game is *Welcome to Summoner’s Rift*, which occurs at 00:25 on the game clock (Figure 33). In other cases, these announcements are action triggered (as opposed to time-triggered), such as *Ally Killed* or *Enemy Turret Destroyed*.

**Figure 33**
*Example: Welcome to Summoner’s Rift*

For entry into the *Game Progress* column, there are multiple pieces of information to be considered, such as *champion actions, pivotal moments, or requirement fulfillment*. These are not announcements that are directly displayed on the screen, but rather are entered into the corpus to mark the stages of the game as they progress.

**Figure 34**
*Champion Choices for Team Members, Screen Layout*
Game progression entries are recorded as they occur, with GAME PLAY BEGINS and VICTORY or DEFEAT, as the first and last entries respectively. The AI/Bot notices are transcribed as they appear on screen, while scoring entries are presented as running counts. There are three sets of scores which were included: minions killed, Ally vs. Enemy kill counts, and the streamer’s personal scores (i.e., # of enemies killed, # of times assisted in a kill, # of times killed). These Game Play groupings are entered as detailed above and seen in Figure 35.
Figure 35
*Transcription Protocol: Scores & Counts*

---

**Transcription Protocol: Ally & Enemy Kill, Streamer Personal Point Count**

<table>
<thead>
<tr>
<th>Public Chat</th>
<th>Streamer's Video Feed</th>
<th>Transcription Protocol (Game Play)</th>
<th>Personal Chat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

**Streamed Content (Game Play)**

- **Enemy/ally Kill Count**
  - Enemy Kill: 0
  - Ally Kill: 1

- **Streamer Personal Kill**
  - Streamer Kill: 0

---

*Note:* The transcription protocol details the scores and counts associated with the game play, including both ally and enemy kills, as well as personal points for the streamer.
4.4. **Player Chat**

In this grouping there are two components of the same mode (*textual*)—the message itself, and the player who produced it. This chat feature in League allows the current players (5 each per team, Ally/Enemy) to chat with their respective teams within the game space (Figure 36). The different teams show in separate colors on the game screen (e.g., ally is blue, enemy is red), and players have a choice between sending messages to only their own team or to both teams. As seen in Figure 37, when transcribing the message, the sender’s champion is entered under the *Player (Champion)* heading, with the message text itself transcribed under the *Message* heading.

Figure 36
*Transcription Protocol: Player Chat Screen Location*
The transcription procedures described above were completed for each stream, preparing the corpus for the next step of coding the data. This process, which is discussed in the next section, included procedures for identification and coding of both pre-determined and emergent communicative strategies.

5. **Identification and Coding**

With the increasing growth of online gaming and live streaming, the importance of studying the communicative strategies used within these environments has increased as well. The communicative strategies that users employ to effectively convey their message online are chosen carefully, from the way users present themselves to the specific content discussed. These strategies are often employed via specific language features or elements. As previously mentioned much research has been conducted which focuses on digital discourse and elements found to be commonly present include language features such as shortening (e.g., *lol, brb, imo*; Squirell, 2010; Crystal, 2011; McCullough, 2020; Banja, 2018; Komrskova, 2015).
capitalization (e.g., *ALL CAPS for emphasis*; Androutsopoulos, 2011; Grantham et. al., 2010; Thurlow & Mroczek, 2011; Al-Ahdal & Algouzi, 2021); graphic images (e.g., *emojis, emoticons, memes*; Gulsen, 2016; Logi & Zappavigna, 2021; Thurlow & Jaroski, 2020; Giannoulis, 2019), and tagging (i.e., *@username to draw attention*; Wong & Wong, 2017; Jiang, 2019). Some of these features—graphic images, repetition, mentioning, capitalization—have been identified as being specifically common in Twitch.tv live stream chats, as well (Amaghllobeli, 2012; Olejniczak, 2015; Traxel, 2017; Henrik, 2019; Graham 2017, 2018, 2019; Tay 2020; Goulon, 2022; Sundberg, 2022). These language features will be the focus of the quantitative research undertaken in this current research.

5.1. Graphic Images on Twitch

One language feature that is a focus here is graphic images in the chat messages (e.g., emojis). The search for graphic images across this data was operationalized in a similar method to Olejniczak’s (2015) search for ‘emoticons’, but with a different term in place to cover a wider array of linguistic features. Digital visual communication elements, or ‘graphicons,’ as Herring and Dainas (2017) label them, have changed drastically over the years. From *smiley* to *stickers*—and all of the *emoticons* and *emojis* in between—each has become its own staple of communication in western digital culture (Bai et. al., 2019; Zhou et. al., 2017; Stark & Crawford, 2015). While each *graphicon* has its own visual style, purpose, and formation, together they have become an indispensable component of digital communication since they counteract the lack of paralinguistic cues in many digital contexts. While neither the *smiley*, nor *stickers*, were
available in the Twitch Public Chat at the time of this data collection, the use of *graphicons* thrives in this environment. For this study, I focused on four types:

1) **emoticons** *1st introduced in 1872, uses ordinary symbols on a QWERTY keyboard to create a visual representation of a face with a specific expression (e.g., typing ‘:-)’ produces 😄)

2) **Twitch Emotes** formed by typing a pre-programmed name into the Twitch chat, which is then converted into an image, used to convert a wide array of meanings and emotions, often depicts the face of a game developer, or well-known streamer (e.g., typing KAPPA produces 🌺, an image of an original Justin.tv developer, often used to display sarcasm)

3) **subscriber-only emotes** Twitch emotes which are created by individual streamers and made available to subscribers in different tier levels (e.g., on streamer TFBlade’s channel, subscribers have access to the sub-emote 🎈 which is converted by typing ‘tfbBAN’ into the chat, and used to suggest a ban of another user)

4) **emojis** released in 1999 by a Japanese originator; named as a transliteration of the Japanese word _GB (e=picture) _GB (mo=write) _GB (ji=character); these are graphic images created via Unicode that can represent faces, animals, plants, concepts, actions, etc. (e.g., ‘rolling on the floor laughing’ 🤣 ‘hibiscus’ 🌺 ‘rolls eyes’ 🙄)

*Emoticons* were manually identified and coded, either through the typed code or the formed image, depending on stream. *Twitch emotes* were queried, identified, and coded based on a list of nearly 300 enabled for use on Twitch (TwitchMetrics, 2022). A second digital query identified *subscriber only emotes*. Each streamer has a specific prefix with which these sub-

---

8 As of 2020, *stickers* are available with a browser extension for Twitch.tv. As their Twitter byline reads: we are “A Twitch Extension that has helped 450,000+ streamers earn MILLIONS of Bits by enabling their viewers to slap stickers directly on their live stream!” (Stream Stickers, 2020)
emotes begin, as seen in Table 48, and this was used to identify them in each stream. Finally, emojis were identified through a query that identified any lexical item not recognized as a keyboard transaction (i.e., searched for images within text). In line with Graham (2019), ‘failed’ graphicons were also counted—those instances where the user types the name or code for a graphicon, but instead of an image, the text appeared. Because “although such messages do not include the actual image, the presence of the emoji name or emoji code in the chat log indicates an attempt (whether successful or not) to employ emojis . . .” (Graham, 2019).

Table 48
Twitch.tv Streamer Sub-Emotes

<table>
<thead>
<tr>
<th>Streamer</th>
<th>Sub Emote Prefix</th>
<th>Example of Emote Output</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bizzleberry</strong></td>
<td>bizzle -</td>
<td>bizzleHi 🎉</td>
</tr>
<tr>
<td><strong>Cowsep</strong></td>
<td>cow -</td>
<td>cowFail 🎉</td>
</tr>
<tr>
<td><strong>Dekar173</strong></td>
<td>dekar -</td>
<td>dekarChad 🎉</td>
</tr>
<tr>
<td><strong>KayPea</strong></td>
<td>kayp -</td>
<td>KaypFreya 🎉</td>
</tr>
<tr>
<td><strong>llStylish</strong></td>
<td>lls -</td>
<td>llsAyyy 🎉</td>
</tr>
<tr>
<td><strong>loltylerl</strong></td>
<td>tyler1 -</td>
<td>tyler1LUL 🎉</td>
</tr>
<tr>
<td><strong>luxx</strong></td>
<td>luxx -</td>
<td>luxxPog 🎉</td>
</tr>
<tr>
<td><strong>neonpuddles</strong></td>
<td>neomp -</td>
<td>neoplovc 🎉</td>
</tr>
<tr>
<td><strong>QuinnAD</strong></td>
<td>QuinnAD-</td>
<td>QuinnADTHUMP 🎉</td>
</tr>
<tr>
<td><strong>STPeach</strong></td>
<td>peach-</td>
<td>peachSellout 🎉</td>
</tr>
<tr>
<td><strong>YourPrincess</strong></td>
<td>princess -</td>
<td>princessHYPERS 🎉</td>
</tr>
<tr>
<td><strong>yvonnie</strong></td>
<td>yvon -</td>
<td>yvonWave 🎉</td>
</tr>
</tbody>
</table>

5.2. Repetition

A second commonly used feature identified by Olejniczak (2015) was repetition. This use occurs quite often in the Public Chat and can include numerous resources—simple words, phrases, emotes (Example 1), or longer, more complex ‘copy pastas’\(^9\) (Example 2).

\(^9\) Repetitive chunk of text or images
Example 1, Simple Repetition of Twitch Emote

dajewish666
RottenTomatoes -1
alex_689
BeatBotBox6 CANNON
onerednightmare
Hippie_Einstein kekw
Brennanx
soimbad
Xhaileyanne this naut belings in fuckin gold lolololo
Quilord
HuanaMoana
YuYuYuna
Brennanx
itachingutsxd SHNARE HER U PEESH OF SHT
jimi60 They didn’t stay for the gold
namenotfound

Example 2, Complex ‘copy pastas’

dicshoomcgee
form_over_function Rawr🐲 x3😊 nuzzles how are you😊😊 pounces on you😊 you’re😊 so😊 warm😊 oɔo😊 notices😊 you have a bulge茄子 o:😊😊 someone’s happy😊😊 ;)😊😊 nuzzles your necky wecky茄子😊~ murr~ hehehe😊 rubbies👋🤚 your bulgyולגד you’re😊 so big😊😊 :oooo rubbies👋🤚 more on your bulgy يولגד it茄子 doesn’t stop茄子 growing ·///· kisses😍 you😊 and lickies😍💦💦

6 seconds, 4 messages

also_ubeR Rawr🐲 x3😊 nuzzles how are you😊😊 pounces on
Examining the use of repetition can reveal patterns of behavior and insight into the group’s shared understandings (e.g., what is considered spam, what users find rude). The issue that comes with examining repetition, however, is identification. We chose to base our decision on 1) how closely the text was copied and 2) whether the post provided new information to the chat. We identified all subsequent posts (i.e., not the initial one) which occurred within one minute of the previous repetitive post as a ‘repetition’.

5.3. ‘Mention’

The final feature identified by Olejniczak (2015), is the ‘chat mention’. This strategy of typing ‘@’ in front of a username is used to direct the attention of the user toward a specific message (Example X). Chat mentions, like graphicons, are a way for participants to directly
interact with each other and/or the streamer during the live broadcast. By examining the way participants engage with each other through *mentions*, we are able to identify patterns of communication such as who is being addressed, how often, and on what topic.

**Example 3**

Muhammed_Modo  
Brrringdingding  
Muhammed_Modo  
Brrringdingding

---

5.4. **ALL CAPS**

The use of *ALL CAPS* in Twitch Public Chat can be used for multiple purposes or be used to convey a wide range of meaning. For example, capitalization might be used to draw attention to a post or to express excitement or anger. By examining the use of *ALL CAPS* in this dataset, we can better understand how often and under what conditions this language feature is most used.

**Example 4**

lostgame5todiamond  
raekp

*Message Content.* Through an analysis of messages content, we are able to better understand conversational norms of the community surrounding each stream type. The following five categories were found to account all public chat messages:

- **game play references**
  
  *those messages which comment directly on the active game play session*

- **stream(er) references**
  
  *those messages which comment on the physical features of the stream(er) (e.g., comments about streamer’s*
background environment, physical comments about streamer); these references were separated into sexual and non-sexual personal references messages that refer to the participant greetings messages which greet another participant individually, or collectively news/current events messages which contain references to current events off topic/unassigned messages which do not fit into any of the above categories

6. Concluding Remarks

In this chapter, I have detailed the organization and transcription of this multimedium-based multimodal data. This corpus, which was designed to group by medium, separate by mode, and synchronize along a consistent timeline, was coded according to the detailed guidelines, and served as the empirical foundation of this dissertation. The following two chapters will report the quantitative patterns related to gender and stream size (Chapter 5), and 2) the qualitative characteristics of those patterns, as well as of multimodal influences (Chapter 6).
CHAPTER 5: Quantitative Results & Analysis

Discourse supplies meaning and content to our lives—to the world in which we exist. There are numerous factors that must be considered if analysis of this discourse is to occur, including the ever-increasing pervasiveness of ‘being online’, as the digital world is the space in which a large portion of the global population currently exists. In the previous chapter, I presented challenges we faced in designing and compiling a converged media multimodal corpus. In addition, I laid out the structuring of, and subsequent transcription of this corpus, which has, thus far, been capable of handling a multitude of data from the complex world of video game live streaming. To examine this dataset—partially in evidence of the ability of this corpus to allow a thorough analysis—I use a mixed methods approach, exploring the language through both a statistical analysis, but also through an operationalization of Herring’s (2007) language domain toolkit.

Here, in the quantitative analysis chapter, I begin with measures of frequency, central tendency, and dispersion. These tests are conducted in order to set the foundation for the answers to the remaining research questions:

*RQ2: What communicative strategies are employed by participants in a multimedium-based multimodal event (i.e., the Twitch.tv live stream)?*

This question is explored further through a discussion of how these strategies are impacted by both the social characteristics and technological aspects of the live stream:

*RQ2a: How do streamer gender and stream size impact the strategies chosen?*

*RQ2b: How does the availability of multiple mediums and semiotic modes impact this language use?*

The answers to these sub-questions were sought through tests of inferential analysis here in Chapter 5, as well as through multimodal analysis in Chapter 6.
1. Inferential Analysis

Through the series of inferential tests, in combination with the previously mentioned measures (frequency, tendency, dispersion), we can gain better insight into not only which communicative strategies are being employed by chat participants, but also how this digital discourse is impacted by the nature of the platform within which it occurs. The series of inferential tests help to indicate language changes that may occur as either the streamer and/or number of chat participants changes. In order to conduct these tests, however, specific elements of the dataset needed to be established.

1.1. Establishing the Independent Variables

Two independent variables were employed in order to explore the impact of social context on language use within these live streams.

*gender (male/female)* Streamers were identified as male/female through their self-reference in stream using binary pronouns, self-description on their profile pages, and binary on-screen presentation through dress, mannerisms, etc. In addition, audience references to streamer were considered.

*size (small/large).* Upon review of the average viewership across recorded streams, there were multiple occurrences that were inconsistent with the original division of less than/greater than one thousand viewers. Therefore, in order to divide the group in a meaningful way that would account for differences in viewer population, *social density* was measured. While typically measured by the number of people (or interactions) in a given space, Zhou et. al. (2019) extended the idea of ‘being present’ in a digital space to online streaming and based the measurement on the number of words present at a given moment. Building on that study, *social*
density here is defined as the average number of messages per minute in each stream, as seen in Table 6.

Table 6
Messages per Minute (message/length of stream), by Streamer

<table>
<thead>
<tr>
<th>Streamer</th>
<th>message count</th>
<th>length of stream</th>
<th>messages/minute</th>
</tr>
</thead>
<tbody>
<tr>
<td>BizzleBerry</td>
<td>184</td>
<td>24.11</td>
<td>7.74</td>
</tr>
<tr>
<td>Cowsep</td>
<td>155</td>
<td>25.11</td>
<td>6.28</td>
</tr>
<tr>
<td>Dekari73</td>
<td>182</td>
<td>22.75</td>
<td>7.96</td>
</tr>
<tr>
<td>KayPeaLol</td>
<td>430</td>
<td>27.88</td>
<td>15.44</td>
</tr>
<tr>
<td>lilStylish</td>
<td>709</td>
<td>28.12</td>
<td>25.28</td>
</tr>
<tr>
<td>LollTyler1</td>
<td>3,551</td>
<td>21.36</td>
<td>113.55</td>
</tr>
<tr>
<td>luxzbunny</td>
<td>452</td>
<td>29.64</td>
<td>15.25</td>
</tr>
<tr>
<td>NeonPuddles</td>
<td>148</td>
<td>31.05</td>
<td>4.83</td>
</tr>
<tr>
<td>QuinnAD</td>
<td>110</td>
<td>21.48</td>
<td>5.16</td>
</tr>
<tr>
<td>StPeach</td>
<td>346</td>
<td>33.26</td>
<td>10.42</td>
</tr>
<tr>
<td>YourPrincess</td>
<td>1,074</td>
<td>28.73</td>
<td>38.5</td>
</tr>
<tr>
<td>Yvonnie</td>
<td>833</td>
<td>30.89</td>
<td>26.89</td>
</tr>
</tbody>
</table>

To establish stream_size, as seen in Table 9, the streams having 15 or fewer messages per minute were labeled small, while those with more than 15 messages per minute were considered large. Paired with the streamer_gender distinction, four categorical groups were created: male small, male large, female small, and female large (Figure 38).

Figure 38
Four Categorical Groups
As seen above, there are two cells with four streamers each and two with only two streamers. There are certainly limitations to these small cell sizes, such as limited statistical power, wider confidence levels, and possible data quality issues. However, four game sessions were recorded from each streamer, via two independent collections—thereby increasing the actual numbers within each cell.

1.2. Normalization & Assumptions

While absolute frequencies and rates of use reveal the sheer volume of Public Chat messages being analyzed —the data needed normalization to test for significance. The data was all brought into proportion with one another by normalizing the data to occurrences per minute. In addition to normalization of the data, because ANOVA is a parametric test, there are three additional assumptions that must not be violated:

1) Assumption of Normality was tested with a Kolmogorov-Smirnov test, which indicated a normal distribution amongst the data \((D = .082, p = .993)\).

2) Assumption of Homogeneity was met via Levene’s test for quality of variances, which revealed homogeneous data due to a non-significant result \((F (1,20) = 3.482, p = .069)\).
3) *Independence of Observation* was not violated because no individual streamer’s data subset was affected by any other.

### 1.3. Terms to Know

Hereafter, all analysis applies specifically to the current dataset (i.e., not the corpus as a whole)—the twenty-four streams from twelve streamers, as previously described. The following statistical abbreviations are used in these quantitative sections:

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f )</td>
<td>frequency measurement, absolute frequency</td>
</tr>
<tr>
<td>( fn )</td>
<td>frequency measurement, relative frequency</td>
</tr>
<tr>
<td>( M )</td>
<td>mean</td>
</tr>
<tr>
<td>( SD )</td>
<td>standard deviation</td>
</tr>
<tr>
<td>( F )</td>
<td>F-ratio</td>
</tr>
<tr>
<td>( ANOVA )</td>
<td>analysis of variance test</td>
</tr>
<tr>
<td>( p )</td>
<td>probability</td>
</tr>
<tr>
<td>( D )</td>
<td>K-S test statistic (normality)</td>
</tr>
<tr>
<td>*</td>
<td>indicates significant test, ( p &lt; .05 )</td>
</tr>
</tbody>
</table>

In the next section, I present the results from the statistical analysis of the features found to be prominent within the dataset. Here, prominence is defined as being present in at least 10% of either total message count (3,240 out of 32,397 total), or individual stream message count.

### 2. Language Features

#### 2.1. Graphicons \((f = 17,590; M = 732.88; SD = 1,076.69)\)

These “graphical means of communication” (Herring & Dainas, 2017) were found to be present in nearly half of all *Public Chat* messages \((n = 14,917)\), as showing in Figure 27. While the majority of these messages contained a single graphicon, there were instances of use as high as 40 within a single message. In total, more than 17,000 graphicons were identified.
While the term *graphicon* encompasses numerous types, from the *smileys* of the 1980s to the *stickers* and *gifs* of today, recall from Chapter 4 that there are four present in the current dataset: *emoticons, Twitch emotes, subscriber-only emotes,* and *emojis.* Also shown in Figure 39, *emotes* are the primary *graphicon* used, accounting for over 2/3 of all use. The other third is made of up *emoticons, subscriber emotes,* and *emojis.*

Figure 39
*Messages Containing Graphicons & Graphicon Subsets*

These combined measurements of frequency indicate that *graphicons* are not only present, but prominent, in the discourse of the Twitch public chat participants.

2.1.1. **Graphicons, by Gender & Size**

Considering streamer gender, average use across streams was higher in the male streams ($f/n = 2,952; M = 492.09; SD = 259.72$) than in the female streams ($f/n = 2,238; M = 373.11; SD = 230.95$), see Figure 40.

Figure 40
*Graphicon Average, by Streamer Gender*
Depicted in Figure 41 is the average use considering stream size—where the use is higher in large streams ($f/n = 3,243; M = 540.50; SD = 212.59$) than in the small streams ($f/n = 1,947; M = 324.50; SD = 236.86$).
To be mindful of these separations (i.e., male/female, small/large) and to test the differences for statistical significance—to see if these differences in mean and patterns of use are suggestive of a larger population—a series of ANOVA and subsequent simple effects, pairwise comparison tests were conducted, revealing the following main effects, which were qualified by a significant interaction, as seen in Table 7.

Table 7
Main Effects of Gender, Size, & Interaction on Graphicons

<table>
<thead>
<tr>
<th>main effect of</th>
<th>F (1, 20)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer_gender</td>
<td>4.710</td>
<td>0.042</td>
</tr>
<tr>
<td>stream_size</td>
<td>15.558</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>gender*size</td>
<td>4.928</td>
<td>0.038</td>
</tr>
</tbody>
</table>

To explore this interaction further, simple effects tests were conducted to examine the impact of streamer_gender on use in small vs large streams, as well as the impact of stream_size on use in male vs female streams—results as seen in Table 8.
Table 8
Simple Effects of Gender & Size on Graphicons

<table>
<thead>
<tr>
<th>Simple Effect of</th>
<th>$F$ (1, 20)</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer_gender within small streams</td>
<td>20.758</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>streamer_gender within large streams</td>
<td>1.371</td>
<td>0.255</td>
</tr>
<tr>
<td>stream_size within male streams</td>
<td>10.934</td>
<td>0.004</td>
</tr>
<tr>
<td>stream_size within female streams</td>
<td>0.001</td>
<td>0.974</td>
</tr>
</tbody>
</table>

These tests indicate that, while both `streamer_gender` and `stream_size` have an impact on graphicon use in the public chat, the impact each has is dependent on the other. The influence of `streamer_gender`, for example, is only significant within large streams (Figure 42), while the influence of `stream_size` is only significant within male streams (Figure 43).

Figure 42
Impact of Gender on Graphicons in Small vs Large Streams
The initial measures, above, indicate a clear prominence of graphicon use within the public chat. These combined effects tests (i.e., main effect, effect of interaction, simple effects) help to specify use. These tests suggest that, though both the gender of the streamer and the size of the stream are relevant in determining graphicon use across the chat, the strong effect size suggests that the size of the stream is most indicative. Given the simple effects, however, the impact of size is heavily dependent on the gender of the streamer—indicating that, though chat participants in large streams are more likely to post messages containing graphicons, this is especially the case when the streamer is male.

2.1.2. Graphicons, by Categorical Group

Recall from earlier in this chapter, the four categorical groups that were established to account for all combinations of the stream types in the current dataset: male small, male large,
female small, female large. The average use of graphicons across these four groups varies only somewhat, as seen in Figure 44.

Figure 44

Graphicons, by Categorical Group

![Graphicon Usage by Categorical Group](image)

Given the interactional effects of the tests noted above, the impact of the two variables together (i.e., streamer_gender * stream_size) is great enough to cause noteworthy differences. The greatest impact occurs when gender differs across the small streams. The higher average use in male small streams (394 per 1,000 messages) than in female small streams (185 per 1,000 messages) suggests that participants in small streams with male streamers are more likely to use graphicons than those with female streamers. In addition, the impact of size within male streams is large enough to create significant difference. The average here indicates that in male large streams (688/1,000) use is likely to be higher than in male small streams (394/1,000). Combined, and with no other significant interactions, this suggests that participants in the public chat of male large streams are more likely to post
messages containing *graphicons* than those in *male small streams*. The latter, however, are more likely to post *graphicons* than those in small streams with female streamers.

### 2.2. Mentions

\( f = 3,870; M = 158.62; SD = 174.38 \)

The next feature examined for its use in the Twitch chat is ‘tagging’—or ‘mentioning,’ as Twitch.tv calls it. The act of calling the attention of a specific user to a specific message occurs in 11.5% of messages across the current dataset, as seen in Figure 45.

**Figure 45**

*Messages Containing ‘Mentions’*

And while these measures indicate the prominence of ‘mentions’ overall in this dataset, to be mindful of the gender and size groups, the differences in use must be calculated and tested for significance.

#### 2.2.1. Mentions, by Gender and Size

Comparison of use in male streams \((f/n = 1,161; M = 96.71; SD = 58.17)\) versus female \((f/n = 3,322; M = 193.54; SD = 139.04)\) revealed an average use in female streams that was over double that in male streams, as seen in Figure 46.
Depicted below in Figure 47 is average use in small streams \((f/n = 1,371; M = 114.26; SD = 43.33)\) as compared to large streams \((f/n = 3,112; M = 175.99; SD = 155.48)\), which was determined to be approximately half.
To test these differences for statistical significance, ANOVA was conducted, revealing a significant main effect only when considering stream size (Table 9).

Table 9

Main Effects of Gender, Size, & Interaction on ‘Mentions’

<table>
<thead>
<tr>
<th>main effect of</th>
<th>F (1, 20)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer gender</td>
<td>0.234</td>
<td>0.633</td>
</tr>
<tr>
<td>stream size</td>
<td>12.495</td>
<td>0.002*</td>
</tr>
<tr>
<td>gender*size</td>
<td>0.001</td>
<td>0.982</td>
</tr>
</tbody>
</table>

The lack of significance for both the gender and size groups established that there were no further testing requirements for either interaction or simple effects.

The strong effect size when considering small versus large streams indicates that size is an important enough factor to impact the use of ‘mentions’ within. The lack of significance between male and female streams, however, indicated that the influence of gender would not change use to an observable degree. Together, these measurements suggest that the participants in the public chat are more likely to ‘mention’ another participant in large streams, regardless of whether the streams are male or female.

2.2.2. Streamer Mentions ($f = 855; M = 36; SD = 40.71$)

As a subset of the total ‘mentions’ discussed in the last section, ‘streamer mentions’ are those in which a chat participant posts a message which ‘mentions’ the streamer (i.e., uses ‘@streamername’ to draw the attention of the streamer to a specific message). As seen in Figure 48, these ‘streamer mentions’ account for 22.6% of all mentions but occur in less than 10% of the total message count.
Because use did not meet the 10% requirement, no further statistical testing beyond measures of
dispersion and tendency was necessary. However, it is worth noting for future qualitative
discussion, that these streamer specific mentions do account for a large number of the total
mentions in many streams, as seen in Figure 49.

Figure 49
‘Streamer Mention’ use, as Compared to ‘Mentions’
2.2.3. Mentions, by Categorical Group

When describing by the categorical group, given that no significant interactions were present, there were no indicators of combined impact on use of either *mentions* or *streamer mentions*. Though average use in *female large streams* (182/1,000) was higher than use in other groups, as seen in Figure 50, these differences were not noteworthy.

Figure 50
*Mention’s, by Categorical Group*

Therefore, this suggests that the use of both *mentions*, and *streamer mentions* in the current dataset is more dependent on the preferences of individual participants or the cultural norms of individual communities than on the size of the community or the gender of the streamer.

2.3. ALL CAPS (*f* = 4,114; *M* = 171.43; *SD* = 399.47)

The use of capitalization is prominent in the current dataset, given that the use occurs in 12.7% of the total posted messages.
2.3.1. ALL CAPS, by Gender and Size

When examined while considering streamer_gender and stream_size, the average use within male streams (f/n = 835; M = 69.62; SD = 49.29) was higher than in female streams (f/n = 689; M = 57.42; SD = 27.31), while average use in small streams (f/n = 483; M = 40.29; SD = 10.05) was lower than in large (f/n = 1,041; M = 86.75; SD = 43.22). These differences are illustrated below, in Figures 52 and 53 respectively.
Figure 52
ALL CAPS Average, by Streamer Gender

Figure 53
ALL CAPS Average, by Stream Size

*a listed alphabetically*
These differences in use of capitalization were tested for significance via ANVOA and subsequent tests, revealing these main effects. And while both were significant, they were constrained by a qualified interaction (Table 10).

Table 10  
**Main Effects of Gender, Size, & Interaction on ALL CAPS**

<table>
<thead>
<tr>
<th>main effect of</th>
<th>F (1, 20)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer_gender</td>
<td>6.473</td>
<td>0.019</td>
</tr>
<tr>
<td>stream_size</td>
<td>9.971</td>
<td>0.005</td>
</tr>
<tr>
<td>gender*size</td>
<td>6.358</td>
<td>0.020</td>
</tr>
</tbody>
</table>

In order to further explore the gender*size interaction, tests were conducted to examine the simple effects of each variable on the other. These tests, which specifically measure the influence of streamer gender on use within small and large streams, as well as the influence of stream size on use within the male and female streams, revealed the effect levels shown in Table 11.

Table 11  
**Simple Effects of Gender & Size on ALL CAPS**

<table>
<thead>
<tr>
<th>simple effect of</th>
<th>F (1, 20)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer_gender within small streams</td>
<td>14.558</td>
<td>0.001</td>
</tr>
<tr>
<td>streamer_gender within large streams</td>
<td>0.000</td>
<td>0.988</td>
</tr>
<tr>
<td>stream_size within male streams</td>
<td>17.620</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>stream_size within female streams</td>
<td>0.187</td>
<td>0.670</td>
</tr>
</tbody>
</table>

These tests indicate that streamer_gender and stream_size each have an impact on the use of capitalization—an impact that is dependent on the other, however. Streamer_gender, as seen in Figure 54, is only influential within large streams, while stream_size is influential just in the cases when the streamer is male, Figure 55.
Figures 54
*Impact of Gender on ALL CAPS in Small vs Large Streams*

Figures 55
*Impact of Size on ALL CAPS in Male vs Female Streams*
These statistical measures and tests indicate that the use of ALL_CAPS occurs regularly in Twitch chat, and that while the gender of the streamer and the size of stream both influence the amount of use, the size is slightly more influential here. This suggests that the use of capitalization occurs more often in streams with a larger number of chat participants, though it is most likely to occur in those large streams with male streamers.

2.3.2. ALL CAPS, by Categorical Group

Concerning the use of capitalization in the Twitch public chat, average use in the dataset was low across the four categorical groups, as seen in Figure 56.

Figure 56
ALL_CAPS, by Categorical Group

The interactional effects were similar to graphicon use, with an impact of size across male streams that was great enough to cause significant differences in use. And with average use in male large streams (124 per 1,000 messages) three times as high as in male small streams (42/1,000), it is significantly more likely for participants in the former group to post using
ALL_CAPS than in the latter. The impact of the streamer’s gender within small streams is great enough to cause noteworthy variation, as well—with average use in female small streams at 36/1,000 and in male small streams at 42/1,000. Though use in the current dataset is low overall, this suggests that similar to graphicon use, capitalization is more likely to occur in male small streams than in female small, but also more likely in male large streams than in male small.

2.4. Repetition \((f = 2,723; M = 113.46; SD = 181.5)\)

Use of repetition, as previously mentioned, has been found to be regularly present in digital discourse (Gill & Michaud, 2017; Angus & Goncalves, 2018; Baider & Shani, 2019) Across the current dataset, the initial measures did not meet the 10% qualifier for further analysis. Repetition is still noteworthy, however, considering its prominence in multiple individual streams (Figure 57).

Figure 57
Repetitions in Individual Streams
Use of repetition in these five streams (Figure 45) accounts for 94% of all use and though it is not consistently prominent, these measures will be further examined both here and in Chapter 6: Qualitative Analysis.

2.4.1. Repetition, by Gender and Size

Examining this prominence while considering streamer_sex, use in male streams (f/n = 720; M = 41.59; SD = 55.97) was found to be only slightly lower than use in female streams (f/n = 499; M = 60.04; SD = 63.81), see Figure 58. When considering stream_size, use in large streams (f/n = 958; M = 79.86; SD = 61.80) was higher than in small streams (f/n = 261; M = 21.77; SD = 61.80), Figure 59.

Figure 58
Repetitions Average, by Streamer Gender

\[\text{listed alphabetically}\]
An ANOVA and subsequent tests were conducted, revealing significant main effects in the case of both \textit{streamer\_sex} and \textit{stream\_size}, though they were qualified by a significant interaction (Table 11).

Table 12
\begin{tabular}{lcc}
\textbf{main effect of} & \textbf{F (1, 20)} & \textbf{p-value} \\
\hline
\textit{streamer\_gender} & 6.270 & 0.022 \* \\
\textit{stream\_size} & 18.942 & < .001 \* \\
\textit{gender\_size} & 7.468 & 0.013 \* \\
\end{tabular}

In a further exploration of the \textit{gender\_size} interaction, both the influence of \textit{streamer\_sex} on small and large streams, as well as the influence of \textit{stream\_size} on male and female streams were measured, revealing multiple significant simple effects:
Table 13

*Simple Effects of Gender & Size on Repetitions*

<table>
<thead>
<tr>
<th>simple effect of</th>
<th>$F (1, 20)$</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer_gender within small streams</td>
<td>15.494</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>streamer_gender within large streams</td>
<td>0.026</td>
<td>0.874</td>
</tr>
<tr>
<td>stream_size within male streams</td>
<td>27.400</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>stream_size within female streams</td>
<td>1.205</td>
<td>0.028</td>
</tr>
</tbody>
</table>

As illustrated in Table 13, these tests reveal that `streamer_gender` interacts with `stream_size` but is significant only within the large streams. In addition, as seen in Figure 60, `stream_size` is influential in the case of both male and female streams—though the strength of that influence is stronger in male streams given the strength of the effect size.

Figure 60

*Impact of Gender on Repetitions in Small vs Large Streams*
These tests indicate that, while the sex of the streamer and the number of participants each have an impact on the use of repetition in Twitch public chat, they are heavily dependent on one another. Given the measures and effect sizes, the numbers suggest that participants in large streams are much more likely to post repetitive messages than those in small streams. This is the case whether the streamer is male or female, though use in large male streams is slightly more likely than in large female streams.

2.4.2. Repetition, by Categorical Group

As seen in Figure 62, average use across the four categorical groups was low, though recall from above that these tests revealed multiple significant interactions.
Beginning with the impact of stream_size, it was great enough within both male and female streams that differences were noteworthy. Average use in male small streams at 7/1,000 and use in male large streams nearly 15 times higher, at 110/1,000, the analysis indicates that participants in male large streams post more repetitive posts than those in male small streams. This is also the case in female large streams (85/1,000), where repetitions use is higher than in female small streams (51/1,000). However, the use of repetition must be considered parallel to the significant impact of streamer_gender on small streams, where average use is 7/1,000 and 51/1,000 in male and female small streams, respectively.

Collectively, this suggests that participants in large streams, both male large and female large, are more likely to post repetitive messages than their small stream counterparts.
Furthermore, within small streams, participants in female small streams are more likely than those in male small streams to use repletion.

While different groups of participants may use varied combinations of communicative strategies to connect with each other and the streamer, the prominence of the features discussed here show that they play a crucial role in the public chat of video game live streams on the Twitch platform. Through the use of graphicons (primarily Twitch emotes), ‘mentioning’, capitalization, and repetition, participants are able to express themselves and react to the other participants or content in a productive, creating order in a sometimes chaotic and complex environment. In the next section, I examine the content of the chat messages in an effort to determine common topics of discussion overall, and in the four different groups of streams.

3. Message Content

The thematic message types, as detailed in Chapter 4, were located within the dataset and initially analyzed with measures of frequency, dispersion, and central tendency. Three of these message types were identified as prominent within the dataset, using the same 10% criteria as previously discussed.

3.1. Game References ($f = 8,065$, $M = 645.22$, $SD = 769.05$)

A game reference, recall from Chapter 4, is one which references the active game play session. A game reference could be simple, as seen below, where “gg” means “good game”:

<table>
<thead>
<tr>
<th>username</th>
<th>message</th>
</tr>
</thead>
<tbody>
<tr>
<td>pikaChuMoon</td>
<td>gg</td>
</tr>
</tbody>
</table>

Or the reference could be complex, as in this example:

<table>
<thead>
<tr>
<th>username</th>
<th>message</th>
</tr>
</thead>
<tbody>
<tr>
<td>dallasls</td>
<td>graves double kill at 4 minutes</td>
</tr>
</tbody>
</table>
Here, “graves” refers to a League of Legends champion known for his ability to quickly ‘burst kill’ opponents through ‘auto attack.’ ‘Double kill’ refers to Graves’ killing of two opponents within 10 seconds of each other, while ‘at 4 minutes’ is a reference to the game play clock time of that ‘double kill’ occurrence. Finally, the Twitch emote NotLikeThis refers to the frustration of the chat participant in reference to the ‘double kill’ occurrence.

As seen in Figure 63, these game references account for a fourth of all messages and are nearly all direct references to League of Legends champions. Particularly noteworthy is that the large majority of these references consistently occurred within the first seven minutes of their respective stream.

Figure 63
Message Content, Game References vs Other Content

These game references, which allow participants to actively engage with the stream (er), showed similar use across categories (i.e., streamer_sex, male/female; stream_size, small/large). Game references appeared, on average, less often in female streams (f/n = 2,428; M = 202.33; SD = 175.68) than in male streams (f/n = 3,354; M = 279.50; SD = 104.79), and a similar frequency was revealed in small streams (f/n = 2,567; M = 223.25, SD =146.75), as compared to
large streams \( (f/n = 3,215; M = 258.58, SD = 152.09) \), as seen in Figures 52 and 53, respectively.

Figure 64
*Game References Average, by Streamer Gender*

![Graph showing game references average by streamer gender.](image)

Figure 65
*Game References Average, by Stream Size*

![Graph showing game references average by stream size.](image)
Upon further testing—with ANOVA and subsequent tests for significance—neither the main effects of streamer_sex or stream_size nor the interaction effects of streamer_sex*stream_size produced significant effect sizes, as seen in Table 14.

Table 14
Main Effects of Gender, Size, & Interaction on Game References

<table>
<thead>
<tr>
<th>main effect of</th>
<th>$F$ (1, 20)</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>streamer_gender</td>
<td>3.340</td>
<td>0.083</td>
</tr>
<tr>
<td>stream_size</td>
<td>0.934</td>
<td>0.345</td>
</tr>
<tr>
<td>gender*size</td>
<td>3.669</td>
<td>0.070</td>
</tr>
</tbody>
</table>

The lack of significance indicates that the impact of streamer sex or stream size on the use of messages containing game references is small enough that it is not likely to cause a noteworthy difference. This suggests that participants in this dataset posted these relative to individuals rather than to categories of streamers or streams.

3.2. Greetings ($f = 1.554, M = 124.34, SD = 94.17$)

Greetings are messages which are used to ‘greet’ (e.g., say ‘hello’ to) another chat participant or to the streamer. Again, greetings may appear at varying levels of complexity:

<table>
<thead>
<tr>
<th>username</th>
<th>message</th>
</tr>
</thead>
<tbody>
<tr>
<td>Darkcyter</td>
<td>kaypHi</td>
</tr>
<tr>
<td>P4zzie</td>
<td>@nightmares98 how doing?</td>
</tr>
<tr>
<td>nightmares98</td>
<td>@P4zzie just got back from class in time to say hey</td>
</tr>
</tbody>
</table>

While greetings, which are often used to show support for and connection to the stream(er), did not meet the 10% criteria for further testing. It is noteworthy to mention here, however, due to its prominent use in some individual streams, as seen in Figure 66.
3.3. Stream(er) References \((f = 1,903; M = 152.22; SD = 180.09)\)

Similar to ‘greetings,’ the messages which contained references to the streamer (i.e., message which commented on the physical characteristics of either the streamer or the streamer’s physical environment, did not meet the 10% criteria for further testing. However, as seen in Figure 67 there was noteworthy use identified in individual streams.
These measures are worth mentioning for two reasons—regular and consistent use in female streams ($f = 763; M = 49.92, SD = 12.50$) and near absence of use in the majority of male streams ($f = 175; M = 47.50, SD = 30.39$).

### 3.4. Message Content, by Categorical Group

So far in the current section, message content has been examined across streamer_gender and stream_size, focusing on references to game play, greetings, and the streamer/stream environment. Here, I turn the attention again to the four established categorical groups and the message content commonly present in the public chat messages of each, which allows for a more thorough understanding of how content varies based on stream characteristics.

Messages containing game references were the most common overall, though statistical analysis showed no significant effect—individually or in interaction—indicating no noteworthy
differences. This being the case, certainly there were trends to highlight in this dataset, with use in the four groups as follows:

- male small stream ($f/n = 2,380; M = 297.50; S/D = 108.52$)
- male large stream ($f/n = 974; M = 24.35; S/D = 80.83$)
- female small stream ($f/n = 299; M = 74.75; S/D = 14.15$)
- female large stream ($f/n = 1,677; M = 279.50; S/D = 203.01$)

These statistics indicate that participants in male small streams and female large streams, were each about four times as likely to reference active game play as those in female small streams, where the likelihood was three times that of those in male large streams.

The content type ‘greetings’, which were not subjected to ANOVA and subsequent tests due to use below 10% criteria, were low across the dataset, but had the most consistent use when examining average use per 1,000 messages. Considering the four categorical groups, use was as follows:

- male small stream ($f/n = 401; M = 50.13; S/D = 35.38$)
- male large stream ($f/n = 169; M = 42.25; S/D = 10.10$)
- female small stream ($f/n = 150; M = 37.50; S/D = 11.55$)
- female large stream ($f/n = 335; M = 55.83; S/D = 6.85$)

These statistics, with all average use at 56 or below, indicates that the act of ‘greeting’ another user is not particularly common. This suggests that the act is dependent on the preferences and norms of the individual participant rather than being dependent on expectations of the community or Twitch as a whole.

Finally, we explore the content type ‘stream(er) references’ in relation to the four groups of streams. As previously noted, while this content was below the 10% criteria marker, the
frequent use in female streams combined with near lack of use in male streams made the use worth highlighting. Use across the four groups is as follows:

- male small stream \((f/n = 45; M = 5.63; S/D = 7.42)\)
- male large stream \((f/n = 130; M = 32.8; S/D = 37.53)\)
- female small stream \((f/n = 325; M = 81.25; S/D = 51.10)\)
- female large stream \((f/n = 381; M = 63.50; S/D = 15.82)\)

These statistics that participants in both female small and female large streams were 16 and 2 times as more likely, respectively, to make references to the streamer or the streamer’s physical environment than were those in the male counterparts. In addition, participants in female small streams were more likely than those in female large streams to make these references. Furthermore, those participants in the male large streams were more likely than those in the male small streams. This suggests that referencing the streamer or stream environment is more reflective of the individual participants.

Overall, the presence of specific content types in the messages of this dataset did not present as particularly noteworthy or significant. Though this is the case, however, there were clear trends which emerged in this dataset based on the categorical groups. In Figure 68, below, each content type is shown, divided by stream group.
overall message content, by categorical group

Note that male small streams had content in all three of these content types, to a relatively similar degree. Female small streams, on the other hand, accounted for only 4% of game references, but about one third of greetings and stream(er) references. In the case of the large streams, the female large participants contributed nearly half of all game references and a third of the greetings, but only 3% of stream(er) references were made by this group. In male large streams, the participants contributed only a tenth of game references, but a third of greetings, and nearly a half of all stream(er) references.

The content of the public chat messages in these video game live streams is a reflection of the unique relationship between each streamer and their respective viewers. Through game references, the participants are able to interact with, react to, or reflect on the active game play, while the use of greetings and streamer references is a strategy used to interact with the streamer and/or other participants. By examining these content themes, we are able to gain a better understanding of the most compelling topics of conversation in each group of streams.
4. Participatory Patterns

The study of digital discourse via CMDA is focused on language and language use (Herring, 2019), and to address this focus, each context must be considered for its interactions and relationships between language and “social practices” (Herring & Androutsopoulos, 2015). Recalling from Chapter 3 that, in addition to the four primary CMDA language domains, Herring (2004) added a fifth analysis domain—participation—which considers such patterns as frequency and number of posts, or message length.

4.1. Participatory Patterns, by Gender & Size

Each environment allows for different patterns of participation, and therefore, as the last piece of the quantitative analysis, the participatory aspects of the streams were explored, as reported in Table 15.

Table 15
Participatory Statistics, by Gender & Size

<table>
<thead>
<tr>
<th></th>
<th>unique participants</th>
<th>messages per user</th>
<th>messages per minute</th>
<th>words per message</th>
<th>message uptime (in minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>male</td>
<td>498</td>
<td>4.03</td>
<td>27.6</td>
<td>4.93</td>
<td>1.27</td>
</tr>
<tr>
<td>female</td>
<td>208</td>
<td>5.5</td>
<td>18</td>
<td>4.65</td>
<td>1.63</td>
</tr>
<tr>
<td>large</td>
<td>621</td>
<td>4.65</td>
<td>38.4</td>
<td>4.6</td>
<td>0.65</td>
</tr>
<tr>
<td>small</td>
<td>85</td>
<td>4.87</td>
<td>7.2</td>
<td>4.98</td>
<td>2.26</td>
</tr>
</tbody>
</table>

There was a total of 8,472 unique users in the current dataset, with over two times as many participants, on average, in male streams (498) than in female streams (208). In large streams, the divide is even greater, with average participants at 621, while in small streams the average is just 85. These users posted similar quantities of messages, on average in large and small streams, while in female streams (5.5 messages per user), the number was slightly higher
than in male streams (4.03). These messages, on average, were relatively similar in length with a variation of only .3 in both the cases of male vs. female streams and small vs large.

The largest variation in groups was seen in the categories related to time (i.e., messages per minute and message uptime). These numbers are inversely related, in that, as the messages per minute increases, the message uptime decreases, as seen in Figure 69.

Figure 69
Relationship Between Messages per Minute & Message Uptime

Message uptime is a measurement of how long a message is present on the screen. Here it is measured from the time it appears on screen until it scrolls up and out of sight. These measurements illustrate the rapid-fire posting that occurs regularly in larger streams. While the difference in male and female streams is not vastly different, when examining the large and small streams, messages are visible, on average, nearly four times as long in large streams.
4.2. Participatory Patterns, by Categorical Group

Having examined these participatory patterns across gender and size lines, attention is now focused on the patterns that emerged within each of the four categorical stream groups. As seen in Table 16, there was a great deal of variation in the average numbers of both unique users and messages across the four groups.

Table 16
Messages per User, by Categorical Group

<table>
<thead>
<tr>
<th></th>
<th>unique users</th>
<th>messages</th>
<th>message/user</th>
</tr>
</thead>
<tbody>
<tr>
<td>male small</td>
<td>641</td>
<td>152</td>
<td>4.51</td>
</tr>
<tr>
<td>male large</td>
<td>8,519</td>
<td>2,686</td>
<td>3.05</td>
</tr>
<tr>
<td>female small</td>
<td>1,003</td>
<td>205</td>
<td>5.58</td>
</tr>
<tr>
<td>female large</td>
<td>2,697</td>
<td>521</td>
<td>5.43</td>
</tr>
</tbody>
</table>

The measurements of message per user, however, vary only by about two messages. Not that the two groups with female streamers held the highest message per user counts, at 5.6 and 5.4 in the small and large streams, respectively. In male streams, on the other hand, the message count was lower—in male large streams, on average, each user sent only ~ 3 messages, while in male small streams, each user sent ~ 4.5 messages each. These measurements indicate that participants in female streams tend to post more, regardless of the number of participants present, suggesting that they are more engaged with the conversation itself than with the viewing of content. Participants in male streams, however, tend to post less, especially when there are more users present.

These messages being posted vary in content, of course, but also in the amount of content. Messages may contain a single character or graphicon, or they may contain full
sentences and paragraphs—and everything in between. As seen in Table 17, the *words per message* average for each group was relatively short given the abundance of emote and emoji sequences seen regularly.

Table 17
*Words per Message, by Categorical Group*

<table>
<thead>
<tr>
<th></th>
<th>messages</th>
<th>word count</th>
<th>words/message</th>
</tr>
</thead>
<tbody>
<tr>
<td>male small</td>
<td>641</td>
<td>3,284</td>
<td>5.12</td>
</tr>
<tr>
<td>male large</td>
<td>8,519</td>
<td>9,217</td>
<td>2.31</td>
</tr>
<tr>
<td>female small</td>
<td>1,003</td>
<td>4,413</td>
<td>4.58</td>
</tr>
<tr>
<td>female large</td>
<td>2,697</td>
<td>11,444</td>
<td>4.68</td>
</tr>
</tbody>
</table>

These measurements, however, must account for the over 10,000 messages (n = 10,111) that consisted of a single word—where ‘word’ was counted as any single lexical unit or graphicon. When examining these *words per message* counts, *female small* and *female large streams* have similar measurement—4.58 and 4.68, respectively. In male streams, however, the two stream groups are at 5.12 *words per message* in small streams and at 2.31 in large streams. These measurements suggest that participants in female streams may feel more engaged in conversation, as are those participants in *small male streams*. In the case of *male large streams*, however, the focus may be on getting information out quickly.

Finally, are the *messages per second* and *message uptime* measurements—which, as previously noted are related inversely: as *messages per second* increased, *message uptime* decreases (Figure 70).
In *male small streams*, these two measurements indicate that messages appear at the approximate rate of 1 message every 6 seconds and remain visible for just over 2 minutes each. In *male large streams*, on the other hand, the messages appear at a rate faster than 1 message every second but remain visible for only about 20 seconds. These measurements indicate that participants in male streams post messages at a quicker rate as the stream size increases, suggesting that they are posting at a rate that accounts for the lack of visibility (i.e., posting more often because the messages don’t remain for very long).

In female streams, however, where the rate of messages per second is 1 messages every 6 seconds in *female small streams* and 1 message every 2.5 seconds in *female large streams*. Their *message uptime* measurements are, of course reversed, with longer uptime in *female small streams* and shorter uptime in *female large streams*. These measurements indicate that participants in the *female small streams* post less often than those in the *female large streams*. 

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*Figure 70: Average Messages/Second & Message Uptime, by Categorical Group*
4.3. Overall Engagement

Overall, these measurements of participatory patterns are able to create a clear picture of the engagements in each stream group. In exploring the two groups of small streams, for example, the higher message per user and lower messages per second measurements suggest that both male small and female small streams may be more engaged with and interested in maintaining conversations with other participants. In large streams, on the other hand, participants may put more focus on the quick delivery of information. In addition, the lower words per message count in the male large streams may suggest that these participants are more likely to post abbreviated messages.

The similar participatory patterns that emerged in female small and female large streams suggest that these two groups of participants may have similar communicative styles and levels of interest in engagement, regardless of the number of participants present. Additionally, the higher messages per user in these two stream groups (i.e., female small and female large) may indicated that these participants remaining engaged in the chat for longer periods of time and/or more frequently than do those in their counterparts (i.e., male small and male large). Furthermore, the lower messages per user count in the male large streams, on the other hand, also point toward participants being focused on quickly posting the desired message.

There are literally millions of streamer channels on Twitch.tv, each one with its own streamer and surrounding community. Within each of these is a public chat area where the participants can interact and engage with one another. Each stream is different however, with its own characteristics, norms, and expectations. These differences, of course, have a great impact on the communicative strategies used within the public chat—for a participant to ensure their ‘voice’ is ‘heard’ by others, they must learn to adapt to these conditions. The current study seeks
to ‘unpack’ these strategies piece by piece. I considered the use of these strategies across
streamer_gender and stream_size in order to examine the impact each has on language use.
Furthermore, I established the four stream groups and explored each strategy relative to those
groups.

Through the steps laid out in the current chapter, I have examined the ‘how often’ and
‘how much’ of prominent communicative strategies. In the next chapter, I explore how the
strategies are actively used within these streams—how the participants actually use them for
communicative purposes.
Chapter 6: Qualitative Results & Analysis

In the previous chapter, I presented the quantitative results of this research. This statistical analysis was undertaken in an attempt to gain a better understanding of the frequency and distribution of communicative strategies and patterns of communication in the Twitch chat.

In this chapter, in further development of the answer to Research Question 2, I explore how streamer gender and stream size impact communications in the Twitch public chat. Section 1 expands on the description of the Twitch environment begun in Chapter 3, while sections 2 and 3 discuss strategies for creating coherence in small versus large streams and the impact gender has on strategies used to strengthen community ties, respectively. Finally, section 4 explores communications across mediums. Taken overall, this chapter sheds light on the ways in which chat participants adapt their practices in a multimedium-based multimodal environment.

1. The Twitch Environment

When examining an online environment through use of the CMDA paradigm, discourse types should be distinguished from one another in order to complete a thorough analysis and to help remind the researcher to attend to specific properties and affordances (Herring, 2007). The study of digital discourse via CMDA is focused on language and language use (Herring, 2019), and to address this focus, each context must be considered for interactions between language and social practices (Herring & Androutsopoulos, 2015).

As noted in Chapter 3, in addition to the four primary language domains (i.e., structure, meaning, interaction, social), Herring (2004) added a participation domain that examines participatory patterns within a given digital context. In Twitch public chat, these patterns are especially impacted by the number of participants, and previous research has indicated a clear relationship between behavior and the size of the audience. (Flores-Saviaga et. al., 2020; Ford et.
al., 2017). Each environment, however, allows for different patterns of participation, and here, I analyze both the characteristics of the messages themselves, as well as of the participants who posted them.

1.1. Participation Patterns

Initially, I considered the participants themselves—how often and consistently they posted within the chat. In the case of large streams, there were a total 8,061 unique participants, who posted a total of 28,430 messages. The message count in small streams, however, was a total of 3,866, posted by just 825 users. As noted in Chapter 5, as the number of participants in chat increases, so too does the speed with which messages are posted. For example, in Clips 1 and 2, below, there is a clear visual difference when the participant population varies between streams.

Clip 1

*LolTyler_1, Scroll Rate of Chat in Large Stream*

Clip 2
The capture in Clip 1 is the chat from a large stream, LolTyler1_1, where 1,925 users posted 6,605 messages in a 28-minute match, while Clip 2 is from a small stream, StPeach_2, where 141 users posted 634 messages in the same approximate time span. The rate at which these chats move can be determined by examining the properties of the posted messages, through features such as words per message, messages per second and message uptime (i.e., the time span that a message is visible — scrolling upward — before it scrolls off screen). As shown in Chapter 5, relatively speaking, many of these measurements are related—as message uptime increases, messages per second decreases and vice versa.

In Clip 1, where message uptime is approximately 6 seconds, message length stands out as well — with the majority of messages consisting of 1 – 3 lexical items. This is compared to Clip 2, where message uptime is over a minute long — in this small (slower) stream, the message length tends to be much longer—several words, even full sentences.
In large streams with rapid-scrolling text, readers have only a short window to read (and post) messages before they scroll off the screen and are no longer visible. As participants post messages which they know will be visible only briefly, they often commit less time to composing and posting their messages. In these cases, participants often employ repetition strategies (such as using commonly recognized Twitch emotes or copy-pastas) to make their messages coherent within the rapidly moving conversation.

2. Impact of Stream Size on Graphicons and Coherence

Coherence has been widely recognized by researchers as a challenge of digital interaction in multiple online contexts (Lone, 2016; Fitzpatrick, 2010; Herring 2006, 2013; Alhoami 2020; Markman, 2010; Greenfield & Subrahmanyam, 2003; Shih et. al., 2016). In some cases, problems may arise due to varying levels of (a)synchronicity, which may remove makers of coherence available in spoken interaction. While Herring (1999) emphasizes that incoherence and enjoyability may co-exist, some level of coherence must be maintained within virtual interactions.

Maintaining coherence can be especially challenging when there are large numbers of participants in the given interaction. Jones et. al. (2008) point out that viewers can only absorb a limit of approximately 30 messages per minute—one message every two seconds. At that point, and at the point that the active participant count reaches approximately 220 concurrent ‘chatters,’ information overload is reached (Jones et. al., 2008) and coherence may be compromised.

Given the high number of participants and the relatively high rate of messages posted in Twitch Public Chat (even in small streams), here I examine the use of repetition for maintaining coherence in an environment where participation exceeds the limit established by Jones (2008).
As discussed in Chapter 5, there was a prominent use of ‘graphicons’ (Herring & Dainas, 2017) within the large streams, where they occurred at an average rate of 21.69 per minute and appeared in just over half of all messages (15,322 messages, out of 27,827 total). This is in comparison to graphicon use in small streams, where the occurrence rate is 1 every 3 minutes and graphicons appeared in just under a third of all messages (1,578 / 4,570).

There are two types of graphicon-heavy repetitions that are noteworthy as a coherence tool: 1) Twitch emotes used in rapid succession, and 2) emoji-based copy-pastas, both of which are examined in greater detail below.

2.1. Emotes in Rapid Succession

As discussed in Chapter 4, Twitch emotes are graphicons unique to the Twitch platform. They are produced through embedded commands; participants input the code for a particular emote and the corresponding image appears in their message.

Twitch emotes were the most used graphicon in this dataset, appearing 11,745 times within 11,321 messages. On average, they appeared in the large streams more than any other graphicon—5 times more than emoticons, 5.5 times more than subscriber-only emotes, and 8 more times than emojis. The most noteworthy characteristic of emote use in the large streams of this dataset, is that 46% are contained in repetitive messages\textsuperscript{10}. As Graham (2008, 2017, 2018) and Graham & Dutt (2018) have noted, it is the norm for both the Twitch platform and individual streamers to put limitations on the amount of repetition allowed in the public chat. Despite the regulations, however, limitations are often ignored, and repetition arises naturally among chat participants.

\textsuperscript{10} Repetitive messages were identified in three ways: exact copy of messages, close copy with variation in spelling or word order, and close copy with same motif
Across this dataset, in large streams (where message uptime is short) repetition is a strategy employed by chat participants to create and post messages quickly (since they can easily copy and paste repeated content). In such cases, the repetitive content may have less impact than unique content would, but in the average 6-second uptime of a large stream, repetition is a way to contribute and be ‘heard’, even when there is not time to compose long messages. In small streams (where uptime is longer) chat participants may not need to rely on repetition as heavily, since the longer uptime allows more time to compose unique content that will still be coherent when posted in the (continuously) scrolling chat.

In the large stream environment, repetition is often seen in bursts—with the same text and/or image sequences are posted in a chain by multiple participants in a short period of time. Sometimes these bursts arise spontaneously, when a chat participant (re)posts the same copy-pasta multiple times, conveying an invitation for other participants to create a chain by reposting the same message themselves, other times it is pre-negotiated in the chat—a planned ‘takeover’.

**Example 1: YourPrincess (female, large)**

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
</tr>
</thead>
<tbody>
<tr>
<td>487</td>
<td>22:27:37</td>
<td>samuarango</td>
<td>🤸‘s</td>
</tr>
<tr>
<td>488</td>
<td>22:27:39</td>
<td>Threshiix</td>
<td>time to take over WideHard</td>
</tr>
<tr>
<td>491</td>
<td>22:27:44</td>
<td>Mmoondee</td>
<td>*@Threshiix IM IN</td>
</tr>
<tr>
<td>492</td>
<td>22:27:45</td>
<td>Threshiix</td>
<td></td>
</tr>
</tbody>
</table>

The ‘takeover’ attempt begins here in lines 487 & 488, with samuarango posting 🤸 (PogUs) and Threshiix posting “time to take over 🤸”. In line 491, above, Mmoondee acknowledges

---

11 This is image of the Twitch emote WideHard, which is used to indicate determination and being ready to take on whatever challenges come your way.
agreement with the takeover, posting “@Threshiix IM IN”. Before participants are able to begin the sequence of repeated messages, however, *YourPrincess* verbally delays the action by questioning the emote that *Threshiix* proposes (line 500, Streamer Speech), saying that she is not familiar with the emote *PogUs*.

**Example 2: *YourPrincess* (female, large)

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
<th>Streamer Speech</th>
</tr>
</thead>
<tbody>
<tr>
<td>498</td>
<td>22:27:48</td>
<td><em>YourPrincess</em></td>
<td>LULW</td>
<td></td>
</tr>
<tr>
<td>499</td>
<td>22:27:49</td>
<td><em>Threshiix</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>500</td>
<td>22:27:50</td>
<td><em>DaddyMcDaddyFace</em></td>
<td>back to plat 3 OKayChamp</td>
<td></td>
</tr>
<tr>
<td>501</td>
<td>22:27:50</td>
<td><em>Threshiix</em></td>
<td>CHAMPERS</td>
<td></td>
</tr>
<tr>
<td>502</td>
<td>22:27:53</td>
<td><em>Stormbleased</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>503</td>
<td>22:27:53</td>
<td><em>Feelin_32_</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>504</td>
<td>22:27:53</td>
<td><em>Jives</em></td>
<td>KEKSiii @Threshiix</td>
<td></td>
</tr>
<tr>
<td>505</td>
<td>22:27:55</td>
<td><em>coinedoperated</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>506</td>
<td>22:27:56</td>
<td><em>spsms</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>507</td>
<td>22:27:56</td>
<td><em>Stormbleased</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>508</td>
<td>22:27:57</td>
<td><em>VivynKitty</em></td>
<td>princess.Lark</td>
<td></td>
</tr>
<tr>
<td>509</td>
<td>22:28:00</td>
<td><em>slushup</em></td>
<td>peepoFriendship</td>
<td></td>
</tr>
<tr>
<td>510</td>
<td>22:28:01</td>
<td><em>Threshiix</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>511</td>
<td>22:28:01</td>
<td><em>bruttydoes</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>512</td>
<td>22:28:01</td>
<td><em>iToDdimmy</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>513</td>
<td>22:28:02</td>
<td><em>DaddyMcDaddyFace</em></td>
<td><em>It us in @Threshiix's cult PogUs</em></td>
<td></td>
</tr>
<tr>
<td>514</td>
<td>22:28:08</td>
<td><em>nightzeakriol</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>515</td>
<td>22:28:08</td>
<td><em>Feelin_32_</em></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

These combined events trigger a rapid-fire posting of the emote *PogUs* in the chat—it is posted 54 times over the course of the next minute, across 61 messages, as in lines 501 - 515.

Repetitious events like the one above are commonplace in larger streams, where the chat participants act as one, similar to a crowd cheering at a baseball game. In this case, they collaborate in ‘vamping themselves up’ with a cheer of “*PogUs, PogUs*” meaning “*We’re epic, we’re amazing, etc*”. To a participant unfamiliar with large streams, the rapid repetition may be synonymous with chaos and complexity. To a member of the crowd, however, the repetition creates a cohesiveness across the text—one that, while visually cluttered, fast-paced, and difficult to read, is still completely coherent. This use of a single ‘voice’ in a large chat means that more viewers can participate and communicate effectively. In small streams (where uptime
is longer) chat participants may not need to rely on repetition as heavily, since the longer uptime allows more time to compose unique content that will still be coherent when posted in the (continuously) scrolling chat.

2.2. Repetitive Emoji Stories

A second repetition strategy in large streams versus small streams is the use of emojis. Relative to emote use across all messages, use of emojis (overall) was not particularly high \((n = 1,848)\) and use across the streams did not vary greatly. In small streams, 118 messages per 1,000 contained emojis, averaging 19.74 per stream, while in large streams, use was 506 per 1,000, with average use at 39 per stream. The repetitive use of emojis here, similar to that of emotes, was particularly noteworthy. As mentioned, there were just under 2,000 emojis in this dataset of over 30,000 messages. Interestingly, these were contained within 202 messages, with the majority (70\%) contained in just 24 messages. This intense use of emojis in so few messages can be attributed to ‘copy-pastas’ (rapid and repetitive use of chunks of text and/or images). Copy-pastas often contain large chunks of text and emojis and can, at times, turn the chat into an “illegible waterfall of text” (Hamilton et. al., 2014). Because they are produced with simple copy-and-paste commands they take little time to post, making it unnecessary for viewers to read the entire message while still facilitating overall participation and reinforcing coherence. Copy-pasta messages can be complex and are often presented as an emoji-based story (line 3790), as seen in Example 3:

Example 3: *LolTyler1 (male, large)*
In this case, the copy-pasta relates a physical encounter with detailed descriptions of the story characters’ actions and emotions. Many of the words in the text are punctuated with emojis that either replicate the semantic meanings of the words themselves or depict the characters’ reactions to story events. Since emojis were first developed to convey emotions via easily read visual images, one of their potential functions in this copy-pasta is to make the text-heavy story more ‘readable’ by viewers in the quickly scrolling chat.

Despite their frequency, copy-pasta takeover attempts are not always successful. In some cases, this is because multiple takeovers co-occur. Example 3, above, shows an attempt by lumpy_seal that occurs at 23:10:51 (Example X, line 3790). The attempt, however, is not immediately taken up by other participants, as another copy-pasta, seen below, was already in play (lines 3791, 3799, 3810). However, other participants began expressing annoyance and closer members of the community began asking for the moderators to help (Example 4, line 3798, 3818).

Example 4: LolTyler1 (male, large)
19 seconds later, at 23:11:10 (line 3830), *lumpy_seal* tries again:

**Example 6: LolTyler1 (male, large)**

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
</tr>
</thead>
<tbody>
<tr>
<td>3830</td>
<td>23:11:10</td>
<td>lumpy_seal</td>
<td>Rawr Rawr x3 x3 x3 x3 x3 pounces on you you're so warm o3o3o3o3o you have a bulgy o3o3o3o3o someone's happy you're so big oooooo nibbies o3o3o3o3o more on your bulgy wolgy it doesn't stop growing o3o3o3o3o kisses you and lickies o3o3o3o3o</td>
</tr>
<tr>
<td>3831</td>
<td>23:11:11</td>
<td>salad505</td>
<td>terrible pasta WeirdChamp</td>
</tr>
<tr>
<td>3836</td>
<td>23:11:15</td>
<td>O1X1</td>
<td>Rawr Rawr x3 x3 x3 x3 x3 pounces on you you're so warm o3o3o3o3o you have a bulgy o3o3o3o3o someone's happy you're so big oooooo nibbies o3o3o3o3o more on your bulgy wolgy it doesn't stop growing o3o3o3o3o kisses you and lickies o3o3o3o3o</td>
</tr>
<tr>
<td>3843</td>
<td>23:11:17</td>
<td>grim_punch</td>
<td>SPAM IS FUNNY</td>
</tr>
<tr>
<td>3851</td>
<td>23:11:21</td>
<td>form_over_function</td>
<td>Rawr Rawr x3 x3 x3 x3 x3 pounces on you you're so warm o3o3o3o3o you have a bulgy o3o3o3o3o someone's happy you're so big oooooo nibbies o3o3o3o3o more on your bulgy wolgy it doesn't stop growing o3o3o3o3o kisses you and lickies o3o3o3o3o</td>
</tr>
<tr>
<td>3852</td>
<td>23:11:21</td>
<td>shadowtale123</td>
<td>Rawr Rawr x3 x3 x3 x3 x3 pounces on you you're so warm o3o3o3o3o you have a bulgy o3o3o3o3o someone's happy you're so big oooooo nibbies o3o3o3o3o more on your bulgy wolgy it doesn't stop growing o3o3o3o3o kisses you and lickies o3o3o3o3o</td>
</tr>
</tbody>
</table>

This time, the attempted takeover is successful and within the next 30 seconds, it is posted 13 more times (as in lines 3831 – 3852), slowly coming to an end over the course of the next minute.

Copy-pasta repetition is relatively rare in small streams (where the chat moves at a slower rate, allowing more time to construct unique message content). As seen in the previous examples, it is a common occurrence in large streams, however, where limited uptime makes it more difficult for messages to stand out or receive acknowledgement (whether from the streamer or other chat members). Therefore, participants may attempt to post a copy-pasta in an attempt to trigger additional repetitions by multiple other viewers. When these attempts are successful,
they give validation to the originator and increase their visibility in the conversation and community. The use of emojis in these repetitions gives participants access to easily-processed and eye-catching messages in a fast-moving chat. This strategy allows participants to have their voices ‘heard’ in this fast-moving environment, where average message uptime is a mere 7.8 seconds—requiring them to compose and post their messages quickly and efficiently.

Because of the highly interactive, rapid-fire nature of larger streams, specific communicative strategies are employed regularly (e.g., rapid repetition, heavy use of graphicons) and may begin to take hold in the communities surrounding these streams. While the use of these strategies has a clear impact on coherence, it is also important to note that (consistent with the findings of Graham (2017), copy-pasta sequences and repetition also play a role in forming the culture of the stream community—one where spam or other rapid visual representations are seen not as negative or inappropriate, but as part of the common social practice.

The current data shows that fewer unique voices, repeated (and image-heavy) posts, and a shared sense of meaning all help to maintain coherence. Without this maintenance, the audience must focus on the message content for an extended amount of time—losing the ability to effectively communicate within a chaotic, multiplex (i.e., both multimedium-based and multimodal) environment.

3. Impact of Streamer Gender on Graphicons, Tagging, and Investment

While previous research has demonstrated how males and females use language differently on Twitch.tv (Graham, 2017; Cardillo, 2022; van der Wijden, 2018), not much is known about how the gender of the streamer impacts the language use of their surrounding stream community (although, see Graham, 2017 and Nakandala, 2017). In the next section, I examine the impact of
streamer gender on graphicon use and ‘mention’ing of other participants—and how those strategies are used to emphasize community presence and connection.

3.1 To KEKW or LUL?

As I showed in Chapter 5, graphicons were prominent in both male and female streams. One specific graphicon that is noteworthy is the Twitch emote, as previously mentioned. These emotes can be used to convey a number of actions and/or emotions, such as in the case of LUL\(^{12}\) (/lal/) and KEKW\(^{13}\) (/kek ’dabəl ju/) which are both intended to convey ‘laughing’. As seen in Figure 71, these were the two most used emotes across the dataset as a whole.

Figure 71
*Twitch Emote Word Cloud for Current Dataset*

In total, there were 4,256 instances of KEKW (mış) and 3,355 of LUL (miş); together they account for over 60% of all emote use (Figure 72).

Figure 72
*Percent of Emote Use: KEKW, LUL, and Other*

---

\(^{12}\) LUL is an emoted used to express laughter, face of TotalBiscuit, famous British streamer  
\(^{13}\) KEKW is an emote used to indicate large laughter, face of Spanish actor Juan Joya Borja
What is particularly noteworthy here, is the use of these two emotes in relation to streamer gender. While both are used to ‘laugh’ at an in-stream event, there is a difference in meaning. The streamer, Asmongold, who, in 2022, overtook xQc as the most watched streamer on Twitch.tv, explains it in this way:

**LUL** “is like a genuine live audience at a comedy show. They laugh at the right times, and when it’s funny.”

**KEKW** “is like a laugh track for the Big Bang Theory. Sheldon walks in and ‘ahhahahahahaha hahah’ (mimics loud, extended, annoying laughter), you know? And it’s just like anything happens, you know? ‘Bazinga’!! and ‘ahhahahahahahahahah’, you know? That’s what the fu-, that’s what it is. It’s disgusting”

In this dataset, LUL is primarily used in female streams, \( n = 2,915 \), at a rate of nearly 7 times that in male streams \( n = 436 \), while KEKW is just the reverse—used
most often in male streams \((n = 3,405)\), at a rate of 4 times that in female streams \((n = 851)\), as depicted in Figure 73.

Figure 73
Use of KEKW and LUL in Male vs Female Streams

While not all streamers find it ‘disgusting,’ as Asmongold does, KEKW is generally considered to be a much more emphatic laugh than LUL. LUL is a ‘simple, yet genuine’ laugh that occurs when something humorous happens, or another participant (typically the streamer) makes a joke. It is typically not used in a repetitive manner and quiets quickly. KEKW, on the other hand, is typically used in an exaggerated and extended manner, is regularly spammed, and tends to become a ‘collective laugh’ by the end of the sequence. It often begins as a laugh at the expense of another participant but grows quickly to just laughing for the sake of laughing and being part of the group. One key difference is that to KEKW-laugh, you just need to join the crowd, while to LUL-laugh, you need to find something funny.

The higher frequency of LUL in female streams may suggest that those participants are more attentive to the stream progression, genuinely ‘laughing’ when a humorous event takes place. This maintains the integrity of the content—‘laughing’ when an occurrence is genuinely funny, rather than when obligated or prompted (e.g., when everyone else is doing is). By remaining attentive to the stream—and laughing at appropriate moments—participants in female streams are able to emphasize their investment in, and focus on, the streamer’s community.
Participants in male streams, however, may be more likely to join in a KEKW ‘empty laugh’ sequence than LUL ‘genuinely’ laugh at a specific moment, decreasing the need for close attention to the streamed content.

Take the following examples, from KayPeaLol and llStylish:

Example 7: KayPeaLol (female, large)

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
<th>Streamer Speech</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>13:54:02</td>
<td>deathtimer1</td>
<td>what the hell?</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>13:54:03</td>
<td>iomdflynn</td>
<td>tume?</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>13:54:15</td>
<td>GuiltyPrawn99</td>
<td>@KayPeaLol: You declined the game 😂</td>
<td>I’m tired</td>
</tr>
<tr>
<td>8</td>
<td>13:54:17</td>
<td>AndeniousCrow</td>
<td>you declined!</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>13:54:20</td>
<td>Encre1495</td>
<td>you declined!</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>13:54:20</td>
<td>victorjohns</td>
<td>you declined!</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>13:54:22</td>
<td>dalila8</td>
<td>there, a smile, it made my day already lol.</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>13:54:22</td>
<td>victorjohns</td>
<td>X:D</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>13:54:40</td>
<td>Khanna</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>13:54:40</td>
<td>wickedbitcher01</td>
<td>Am I tickled?!</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>13:54:42</td>
<td>Khanna</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>13:54:44</td>
<td>hookaiah99</td>
<td>back yes teenage dillbag!</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>13:54:46</td>
<td>Darkkyser</td>
<td>you declined!; there’s a new kayPeLUL.</td>
<td></td>
</tr>
</tbody>
</table>

In this example, KayPeaLol is unsure about what happened to her current game—she was choosing a champion and it disappeared—and voices her (slight) frustration (line 6).

Immediately (line 7), GuiltyPrawn99 responds to tell KayPea she accidently declined the match and then posts LUL, laughing at the occurrence. As seen in lines 9 and 11, LUL is often used in conjunction with ‘lol’.
Example 8: *llStylish* (male, large)

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>411</td>
<td>13:22:05</td>
<td>isdynamite!</td>
<td>she deals 20% of ability damage</td>
<td>Oh that’s the worst way of engaging</td>
<td></td>
</tr>
<tr>
<td>412</td>
<td>13:22:14</td>
<td>138ken</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>413</td>
<td>13:22:15</td>
<td>Nimdif</td>
<td><em>@llStylish</em> what do you play if red velvet cake eats lst banana? <em>Where did the banana come from?</em></td>
<td></td>
<td></td>
</tr>
<tr>
<td>414</td>
<td>13:22:17</td>
<td>1234fivefifteen1334</td>
<td>is this intentional?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>415</td>
<td>13:22:18</td>
<td>gkknkknk</td>
<td>balanced</td>
<td></td>
<td></td>
</tr>
<tr>
<td>416</td>
<td>13:22:18</td>
<td>Tarpineus</td>
<td></td>
<td>3 ways gonna say that’s the worst way to engage a fight against Zed: wait with Crome</td>
<td></td>
</tr>
<tr>
<td>417</td>
<td>13:22:19</td>
<td>andicane95</td>
<td>ykr ignite and 1</td>
<td></td>
<td>Enem Kill (+64) Zed: Death +1 (2)</td>
</tr>
<tr>
<td>418</td>
<td>13:22:19</td>
<td>splitaheadfire</td>
<td><em>@jenshowmen123</em> there’s a bit more to climbing that</td>
<td>And then I just find… Wait a minute I didn’t even see the banana chat</td>
<td></td>
</tr>
</tbody>
</table>

3 messages 1 second

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>422</td>
<td>13:22:20</td>
<td>zCrew</td>
<td>Crome broken</td>
<td>Dunn: Dude</td>
<td></td>
</tr>
<tr>
<td>423</td>
<td>13:22:20</td>
<td>nasagai12356</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>424</td>
<td>13:22:21</td>
<td>Drillhead</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>425</td>
<td>13:22:23</td>
<td>nasagai12356</td>
<td>SHAFTOR</td>
<td></td>
<td></td>
</tr>
<tr>
<td>426</td>
<td>13:22:23</td>
<td>threeshoot99</td>
<td>yez that’s crome for you</td>
<td></td>
<td></td>
</tr>
<tr>
<td>427</td>
<td>13:22:24</td>
<td>ghostdragon5562</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>428</td>
<td>13:22:24</td>
<td>Mrolla, Mavis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>429</td>
<td>13:22:24</td>
<td>ord_Chenk, Dick</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>430</td>
<td>13:22:24</td>
<td>andicane95</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

25 messages—2 KEKWs; 32 seconds

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>455</td>
<td>13:22:54</td>
<td>Mrolla, Mavis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>456</td>
<td>13:22:54</td>
<td>ovialal</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>457</td>
<td>13:23:01</td>
<td>ovialal</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

9 messages—4 KEKWs; 19 seconds

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>466</td>
<td>13:23:19</td>
<td>swybyorg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>467</td>
<td>13:23:19</td>
<td>wawab</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As seen above at 13:22:05 (line 411), *llStylish* began speaking, with “oh, that’s the worst way to . . .”, discussing the way another player, who has been ridiculed several times this match, is engaging in a battle with him. Thirteen seconds later, at 13:22:18, *Zed* (*llStylish*’s champion) is killed. *llStylish* then indicates frustration, clearly shocked by what just occurred. At this point, *llStylish*, puts his hands over his face, sheepishly lowers his head, and mutters “damn dude”—and the chat erupts with *KEKW* for almost a full minute.

By responding to *llStylish*’s error with *KEKW*, the participants shift from genuine humorous laughter, to empty (non-humorous) laughter that focuses on the shared experience of giving *llStylish* a hard time. This exaggerated and prolonged ‘empty laugh’ is common in male
streams across this dataset—especially at the moment the streamer realizes a (sometimes-obvious) mistake.

3.2. The Place of ‘@’ in Chat

In an examination of language use on the interactional level (Herring, 2004), one feature stood out as having a distinctly different use in male versus female streams: ‘mentioning’ (i.e., using ‘@’ to tag another participant). ‘Mentioning’ (which appears as @username) can be used to create coherence, since it provides some call-response structure similar to adjacency pairs in spoken discourse. It can also reinforce the community, however, by creating sustained, targeted conversations between a small group of users, despite the large number of people present in the chat.

It is noteworthy that @username is used more often in female streams than in male streams—3.34 times more, in fact. In KayPeaLol_2, for example, ‘mentioning’ occurs 226 times—102 (45%) of which help to sustain a conversation between two or more chat participants (see Example 10 below).
Example 10: KayPeaLol (female, large)

Example 10 highlights 20 chat messages containing ‘@’ – 4 in a conversation between Halsti and tammyg1rl and 6 in a conversation between tammyg1rl and NukedToasty. These conversations, which carry on for several minutes each, are playful in nature and are off topic (not concerning the current game play).

Because female streamers tend to promote interpersonal communication and relationships (Darien et. al., 2019; Malone et. al., 2020), and because chat participants tend to behave in ways which reflect the streamer’s behavior (Flores-Saviaga et. al., 2020), it follows that participants in these streams would behave in a manner to create and sustain interpersonal conversation. By
‘mentioning’ other users, participants are able to assert their social presence or identity as members of the community.

Mentions are used differently in male-centered streams, however. In fact, conversations sustained through tagging were identified just 67 times across the male-centered. While the ‘@’ is still used in male-centered streams to direct attention to a message intended for another participant, mentioning occurs primarily to answer a specific question or give the streamer information/make a suggestion.

Example 11: *QuinnAD (male, small)*

<table>
<thead>
<tr>
<th>Line #</th>
<th>Time Stamp</th>
<th>User Name</th>
<th>Message</th>
</tr>
</thead>
<tbody>
<tr>
<td>84</td>
<td>16:10:11</td>
<td>ooKHANoo</td>
<td>do you ever build AP defence when playing a AP champ top?</td>
</tr>
<tr>
<td>85</td>
<td>16:10:11</td>
<td>Diablo645</td>
<td>@QuinnAD i still stick to quinn adc, i prefer her as adc, harder to gank me bot</td>
</tr>
<tr>
<td>86</td>
<td>16:10:40</td>
<td>+Santo1_1Muerte</td>
<td>I'm playing Quinn Top, Mid and Bot lane. 🎮</td>
</tr>
<tr>
<td>87</td>
<td>16:11:05</td>
<td>koonala19</td>
<td>leave me fuckin alone bitch</td>
</tr>
<tr>
<td>88</td>
<td>16:11:11</td>
<td>valoromtsalty</td>
<td>its rly hard to find good jungler that Will do drakea deal drg and still ganks</td>
</tr>
<tr>
<td>89</td>
<td>16:13:07</td>
<td>+Santo1_1Muerte</td>
<td>GJ Annie!!</td>
</tr>
<tr>
<td>90</td>
<td>16:13:13</td>
<td>panzerswine</td>
<td>@ookhaneo if you look at his youtube youll see witts end build for ap enemy teams</td>
</tr>
<tr>
<td>91</td>
<td>16:13:14</td>
<td>valoromtsalty</td>
<td>i used to main nasus</td>
</tr>
<tr>
<td>92</td>
<td>16:13:37</td>
<td>+Santo1_1Muerte</td>
<td>Right</td>
</tr>
<tr>
<td>93</td>
<td>16:14:06</td>
<td>@%+Anglan</td>
<td>Wohooohoo</td>
</tr>
<tr>
<td>94</td>
<td>16:14:51</td>
<td>panzerswine</td>
<td>my internet is horrible today. im on 360 and still lagging out</td>
</tr>
<tr>
<td>95</td>
<td>16:15:27</td>
<td>valoromtsalty</td>
<td>no</td>
</tr>
<tr>
<td>96</td>
<td>16:15:48</td>
<td>@%+Anglan</td>
<td>@ooKHANoo yes building magic resist into heavy AP teams is pretty effective, but not worth it into this team as veigar is the only magic threat right now</td>
</tr>
</tbody>
</table>

This type of tagging draws the attention not only of the ‘tagged’ user, but also to something that user has said or done. It is sometimes presented in a way that is playful or joking but may not be perceived that way. By calling attention in this manner, the participant may be attempting to
assert not just presence, but dominance within the community, establishing a social hierarchy of sorts.

Although the difference in use of ‘mentions’ between male and female streams was not found to be statistically significant, it does appear to play an important role in both stream types, since, like repeated emotes or emojis, its use contributes to creating order (while also reflecting community ties) in a fast-paced environment.

In the preceding sections of this chapter, I examined some of the most prominent language features found in this dataset, exploring the influences that social characteristics of a live stream (i.e., streamer gender, stream size) has on chat discourse. In the next section, I look at intended recipients of chat messages, and how participants take advantage of the various multimedium-based multimodal aspects in order to be productive in their communications.

4. Communication Across Mediums

As previously noted in Chapter 4, there are four mediums present in the live streams for the current dataset: public chat, streamer’s video feed, streamed game play, and player chat. In this section I examine the intended recipient in chat messages across the four stream groups (i.e., male small, male large, female small, female large), and the medium within which those recipients are participating. To determine intended recipient, I looked for ‘mentions’ of specific participants and reactions to messages from other users, (identified by the content of the subsequent messages). In addition, I explore how the available modes are used in combination within each medium.

4.1. Terms to Know
intended recipient  the user or users each message is directed toward; in this data there are four basic possibilities—individual chat participant, collective chat, streamer, streamed content

medium directional  the medium toward which the message is directed; if the collective chat is the intended recipient, then the medium directional is the public chat; if streamer is recipient, then directional is the streamer’s video feed

intermedium communication  a communication which occur within a single medium (e.g., a chat message posted for another chat participant)

cross-medium communication  a communication which occurs across medium lines (e.g., a chat message posted that is directed at the streamer—posted in the chat, received in the video feed)

cross-modal exchange  occurs using more than one mode of communication (e.g., streamer verbally responds to a textual message)

4.2. Large Streams, Male & Female

In male large streams, I found that the majority of chat messages (approximately 60%) were intended for other participants in the chat, either collectively or individually. These exchanges, then are directed toward (and stay within) the public chat medium. These intermedial exchanges focus either on the active game play session or, as the chat size increases, on off-topic subjects which often quickly progresses into a rapid-fire repetitive post (e.g., copy-
pastas), as shown previously. This becomes increasingly true as the individual streams grow larger.

It should be noted that often in these large male streams, approximately the first and last five minutes involves a great deal of *cross-medium communication*, as the chat is primarily focused on the streamer and/or the active match. In the first minutes of the stream, the medium directional is the *video feed medium*, with the messages intended for the streamer. In the last minutes of the game, with the intended recipient again the streamer, most content involves ‘hyping’ the streamer for the final battle and reacting to the subsequent victory or defeat.

Next, I examined the communications of the female large streams for medium and modal interplays (i.e., *intermedium, cross-medium, cross-modal*). In these streams there is a similar occurrence of messages which are intended for other chat participants, either collectively or individually (*intermedium communication*) and those directed toward the *video feed medium*, intended for the streamer. The content in these female large streams focus primarily on the active game play, with positive comments and welcomed suggestions to the streamer and with off-topic shortly-sustained conversations which are less likely than the male large streams to contain repetition or rapid-fire emote/emoji use.

2.2.1. *Reception & Conceptualization of Message*

Another consideration here is the media and modes involved, not just in production, but in the reception and conceptualization of the message, as well. In other words, I considered what was being communicated, how it was received by the intended recipient, and which mediums and modes were involved in that representation of meaning. As seen in this example from llStylish_{1}:
Example 11: *IlStylish (male, large)*

At 19:38 on the game clock, the champion *Camille*, played by streamer *PhenomEx*, kills champion *Zed*, played by current streamer *IlStylish*. This event is received within the *streamed content medium* via representations afforded by all available modes (i.e., *textual, visual, mechanic, auditory*).

Figure 74
*Visual Representation of Modes used During Event “Camille kills Zed”*

This sequence of events leads user *waterJB* to post the following message:

Example 12: *IlStylish (male, large)*

The message is not received kindly by *IlStylish*, who responds verbally (*textual and auditory modes*) within the *video feed medium* and with facial expressions of annoyance (*gestural subset of the visual mode*):
Example 13: *llStylish (male, large)*

<table>
<thead>
<tr>
<th>Time Stamp</th>
<th>UserName</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>Streamer Non-Verbal</th>
<th>Game Clock</th>
<th>In-Game Announcements</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>13:24:07</td>
<td>gosudragon6552</td>
<td>what camilla is thinking?</td>
<td><em>What plans are you playing?</em></td>
<td>you like hand and eyes</td>
<td>19:57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13:24:14</td>
<td>waterJB</td>
<td>what q?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13:24:15</td>
<td>shouldbe99</td>
<td>LDM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*llStylish's* response is received, prompting *waterJB* to respond, again, within the *public chat medium*, via the *textual mode*:

Example 14: *llStylish (male, large)*

<table>
<thead>
<tr>
<th>Time Stamp</th>
<th>UserName</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>Streamer Non-Verbal</th>
<th>Game Clock</th>
<th>In-Game Announcements</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>13:24:24</td>
<td>waterJB</td>
<td>what shield did you play?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Just under one minute later, at 20:59 on the game clock, champion *Camille (PhenomEx)* kills *Zed (llStylish)* again, perpetuating this conversation.

Example 15: *llStylish (male, large)*

<table>
<thead>
<tr>
<th>Time Stamp</th>
<th>UserName</th>
<th>Message</th>
<th>Streamer Speech</th>
<th>Streamer Non-Verbal</th>
<th>Game Clock</th>
<th>In-Game Announcements</th>
<th>In-Game Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>13:24:43</td>
<td>koel Holem</td>
<td>they barely have enough healing!</td>
<td></td>
<td></td>
<td>29:42</td>
<td>PhenomEx is on a rampage!</td>
<td>毡斗: 11.8</td>
</tr>
</tbody>
</table>

What is especially noteworthy about this sequence is that in just 81 seconds there were 19 *cross-modal* realizations of meaning, manifested via 10 separate modes of representation. This is in addition to the two *cross-medium* productions of content via the text manifestation of the *textual mode*. These sequences requiring a large number of *medium-based* and *modal* interplays are a common occurrence across the large stream groups, regardless of whether the streamer is male or female.

In order to examine these highly multiplex (i.e., multimedium-based, and multimodal) environments and to track communications across the entire live stream, having a corpus that could allow data from multiple participants via multiple modes and within multiple mediums was imperative. The corpus developed by Dr. Graham and me has proven itself to be useful and to allow for analysis of numerous interplays at once. By allotting space in the template for each
medium and mode separately, we are able to quickly visualize the medium-based and modal interplays at every step of the process.

4.3. Small Streams, Male & Female

Finally, I examined the two groups of small streams (i.e., male small streams, female small streams) for their primary medium directional, intended recipient, and medial/modal interplays. In the case of both sets, messages were directed at other members of the public chat medium, with the intended recipient as other chat members. In the case of small female streams, the messages were primarily directed toward individual chat participants (58%), while in the small male streams, the messages were directed at the collective (63%). In addition, the second highest group of messages were directed at video feed medium, with messages intended for the streamer—again, this was true for both the female (32%) and male-loose streams (26%). Interestingly, what is also similar in small streams are the general topic of conversation—the streamer him/herself. Regardless of whether the streamer is male or female, the communities surrounding them are more focused on the streamer, than the gaming content. The game content instead serves as a catalyst for conversation, rather than as a primary point of focus.

With the primary medium directional being the public chat medium itself, there are no medium boundaries crossed in message production, though depending on message type (i.e., whether textual or visual), there may be modes working together (as is always the case in the production of these chat messages). And in the cases where the streamer is the intended recipient, there is a cross-medium interplay from the public chat medium to the video feed medium.

5. Concluding Remarks
The qualitative portion of this dissertation has explored how ‘laughing’ (via the emotes KEKW and LUL) and ‘mentioning’ in chat influence coherence and community structure in a live stream. In addition to the social-context impact within the chat medium, I also examined the live stream as a converged media multimodal artefact, taking inventory and examining interplays when participants communicate across mediums with specifically identified recipients. This analysis highlights the complexity of both language within the chat, but also of the live stream within which it is housed. In the last section of this dissertation, I discuss this data and what implications it has for future research.
Chapter 7: Discussion & Conclusion

In this study, I have attempted to 1) detail the procedures for creation of a tool which allows for a thorough analysis of multimedium-based multimodal data, 2) examine the language use in the public chat of a video game live stream, and 3) explore the impact that streamer gender and stream size has on that language use. I have aimed to do this while always being mindful of the complex nature of the data and the interplays of the multiple mediums and modes.

1. Summary of Findings

The first research question was designed in order to determine the most effective way of organizing and transcribing complex data that would allow for a thorough analysis—one which is accurate, reliable, and replicable.

RQ1: How can the data from a converged media multimodal platform be organized to allow for analysis?

To answer this question, we first examined previous transcription models. The issues that emerged were difficulties in data alignment, temporal synchronization, and organization of numerous events co-occurring across multiple mediums. Because we must have a way to coordinate simultaneous activity, synchronization of the chatty time stamp and game play clock was necessary. We chose to align with the chatty time stamp as it is relevant to all participants and is a constant throughout the stream. To accomplish this synchronization, all data was aligned to the message most recently posted at time of event.

Because there was no standard model in place, we created a corpus template that would account for multiple multimodal mediums. To accomplish this task, a multimodal inventory and medium decomposition was undertaken. This allowed for a complete identification of all
available modes within each of the four mediums present in a League of Legends live stream: public chat, streamer’s video feed, streamed content (game play), and player chat. After breaking down the live stream into its constituent parts, we decided that the best method of organization was to separate by mode and group by medium. The finalized template, in its entirety, is shown in Appendix 1 to this dissertation. The data from this study was then able to be transcribed, setting the foundation to answer the remaining research questions posed in Chapter 2.

My second research question focused on the Twitch.tv live stream public chat, in an effort to better understand how language is adapted for use in a complex digital environment.

*RQ2: What communicative strategies are employed by participants in a multimedium-based multimodal event (i.e., the Twitch.tv live stream)?

To answer this question, I collected data from (i.e., recorded) League of Legends live streams—24 recordings from 12 streams. The streamers were chosen to be representative of the larger Twitch population and consisted of 6 males and 6 females, divided also by 6 streamers with small active chat populations and 6 streamers with large active chat populations.

To initially examine the dataset, I used descriptive analyses, first identifying four prominent language features used as communicative strategies: graphicons, mentions, repetition, and capitalization. I found that graphicons, which can take on a number of meanings and convey a wide range of emotions, appeared in a third of all messages, making it the most prominent feature discussed. In addition, I located repetition and capitalization in use in at least 10% of all messages. Given their prominence, statistical analyses were completed for use of graphicons, repetition, and capitalization across the dataset. Mentions, on the other hand, while used regularly in multiple streams, did not appear prominently (n < 10%) across the dataset as a
whole. They were, however, worth noting, as their use was prominent in multiple individual streams while wholly absent in others. Total use statistics of these features can be viewed in Appendix 2 to this dissertation.

In addition to the prominent language features, I also examined message content within the Twitch chat. Three themes or topics were found to be regularly present in this dataset: game references, greetings, and stream(er) references. Game references accounted for a quarter of all messages, and 60% of these were found to directly reference a game character. In addition I found that participants greeted each other (or the streamer) only occasionally overall (4% of messages), but in some streams this act occurred in as high as 27% of messages. Lastly, messages with references to the streamer were examined, and I found again that, while use was low overall (3.7%), in some individual streams use was higher (13%). Total content type counts across the dataset can be viewed in Appendix 2 to this dissertation.

In addition to the primary one, this research question had sub-questions which would help to ascertain any impact that social characteristics (streamer gender, stream size) had on these communicative strategies. Furthermore, I wanted to determine the specific impact that the multiple multimodal mediums had on the language use.

*RQ2a: How do streamer gender and stream size impact the strategies chosen?*

*RQ2b: How does the availability of multiple mediums and semiotic modes impact this language use?*

In order to examine the first of these sub-questions, I explored these four language features (i.e., graphicons, repetition, capitalization, mentions) for their use, and differences in use, across streamer gender and stream size. To do this in a quantitative manner, an inferential analyses was undertaken, specifically through use of the ANOVA and its subsequent testing for interactional
significance. I found that participants in streams with male streamers (male streams) were significantly more likely to use graphicons overall than those participants in streams with female streamers (male streams). This was also the case for capitalization, where participants in male streams had significantly higher rates of use. In female streams, however, participants were significantly more likely to be repetitive (especially with regard to repetitive emotes), while mentions were not impacted enough by streamer gender to cause noteworthy differences in use. In addition, stream size had a significant impact on the use of all four language features (graphicons, repetition, capitalization, mentions). In fact, all four were found to be significantly more likely to appear in large streams than those in small streams.

In addition to completing a statistical analyses, I also examined specific use of prominent features across streamer gender and stream size. In terms of graphicon use, especially in regard to the use of Twitch emotes, I found that participants in female streams are more likely to genuinely ‘laugh’ via LUL, while participants in male streams are more likely to provide an ‘empty laugh’ via KEKW. While these uses are different, they both serve the purpose of reinforcing community membership—through attentiveness to the stream in female streams and through shared experience in male streams. In addition, I found that ‘@’ is used in both male and female streams to maintain conversations within an asynchronous environment that is often lacking in conversational coherence. In male streams, these conversation tend to focus on game-specific questions or suggestions, while in female streams the conversations are primarily interpersonal in nature.

When analyzing the use of the prominent features across stream sizes, coherence proved to be a crucial aspect of communication. In large streams, I found that a rapid-fire repetitive use of Twitch emotes helped to maintain a cohesiveness in the text, creating a single ‘voice’ and
allowing more viewers to participate and communicate effectively. A second use of repetitive graphicons was the emoji-based copy pasta. I found that this use gave participants access to easily-process and eye-catching messages, allowing users to have their voices ‘heard’ while still maintaining readability in a fast-moving environment.

The last analytical component, in aiming to answer the second sub-question, was an examination of intended recipient and medium directionality, based on streamer gender and stream size. In the case of large streams, both male and female, the participants tend to begin streams with messages directed toward the streamer (cross-medium communication). After the initial approximately five minutes, however, their chat messages are more directed at other chat participants (intermedium communication). During the final five to seven minutes, the intended recipient shifts back to the streamer (cross-medium). In small streams, the primary intended recipients were other chat participants (intermedium)—to individual participants in female streams, while to the collective chat in male streams.

Overall, I found that in terms of medium directionality, the majority of communications from the chat medium were intermedium—directed back to the chat itself, either individually or collectively. This piece of the analysis, combined with the message content examination above, revealed that in large streams the primary topic of conversation involved the game play or off-topic content. In contrast to this, in small streams the chat participants are more focused on the streamer than gaming content, indicating that the game content serves as a catalyst for conversation rather than as the primary point of focus.

2. **Stream Characteristics, by Categorical Group**

Combining the results from these multiple analyses, I was able to create a description of each stream group:
Male large streams

This group is characterized by a large number of viewers posting fewer messages quickly. Each message is short (~2 words) and remains visible for only ~20 seconds. These messages are graphicon-heavy, repetitive in nature, often capitalized and rarely ‘mention’ other participants. The messages regularly focus on active game play in the first and last few minutes of the stream, but much of the conversation is off-topic and collective in nature.

Male small streams

This group is characterized by the fewest number of participants, who post regularly (4.5 messages each) and at length (5.1 words). These messages are delivered at a slower rate (6 per minute) and remain visible for over two minutes each. The messages contain the lowest number of graphicons but use a good deal of subscriber only emotes. ‘Mentions’ are used often, as are game references (though not always focused on active game play).

Female large streams

This group had the second highest number of users, who posted a higher number of messages each, which are longer (4.7 words) and posted quickly (though not in a rapid-fire manner). These messages remain visible for only about a minute and contain a large number of graphicons, especially Twitch emotes. ‘Mentions’ are used regularly, with approximately 25% directed at the streamer and 75% at other chat participants. The talk focuses around game play but references the streamer occasionally.

Female small streams

This group is characterized by a moderate number of participants (~200) who post regularly (~6 per), but not quickly (6 per minute). Messages are often full sentence length and remain visible for approximately two minutes each. These messages contain a relatively high
number of graphicons, primarily Twitch emotes. ‘Mentions’ are regular, but ‘streamer mentions’ few. Content focuses on the streamer herself, with some game content.

3. Limitations & Future Research

There were several limitations to this study, which should be examined for further research. This study focused on League of Legends game play live streams and did not examine other games or other stream categories (e.g., Just Chatting). Expanding this research to diverse stream types could provide a more representative picture of Twitch chat (and live stream practices) overall. In addition, chat communications could be examined based on level of game play (e.g., causal, professional, competitive).

This study focused only on binary gendered streamers and did not explore the language use of chat participants in other streams. This is an area that could be further explored to gain a more comprehensive understanding of communications strategies used across different gender identities, providing a more holistic representation of the Twitch user population.

Since this data was collected, more opportunities for visual communication on Twitch.tv have been added (i.e., stickers, animated emotes). An exploration of how these graphicons contribute to the interplay of semiotic modes and the ways in which they impact how meaning is made could prove useful for a further understanding of multimodal. In addition, this study focused wholly on the communications originating in the public chat medium. Future research could expand the number of language features beyond those examined here (graphicons, repetition, mentions, capitalization) to provide a more complete view of multimedium-based multimodal communications.

Furthermore, there are other language features observed during coding and analysis that could be further examined for a more complete picture of the discourse that takes place in this
multimedium-based multimodal environment. This includes features such as using punctuation as letters in words (e.g., PI$$ED), or the use of game-based neologisms, such as using the champion (character) name as a verb (e.g., “let’s Kai’Sa this bitch up”). These game-based neologisms were originally grouped with other categories, but a more thorough examination into this use is warranted, given its high occurrence in the public chat.

The multimodal transcription system detailed here could be used in any of these future research endeavors (plus many others). Because the model allows for addition of multiple modes and/or mediums, there would be the capability of a more comprehensive dataset, allowing for an enhanced data analysis. In addition, by using this model, which unfolds along a comprehensive timeline, there can be a stronger delineation of concurrent vs consecutive events. This clarity allows for a more thorough analysis of player motivation and engagement, as well as social dynamics. Overall, use of this transcription system allows for expansion along a common point—in a format that allows for cross-referencing of multiple modes and multiple mediums at the same time.
4. Conclusion

A major challenge of this study was how to effectively organize and transcribe the large amount of data collected from the complex environment of the Twitch live stream. Through careful development of a multiplex corpus, an exploration of the various semiotic modes across multiple mediums was possible. While there may be opportunities for improvement and refinement of the organizational template in the future, the corpus detailed in this dissertation provided a solid foundation for the analysis of language use and multimodal communication in Twitch chat.

This analysis has illustrated multiple communicative strategies employed by participants in Twitch.tv public chats. These strategies included use of a variety of specific language features, content types, and modal interplays. While there are other factors that impact use, the strategies employed in each chat appear to be tailored to the specific needs of that community, reflecting shared norms and values. Because the chat often moves at a fast pace (even in streams with smaller populations), participants must be able to quickly read and process the messages being sent. Therefore, a key factor in successful communication in this live stream environment is the ability to use language that maintains coherence. In addition to these specific strategies, through an analysis that included the ability to cross-reference and simultaneously view multiple mediums and modes, this study demonstrated how often medium and mode lines are crossed in order to effectively communicate in this highly interactive environment.

Overall, these finding demonstrate that participants in Twitch.tv public chats use language and other semiotic resources in ways which are best suited for their community, with importance placed on clear communication and effective participation.
| Message | Emotion | Room
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Player Chat</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Game check | Genre 프로토 | Series | Genre 프로토
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Game Play)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Streamer's Video Feed</th>
<th>Streamer's Name</th>
<th>Streamer's M-Face</th>
<th>Enterprise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Reference</th>
<th>Demographic</th>
<th>Genre 프로토</th>
<th>Series</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Appendix 2: Frequency Counts for Language Features & Message Content

| Female Large | Male Large | Female Small | Male Small | Female Medium | Male Medium | Female Small | Male Small | Female Medium | Male Medium | Female | Male | Female | Male | Female | Male | Female | Male |
|--------------|------------|--------------|------------|--------------|-------------|--------------|------------|--------------|-------------|---------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1239         | 1234       | 1235         | 1236       | 1237         | 1238        | 1239         | 1240       | 1241         | 1242       | 1243    | 1244  | 1245  | 1246  | 1247  | 1248  | 1249  | 1250  |
| 1231         | 1232       | 1233         | 1234       | 1235         | 1236        | 1237         | 1238       | 1239         | 1240       | 1241    | 1242  | 1243  | 1244  | 1245  | 1246  | 1247  | 1248  |
| 1230         | 1231       | 1232         | 1233       | 1234         | 1235        | 1236         | 1237       | 1238         | 1239       | 1240    | 1241  | 1242  | 1243  | 1244  | 1245  | 1246  | 1247  |
| 1229         | 1230       | 1231         | 1232       | 1233         | 1234        | 1235         | 1236       | 1237         | 1238       | 1240    | 1241  | 1242  | 1243  | 1244  | 1245  | 1246  | 1247  |
| 1228         | 1229       | 1230         | 1231       | 1232         | 1233        | 1234         | 1235       | 1236         | 1237       | 1239    | 1241  | 1242  | 1243  | 1244  | 1245  | 1246  | 1247  |
| 1227         | 1228       | 1229         | 1230       | 1231         | 1232        | 1233         | 1234       | 1235         | 1236       | 1238    | 1239  | 1241  | 1242  | 1243  | 1244  | 1245  | 1246  |
| 1226         | 1227       | 1228         | 1229       | 1230         | 1231        | 1232         | 1233       | 1234         | 1235       | 1237    | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  | 1245  |
| 1225         | 1226       | 1227         | 1228       | 1229         | 1230        | 1231         | 1232       | 1233         | 1235       | 1237    | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  | 1245  |
| 1224         | 1225       | 1226         | 1227       | 1228         | 1229        | 1230         | 1231       | 1232         | 1234       | 1236    | 1237  | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  |
| 1223         | 1224       | 1225         | 1226       | 1227         | 1228        | 1229         | 1230       | 1232         | 1234       | 1236    | 1237  | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  |
| 1222         | 1223       | 1224         | 1225       | 1226         | 1227        | 1228         | 1229       | 1232         | 1234       | 1236    | 1237  | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  |
| 1221         | 1222       | 1223         | 1224       | 1225         | 1226        | 1227         | 1228       | 1232         | 1234       | 1236    | 1237  | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  |
| 1220         | 1221       | 1222         | 1223       | 1224         | 1225        | 1226         | 1227       | 1232         | 1234       | 1236    | 1237  | 1238  | 1239  | 1241  | 1242  | 1243  | 1244  |

**Legend:**
- Textual Features: Text, Sentence, Paragraph
- Message Features: Strength, Tone, Style
- Social Features: Interaction, Relationship, Community
- Psychological Features: Emotion, Reason, Persuasion
- Cognitive Features: Knowledge, Logic, Reasoning
- Cultural Features: Allusions, Metaphors, Symbolism

*Note: The table continues with similar entries for each feature category.*
### Appendix 3: Participatory Statistics by Streamer

<table>
<thead>
<tr>
<th>Streamer</th>
<th>Messages</th>
<th>Users</th>
<th>Length (Minutes)</th>
<th>Total Words</th>
<th>Messages/User</th>
<th>Message/Second</th>
<th>Words/Message</th>
</tr>
</thead>
<tbody>
<tr>
<td>BizzleBerry</td>
<td>757</td>
<td>148</td>
<td>96.46</td>
<td>4045</td>
<td>5.11</td>
<td>7.85</td>
<td>5.34</td>
</tr>
<tr>
<td>Cowseep</td>
<td>630</td>
<td>184</td>
<td>100.43</td>
<td>3801</td>
<td>19.8</td>
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<td>1.85</td>
</tr>
<tr>
<td>Detar173</td>
<td>796</td>
<td>118</td>
<td>91.00</td>
<td>3248</td>
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<td>3.72</td>
<td>4.35</td>
</tr>
<tr>
<td>1730</td>
<td>340</td>
<td>60</td>
<td>91.50</td>
<td>1253</td>
<td>14</td>
<td>4.35</td>
<td>5.12</td>
</tr>
<tr>
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References


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