UNIVERSITY OF TWENTE.

Strategic Communication in Esports:

Predictive Analysis and Optimization for Team Performance

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Abstract

This study establishes the relationship between communication and performance in professional League of Legends esports teams. Starting from a dataset of 38 recorded hours of voice and video from two high-level teams, this study quantifies communication with features around speech rate, overlap, and silence, with special attention to specific game events around the critical 20th minute, to find patterns in team communication that optimize performance. First, transcription had to be done of data analysis in the matches, while the detection and flagging of overlapping speech was performed. After this, computation of communication metrics was performed and matched with the game outcomes. Furthermore, the game state was extracted by OCR so that context would be provided for the communication. Topic modeling was also used to classify the in-game chat content to further investigate how the communication content was related to team success or failure. The results showed that some strategies in communication, such as deliberate overlap in periods of chaos and heightened attention around the 20-minute mark, were associated with better performance. Winning teams spoke in a more dominant way: more overlap and less silence.

Losing teams, on the other hand, are quieter and involve less strategic coordination during key moments of the game. From these findings, some actionable insights have been derived that help in developing better team communication strategies in esports, particularly within high-pressure settings. It gives insight into the relationship between the patterns of communication and performance so that teams can refine their coordination at critical moments of the game. The findings will also add to the body of knowledge from other disciplines where teams must communicate quickly and efficiently under pressure, such as emergency operations or military-related work.

Acknowledgment

I would like to express my sincere gratitude to my professors **Joschka Hüllmann**, **Khiet Truong** and **Marcos Machado** for their invaluable guidance and support throughout my academic journey. Their insights and mentorship have been instrumental in helping me navigate this thesis project and beyond.

A special thank you to **Joschka Hüllmann** for our collaboration on multiple projects beyond this thesis. Your encouragement, expertise, and dedication have profoundly shaped my academic and professional development, and I deeply appreciate the opportunity to work alongside you.

I am also grateful to the teams who generously sponsored the data for this research. Your support was essential in making this project possible, and I appreciate the trust you placed in my work.

As my academic journey comes to a close, I feel both fulfilled and joyful. This has been a period of great learning, challenges, and growth, and I will always look back on this time with fond memories and appreciation.

Contents

1 Introduction

The video game market is expected to reach almost 250 billion dollars in 2023, making it one of the largest markets in the world (Precedence Research, 2023). Within that sector lies the esports domain, gaming in a competitive setting (Mahlmann et al., 2016). In esports, the teams interact and coordinate among themselves at rapid speed while also facing a significant amount of pressure due to a large audience, and while there is also single-player esports, the majority of popular esports titles are multiplayer (Bányai et al., 2019). The audience in esports can be hybrid as there are online tournaments with all viewers watching via live streams and offline tournaments that combine live and online audiences that total to over 450 million people watching per year (Kokkinakis et al., 2020; Neus et al., 2019). To put this into perspective, the 2019 League of Legends (LoL) World Championship finals attracted more than three times the viewership of the 2017 NBA Finals (Railsback & Caporusso, 2018), highlighting that esports has evolved from a casual hobby into a globally relevant business—and for many, a career.

Esports athletes perform complex routines at a rapid pace and are concerned with playing the game as individuals, which can be highly demanding, but since popular esports games are team-based, the complexity is increased through the need to communicate with the team to share information which is crucial for success (Abramov et al., 2022; Leavitt et al., 2016; Lipovaya et al., 2018; Musick et al., 2021). Communication in esports is predominantly virtual, relying on audio software like TeamSpeak or Discord, which removes the ability to observe gestures or mimicry and can lead to misunderstandings and reduced performance due to the lack of non-verbal cues that are typically present in face-to-face interactions (Bányai et al., 2019; Heller, 2010; Lipovaya et al., 2018). This has been shown in education and business organizations where virtual communication caused a lack of trust, missunderstanding and overall less engagement of the teams (Dulebohn & Hoch, 2017; D. Xu & Jaggars, 2014).

Research on esports communication highlights its crucial role in team cohesion and performance, with both verbal and non-verbal forms being integral for strategic coordination (Freeman & Wohn, 2019, 2019; Leavitt et al., 2016; Lipovaya et al., 2018; Rambusch et al., 2007). While some studies suggest that reduced communication can enhance performance by fostering faster decision-making, others advocate for more frequent exchanges to boost team dynamics (Abramov et al., 2022; Freeman & Wohn, 2019; Lipovaya et al., 2018; Musick et al., 2021; Tan et al., 2022). This debate extends to the mode of communication, where the effectiveness of verbal strategies competes with non-verbal cues like pings and gestures, which may reduce the need for spoken interaction(Cheung et al., 2012; Leavitt et al., 2016; Lipovaya et al., 2018; von Gillern, 2021). The emotional tone within team communication also significantly impacts performance, with effective emotional management linked to better outcomes (Abramov et al., 2022; Orlova et al., 2023). Furthermore, comparisons between amateur and professional teams reveal that professional strategies, which often emphasize efficient verbal communication and superior emotional control, lead to higher performance under stress (Karakuş, 2022;

Orlova et al., 2023; von Gillern, 2021). However, it is essential to note that most research in this area does not utilize data from professional teams due to the sensitivity of such data, which limits access to robust datasets. These findings underscore a need for further research to explore how different communication strategies specifically affect esports team performance. Such studies could help refine communication training programs, tailoring them to various competitive levels and enhancing team success in esports.

Esports teams frequently operate under high-pressure conditions, developing sophisticated communication systems that integrate verbal, non-verbal, and in-game cues to minimize verbal interaction and facilitate rapid decision-making (Musick et al., 2021). These strategies enhance 'team cognition,' a collective mental model that enables players to anticipate their teammates' actions and make instantaneous decisions, skills applicable to other virtual groups requiring swift, synchronized responses (J. G. Reitman & Steinkuehler, 2021). Advanced multimodal communication techniques such as voice, game-specific indicators, and position-based cues further enable seamless collaboration, with the dynamic interplay between competition and teamwork in esports fostering effective coordination (Leavitt et al., 2016; Lipovaya et al., 2018; Musick et al., 2021). This makes esports a valuable model for improving communication and efficiency in other high-performance virtual (Freeman & Wohn, 2019; Lipovaya et al., 2018).

The key difference between this project and previous research lies in the perspective taken as this study starts with the state of the game, examining how communication patterns shift based on whether a team is winning or losing. In contrast, earlier studies primarily focused on analyzing communication behaviors and their correlation with performance outcomes. The research gap presents a need to research larger data sets of professional teams while connecting the content and communication to the state of the game, i.e., whether the team is winning or losing (See chapter 3). This research project will address that gap by tackling two primary objectives. First, understand how professional esports teams communicate based on the state of the game, i.e., losing or winning. By analyzing the speech and content for patterns using established concepts from previous esports communication research. This enables comparisons on whether the change of perspective results in new findings. The In the second part, these unveiled patterns should be analyzed to see if they are generalizable and can be used by other teams that rely on digital communication under similar conditions.

Furthermore, it should be explored if communication transformed into different features can predict whether a team will win or lose the following sequence. As a result of the presented research gap the research questions are as follows:

1. How do communication metrics such as speech rate, share of silence, average volumne, share of fillwords and share of overlap relate to team performance in professional esports, and how can these metrics inform strategies for optimizing team coordination and success?

2. How can metrics such as speech rate, share of silence, average volumne, share of fillwords, share of overlap paired with content topics be used to predict match outcomes in professional esports, and what communication patterns are most indicative of a team's likelihood to win or lose?

This research will try to answer these questions using 38 hours of voice and video recording of two esports teams competing in the highest LoL divisions. This presents a rare opportunity as these teams are usually very protective of their data as it can reveal their strategies. Also, the size of the dataset is considerably more extensive than that of previous research projects. The results will contribute to the current research by explaining how communication in esports is influenced by the state of the game and if there is a connection between communication and performance. Secondly, it will provide insight for professionals in the industry to understand common patterns that can be used to optimize communcation and hence the chances of success in matches. Lastly, it will examine. how other domains that share similar conditions can use practices from esports for them

2 Background

This chapter will provide further scope and required information for the following sections. It will be used to define key terms and underline the relevance of each aspect.

2.1 Action Teams

Action teams can be defined as a group of individuals that perform a task for a single time event under the constraint of limited time (Ishak & Ballard, 2012). Based on this, esport teams can and have been classified as extreme action teams when following the definition of Klein et al. (2006), who define them as “teams whose highly skilled members cooperate to perform urgent, unpredictable, interdependent, and highly consequential tasks while simultaneously coping with frequent changes in team composition and training their teams' novice members”(Klein et al., 2006). When following the definition of Ishak & Ballard (2012), they can be divided into three categories: contending, critical, and performing action teams. These categories vary in characteristics and properties, such as team focus or the goal of the task (See Figure 1) (Ishak & Ballard, 2012). When combining this with the research of Hollenbeck et al. (2012), who created a scaling framework for describing teams using a three-dimensional scale with the dimensions of authority differentiation, temporal stability, and skill differentiation, it becomes decisive to precisely define an action team (Hollenbeck et al., 2012). When sorting esport teams into one of the three types of Ishak & Ballard, they should be considered a contending extreme action team as they meet all the criteria for contending action teams. In detail, they have a binary evaluation of success in win or lose, and the performance events in the form of matches or tournaments are planned and scheduled (Ishak & Ballard, 2012). Overall, the assignment appears straightforward when considering that professional sports teams are also considered contending action teams with the simple difference of lacking the digital component and having a more intensive physical component. Communication, especially voice communication, has been identified as a critical factor influencing team performance (Krenz & Burtscher, 2021). In their research, Krenz & Burtscher (2021) explicitly focused on the voice component in the communication in action teams in high-reliability environments (Krenz & Burtscher, 2021). One of the key suggestions after reviewing 26 empirical studies in the industries of aviation, healthcare, and military is that they suggest that action teams should be trained in their communication to practice communication in terms of expressing information as well as receiving information as each aspect is equally essential (Krenz & Burtscher, 2021). Nevertheless, there could be the possibility that this is already part of their training routine, which would be an interesting insight considering that while esports is a highly competitive and professional environment, it is assumably less developed than high-reliability organizations such as military or healthcare.

	Action Team Type		
	Contending	**Critical**	**Performing**
Examples	Professional sports teams, political campaign teams, some legal teams	Fire crews, surgical units, military teams, bomb squads, S.W.A.T. units	Choirs, orchestras, theater troupes
Task goal	Dynamic competition against adversary	Dynamic competition coupled with predetermined performance	Predetermined performance in front of an audience
Timing of performance events	Planned	Generally unplanned	Planned
Team focus	Inward (team performance) and outward (performance of adversary)	Inward (team performance) and outward (performance of adversary)	Inward (team performance)
Evaluation of success	Evaluated using a binary set (e.g., win/loss) by an external, objective application of rules	Evaluated on a spectrum and using a binary set (both can be either subjective or objective, external or internal)	Evaluated subjectively on a spectrum by external judges (e.g., mediators, audiences)
Expectations of improvisation	Necessary component due to a dynamic adversary	Necessary at times due to dynamic adversary	Should be unnecessary since performance should follow predetermined plans

Figure 1 Three different types of action teams defined by Ishask & Ballard (Ishak & Ballard, 2012)

2.2 Esports

"Esport is a new area in the gaming culture and is starting to become one of the most essential and popular part of video game communities, especially among adolescents and emerging adults" (Bányai et al., 2019)**.** Esports has grown greatly in recent years, resulting in larger viewership and general awareness. For example, a single event in the final of the LoL world championship in 2016 recorded 1.5 million unique live viewers (Esports Charts, n.d.). In 2023, the number of viewers has grown to 6.4 million (Esports Charts, n.d.). When further characterizing esports in terms of the requirements to be a player, one must have fast and precise hand movements while processing a large amount of information and coordinating with their team (Freeman & Wohn, 2019). When competing, the players communicate via a digital medium in the form of software such as "TeamSpeak," "Discord," or in-game voice chat channels (Lipovaya et al., 2018). In one-third of the cases, this voice communication is supported by in-game visual measures of communication (Lipovaya et al., 2018).

Regarding research, esports has gained much traction and is now covered in seven disciplines that focus on different aspects of the field (J. Reitman, 2018) (See Table 1). The number of publications increased yearly, with media studies having the most publications where every domain works relatively isolated and on different topics (J. Reitman, 2018). The variety of research fields and increasing amount of publications indicate the growing relevance of esports research but also show that it lacks more holistic view such as combining knowledge from different domains. This thesis attempts more holisitc approach by combining concepts of informatics and communication research.

Discipline	Research Focus
Business	Explores consumer behavior, marketing strategies, and economic impacts in esports.
Sports Science	Compares esports with traditional sports to assess its legitimacy as a competitive sport.
Cognitive Science	Studies the mental skills that distinguish expert players from novices.
Informatics	Uses data analytics to explore game telemetry, player performance, and team dynamics.
Law	Addresses legal issues such as copyright, intellectual property, and regulations in the esports domain.
Media Studies	Investigates how media influences esports through streaming, spectatorship, and community engagement.
Sociology	Examines social dynamics, gender issues, and cultural impacts of esports on community and identity.

Table 1 Presents the different domains that are concerned with esports research and their publication count (Reitmann, 2018)

2.3 League of Legends

The game “League of Legends” (LoL) is a video game of the category multiplayer online battle arena (MOBA from the publisher “Riot Games” where two teams of five players each try to win the game by destroying the base of the opponent team (J. Reitman, 2018). It is currently the most popular video game in the world, with a player base of 67 million (Kim et al., 2017).

In LoL, esports is structured regionally across nine regions. There are four major regions in Europe, South Korea, China, and North America, and five minor regions in Pacific, Vietnam, Brazil, Japan, and Latin America. Each of these regions hosts multiple professional leagues with one premiere division. The premier leagues consist of 8 to 17 teams which play each other throughout two splits over the year where the best two to three teams per region can qualify for an international tournament in the World Championship (Worlds) or the Mid-Season Invitational (MSI) to compete against the best teams in the world. In Europe, the “LoL EMEA Championship” (LEC) hosts the best teams in Europe. While it was previously a system in which teams could be promoted or relegated, it is now a franchise system with consistently the same teams. Below are minor regional leagues where the highest per country is usually considered professional, allowing players to make a living by playing. Within these regional leagues, promotions and relegations still exist.

To win, the players aim to claim different objectives that yield them gold, which is the in-game currency that increases the strength of the individual characters. They can earn gold by killing enemies, neutral monsters, enemy structures, and enemy minions (J. Reitman, 2018). The latter are tiny monsters permanently created in a rhythm of every 30 seconds from minute 1:05. Ultimately, the money indicates which team is stronger. Through that, one can, to a certain extent, predict which team will win. However, this is only partially true as the individual capabilities of the players and a team can overpower the economic odds, and the team with less gold can still win. When watching LOL through the observer mode, which grants you insight into the state of the game and the objectives claimed, you can predict the team that will likely win the game. Figure 2 shows the part of the observer layout that gives insight into this metadata. While LoL is primarily a videogame designed for entertainment purposes, there is also a competitive scene that plays professionally. In this scene, teams of the best players compete against each other in a league system. This high-level coordination via digital communication is crucial to win (Lipovaya et al., 2018; J. Reitman, 2018).

Figure 2 Example of the game state bar in the observer perspective ((Source: own creation) from dataset)

3 Related Work

3.1 Team Cohesion

Team cohesion can influence the performance. Understanding the connection between communication and team performance is a critical area of research in esports. One of the first papers to do this was by Rambusch et al. (2007), who investigated various aspects that influence the performance of Counterstrike. One of their primary results is the connection between team cohesion and performance, which is enabled by effective communication. However, their focus evolved around out-of-game communication. Following up on this was the study of Freeman & Wohn (2019), who examined team formation and coordination mechanisms. Their results emphasize that a team requires good communication for effective coordination and overall performance (Freeman & Wohn, 2019). This supports the claim made by Rambusch et al. (2007) and further pushes the notion that team cohesion mediated by verbal communication impacts performance. This notion is extended by Tan et al. (2022), who analyzed team cohesion by studying communication patterns, finding that team cohesion correlates with word frequency. Given the results of previous research, which indicate that word frequency or speech rate is an indicator of team cohesion, it will be operationalized and used as a feature for prediction in this research. They also mention the state of the game but do not relate it to communication or performance. Ultimately, these studies underscore that communication is a central element influencing team cohesion and performance in esports.

3.2 Mode of Communication

Esports uses various modes of communication, and currently, there is a lack of agreement regarding verbal communication. Freeman & Wohn (2019) clearly state that verbal communication is a crucial factor for teams, which contrasts with the findings of Kim et al. (2017), stating that non-verbal communication and a shared understanding are more important for team performance. One of the papers that supports the claim of Freeman & Wohn (2019) is the study of van Gillern (2021), highlighting that professional esports teams rely on verbal communication for crucial aspects of their game, such as strategy, encouragement, and commentary (von Gillern, 2021). They argue that oral communication is more efficient in the fast-paced context of esports. With such an awareness of the importance of the requirement, it appears that teams are trying to convey information as efficiently as possible. Hence, analyzing the content for inefficiencies such as stopwords might provide insight into practices used. Cheung et al. (2012) demonstrate that players use a combination of virtual and physical communication mechanisms, primarily relying on auditory cues and virtual physical gestures, further emphasizing communication's importance in esports. This study shows that verbal and auditory interactions play a significant role in strategy formulation, which contradicts Kim et al.'s (2017) emphasis on tacit communication. Lipovaya et al. (2018) show that esports teams rely on a wide range of communication

channels but stress the importance of non-verbal communication, strengthing the position of Kim et al. (2017) (Lipovaya et al., 2018).
Additionally, they introduce a new limitation, claiming that the communication strategies of teams in esports are game-specific. Leavitt et al. (2016) show a positive correlation between the use of pings (a form of non-verbal communication) and player performance, supporting the importance of non-verbal cues as highlighted by Kim et al. (2017) and Lipovaya et al. (2018). This suggests that teams may have developed efficient non-verbal communication protocols that reduce the need for verbal interactions.

Overall, these studies show the variety of communication modes used in esports and the yet now clearly gained confidence in their importance. This creates the need for further research to reach an aligned understanding of the communication in esports in relation to performance.

3.3 Communication Frequency

In the context of communication frequency and its impact on team performance in esports, several studies present diverse findings that shed light on the complexity of this relationship. Musick et al. (2021) present that teams often create mutual understandings and predict responses to minimize communication and foster faster decision-making, suggesting that less communication can enhance performance. This contrasts with other research claiming that higher communication frequency correlates with better performance (Gervits et al., 2016; Tan et al., 2022). Abramov et al. (2022) discovered a correlation between team performance, amount of communication, and emotional sentiment, showing that winning teams in a professional tournament often had lower communication and, hence, more sequences of silence. This resonates with the findings of Musick et al. (2021), indicating that teams either have a mutual understanding or use other ways of communication, as shown in Leavitt et al. (2016) and the use of smart pings in games such as LoL, which eliminates some part of verbal communication.
Furthermore, this is supported by Smith et al. (2019), who inspected the stressors that esports athletes faced, where it was discovered that communication can also be a stressor for players. This indicates a balance required to reach optimal performance, as neither excessive nor insufficient communication provides the best performance. The point of less communication is again picked up by Lipovaya et al. (2018), also clearly indicating that professional teams that perform better require less communication, where they argue it by creating a streamlined communication process that the teams follow. Hence, it appears logical also to pay attention to sequences of silences and when they occur. A study that limits this claim to a degree since it involves amateur players is the study of Hanghøj et al. (2023), who showed that amateur players tend to be so absorbed by the in-game activities and may not respond to communication, suggesting that lower communication frequency might be a result of intense focus rather than strategic choice (Hanghøj et al., 2023). This underscores the difference between amateur

and professional teams, where the latter might be better equipped to manage their communication effectively without compromising performance.
These studies collectively illustrate the nuanced relationship between communication frequency and team performance. While some research supports the idea that less communication can lead to better performance through efficient mutual understanding and silent coordination, others highlight the positive impact of frequent communication on team cohesion and performance. Therefore, the optimal communication strategy likely varies depending on the team's experience level and specific in-game contexts, emphasizing the need for further research to delineate these dynamics more clearly.

3.4 Emotion, Communication & Performance

In the research on emotion and communication related to team performance in esports, several studies show a clear connection between these components. One of these studies is from Abramov et al. (2022), who presents a clear correlation between team performance, team communication, and the emotional sentiment of the communication. They connect the state of the game to communication and the emotional sentiment created by it, which allows them to predict emotion from audio and, based on that prediction, also predict the outcomes of match rounds. The claim of Abramov is validated by Orlova et al. (2023), who demonstrated a statistically significant connection between performance and emotion. Their research utilized game-state data to show that emotions could reliably predict round outcomes, reinforcing that emotional states are integral to understanding and enhancing team performance (Orlova et al., 2023). Because of that, it also makes sense to track the players' emotional state when analyzing communication. Smith et al. (2019) explored the stress induced by communication, showing that if communication is not managed correctly, it can create negative emotions that adversely affect team performance (Smith et al., 2019). This aligns with Abramov and Orlova's findings by emphasizing that emotional states, whether positive or negative, are pivotal in predicting performance outcomes. Smith's work further argues that emotion is a key predictor, suggesting that managing the emotional impact of communication is crucial for maintaining high-performance levels. This will probably also be reflected in the intensity of the conversation in terms of word frequency and loudness, which suggests that observing loudness can also yield valuable insights. Hanghøj et al. (2023) examined the adherence to social norms in in-game communication, noting that frequent interruptions and personal attacks among players posed challenges (Hanghøj et al., 2023). This study highlights the importance of managing interpersonal dynamics and maintaining positive emotional environments to prevent performance degradation. The findings suggest that professional teams, likely better equipped to handle these dynamics, could use these insights to improve their communication strategies. As social norms seem to impact emotion, it seems logical to observe interruptions and their impact on gameplay.
Collectively, these studies underscore the critical role of emotion in communication and its direct impact on performance. Emotion, whether through the stress of communication as noted by Smith et al. (2019) or through the emotional sentiment of interactions as shown by Abramov et al. (2022) and Orlova

et al. (2023), emerges as a key predictor of team performance. Effective communication strategies must, therefore, account for emotional management to optimize team cohesion and success in esports. Combined with the previous section, it could also be possible that emotion influences the frequency and mode of communication, which has not yet been researched.

3.5 Amateur vs Professional

There are apparent differences in the communication between amateur and professional esports teams. One of the studies showing this is from von Gillern (2021), who conducted a comparative analysis that shows that professional teams heavily rely on verbal communication to convey strategy, encouragement, or commentary as they perceive it as more efficient than other channels, such as chat. Other studies show that professional players are more in control of their emotions, which suggests training and experience, which is essential, as shown in the previous section, as emotion influences team performance, allowing professional teams to perform at a high level even in stressful situations (Orlova et al., 2023). Even simply identifying yourself as an athlete will help esports players improve their communicative abilities, as identified by Karakus et al. (2019). They identified a positive relationship between athlete identity and effective communication levels (Karakuş, 2022). As players more closely identify with being athletes, their communication skills tend to improve. This insight is particularly relevant for professional players, who typically have a strong athlete identity, suggesting that their recognition of communication as a vital performance tool enhances their communication abilities. This reinforces that professional players are better equipped and more motivated to use effective communication strategies.

These studies underscore the differences in communication strategies between amateur and professional teams. Professional teams' reliance on efficient oral communication, better emotional control, and stronger athlete identity contribute to their superior performance. This research supports the idea that amateurs can improve by adopting the communication practices of professionals, emphasizing the importance of effective communication as a critical component of success in esports. Additionally, it clearly shows that there is little communication research with the involvement of professional teams, and when there is, it shows considerable differences in how it is approached.

3.6 Summary of Findings

Despite the insights provided by these studies, several research gaps highlight the need for further investigation. Firstly, there is a lack of integration of game state variables—specifically whether a team is winning or losing—into the communication analysis. While some studies, like those by Abramov et al. (2022) and Orlova et al. (2023), consider emotional states, they do not fully explore how game state impacts communication dynamics. Understanding how communication varies with the game state could provide deeper insights into optimizing team performance.

Secondly, there is limited research involving professional teams, primarily due to the sensitivity of communication data that could affect their competitive edge. Most studies, like those by Freeman & Wohn and Hanghøj et al. (2023), focus on amateur or mixed teams. Only a few, such as Abramov et al. (2022), von Gillern (2022), and Orlova et al. (2023), involve professional players. Studying professional teams more extensively could uncover best practices that can be transferred to amateur teams.
Third, many qualitative studies rely on small sample sizes, limiting the generalizability of their findings. This is understandable given the high effort required to analyze communication data. However, with advances in computational methods and AI, automating parts of the data analysis process is now possible, allowing for examining larger datasets and potentially more robust conclusions.
Lastly, while many papers acknowledge the importance of communication for esport teams, no research quantitatively connected communication to team performance and has yet to determine the relationship. Deriving features from the communication and using them in predictive machine learning algorithms will provide the opportunity to learn the feature importance and make clear statements about currently contradicting knowledge, such as the speech rate. Given some of the variables already explored in a qualitative context, this project will quantify them and evaluate their importance.

To address these gaps, this research project proposes to analyze the communication of professional esports teams concerning the game state, utilizing a large dataset to derive more generalizable knowledge. Such an approach could provide practical implications for improving team performance and theoretical insights into the limitations of previous research due to small data samples and the exclusion of game state variables. Additionally, this research could also help in answering whether verbal communication is a crucial element influencing performance or if it is not a factor. This project aims to contribute to a more comprehensive understanding of the interplay between communication, emotion, and performance in esports.

4 Research Methodology

The following section describes the methodlogoy of this research, gives an overview of the data used and describes the preprocessing steps done to prepare the data for further usage. The overall process can be seen in figure 3.

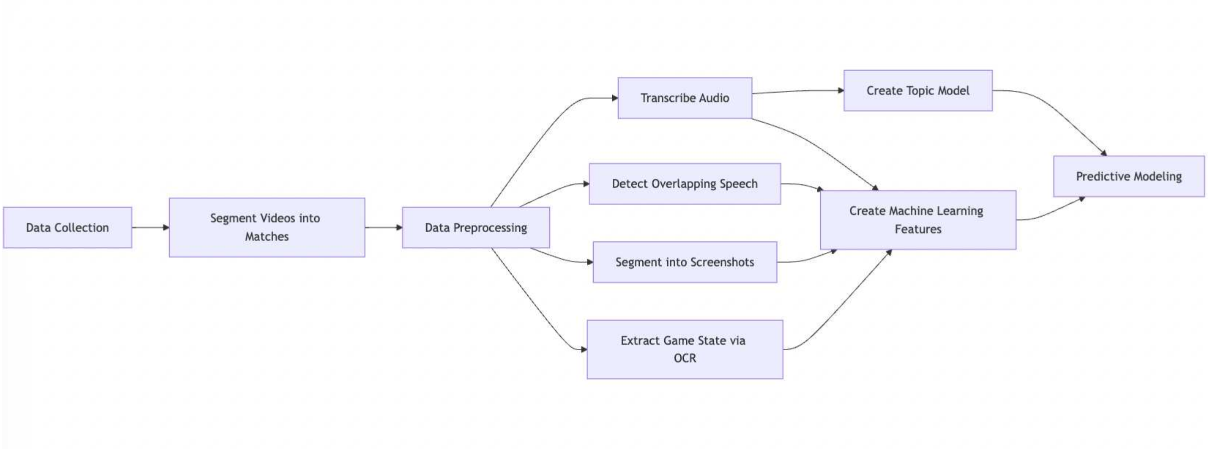


Figure 3 Overview of the research process ((Source: own creation))

4.1 Case Characteristics

The foundation of this research project are two data sets shared by two professional LoL teams located in Germany. The first team is a team that competes in the “Prime League,” whixch is the second highest level in Europe. The second team is part of the “LoL EMEA Championship”) “LEC” is Europe's highest level of play. In general, there are regional leagues such as the “Prime League” and one overarching league like the “LEC” (Further details can be found in the Esports and LoL Chapter in the previous sections). Like other sports teams, esports teams have regular practice sessions. In this case, these are practice sessions during their regular season in which they play against other professional teams daily, usually serving as the data foundation, as these sessions are often recorded for review.
In these review sessions, the players and the coaching staff identify flaws in previous games and discuss changes to be implemented. Such a practice session usually contains a block of six matches against the same team, with breaks for a review of 20 minutes between each match. This was shared by the team's manager when discussing a potential collaboration. The recorded sessions contain two primary components. First, there is the video, which is the match from the perspective of an observer. Through this observer perspective, additional metadata is available. This metadata includes live information about the game state, such as the economic situation of each team and the objectives taken or conceded. The “Prime League” team provided 64 practice matches, and the “LEC” team provided ten matches. The of these 74 matches there are 45 wins and 29 losses creating an unbalanced dataset.These matches were recorded in different time windows. For the first team, it was over the course of a month, and for the other team, it was two sessions that were one month apart.

4.2 Data Collection

The raw data was provided via 21 YouTube links, each containing a single practice session. These files were downloaded via the youtube_dl python module and saved as a mp4 file. These files ranged from three and a half hours to five hours and fifty minutes. As previously stated, the teams take breaks between each game to review and adjust for the next match. Hence, there are sequences of ten to fifteen minutes in the files that do not contain any communication. Hence, the first preprocessing step was to adjust the data to contain only the matches. Therefore, the start, end, and file names of each match within a file were noted in a CSV. Afterward, a script reads that CSV and cuts the file into single matches. As a result, there are 74 files, i.e., 74 matches left over, that total 38 hours of content (See Table 2). The average length of a match is 30.36 minutes, while the minimum is 8.55 minutes, and the maximum is 43.45 minutes. The median is at 28.02 minutes. The short matches, such as 8.55 minutes, can be explained by the fact that sometimes the matches end early as the teams agree to forfeit the match. The reason for that can be that the goal of the practice match has already been eliminated for them. The varying length of matches triggers the question whether communcation differs in different phases and if it changes based on the length of the match resulting in a different mode of communication or the priorization of different topics.

Metric	**Value**
Number of Files	74
Hours of Content	38
Average Length in Minutes	30.36
Minimum Length in Minutes	8.55
Maximum Length in Minutes	43.45
Median Length in Minutes	28.01
Standard Deviation	6.08

Table 2 Descriptive Statistics of the researched data set ((Source: own creation))

4.3 Data Preprocessing

4.3.1 Overlap Detection and Removal

After creating the individual files, their content was manually evaluated to determine data quality. During that time, it was noticed that the data contained much overlap, which would falsify the transcription and other steps down the line. Hence the pyannote.audio overlap speech detection is used to detect sequences of overlap and flag them. Sequences with overlap will still be transcribed but not considered once the transcripts are created. Pyannote is an open-source speaker diarization toolkit that utilizes Pytorch deep learning models, providing different modules in the form of pre-trained models for use cases such as overlapped speech detection (Bredin et al., 2020). Due to it is robust, complex modern architecture and mechanisms, it reaches high precision and recall of 90+ percent, making it the most suitable choice for this task (Bredin et al., 2020). However, there are also studies that challenge the quality of the model and point out certain limitations of the model that could lead to a lower reliability of transcripts created from such audio (Agarwal et al., 2024).

4.3.2 Audio Transcription

After preprocessing the data by removing overlap, the data is transcribed using the Open AI whisper Python module. This results in web VTT files that contain a transcript with timestamps, which serves as the foundation for the data analysis. After trying different providers such as Google and IBM Watson, it showed that Whisper performed best amongst them as it could also pick up on the game-specific terminology. While Whisper demonstrates strong performance in several benchmarks, especially in multilingual and diverse speech settings, other services like Amazon Transcribe and Microsoft Azure can sometimes outperform it in specific metrics like Word Error Rate (Ebrahimi et al., 2020; Talafha et al., 2023; B. Xu et al., 2021). The choice of the best transcription service may depend on the specific requirements and conditions of the task at hand (Ferraro et al., 2023). Overall, Whisper is a solid and performant model with a low entry hurdle while still providing valid results, making it a reasonable choice for this research (Agarwal et al., 2024).

4.3.3 Game State Extraction

The last component of the preprocessing is extracting the game state from the video files. The game state is the crucial variable in determining whether a team is winning or losing. The game state is represented in different metrics within the video's overlay (see Figure 2). First is the economic state, represented by the value of money (gold) owned by each team. Second, there is the number of "kills" a team has collected. Lastly, there are the objective-related metrics in "Dragons," "Heralds," Barons," and "Towers." Kills and other objectives all contribute to a team's economic situation. Due to budget constraints, the only extracted variables are the in-game time necessary for syncing audio and game data, the gold of the blue team, and the gold of the red team. While the other objectives, such as towers, dragons, or heralds, could probably give valuable insights, they were neglected for the specified reasons. The game state extraction initially used optical character recognition (OCR) via the Tesseract engine. Tesseract is an open-source OCR framework that allows text extraction in images. As the results of Tesseract were vastly varying in quality, other OCR engines and APIs were tried where the Google Cloud Vision API provided the best results. This API has different modules, and one specializes in extracting text from images, which seemed like the best fit when looking at Figure 2. The first step in capturing the game state was to extract video file frames, i.e., screenshots. In this case, a script was deployed that took a screenshot every 60 seconds. Studies indicate that significant game events in LoL, such as kills and objectives, occur at intervals that justify using a 60-second screenshot interval for effectively capturing the game state without missing key events (Eaton et al., 2018; Ryu et al., 2023). Performance data and player experience studies further support that major game events do not occur in

rapid succession, making the 60-second interval appropriate (Cantallops & Sicilia, 2018; Sapienza et al., 2018).
To ensure high reliability, this process requires preprocessing. This preprocessing consists of the following steps. First, it decreases the image's complexity by defining areas of interest that contain the metadata. In this case, three areas represent the gold, kills, and the in-game time. After defining these areas, the second step involves cropping the image to only contain a single area of interest to remove as much noise as possible. Note that the following steps were removed after initial tries as they worsened the result. Assumably, the API applies its preprocessing steps to optimize the results. Some metrics are colored in blue or red on a black background. In OCR, the contrast of the text to its background can influence the performance; hence, it is converted to greyscale to provide a more evident contrast. Next, the image is rescaled by factor 4, making it larger and easily readable. Different scaling factors were applied to the same image in a test case, and the factor of 4 provided the best results. Then, the image is converted into a NumPy array to perform the last two preprocessing steps. In the penultimate step, thresholding is applied, which creates a binary representation of the image where 0 represents a black pixel and 255 represents a white pixel, increasing the contrast between the background and text. Lastly, this binary image is converted back into an image object that Tesseract requires to perform OCR.

4.4 Data Analysis

While current advances in computation enable a lot of automatic processing and interpretation of data to uncover specific phenomena, they are not yet at a point where they can fully take over. Hence, quantitative and qualitative measures are required. Hence, this research project will leverage a hybrid approach that combines qualitative and quantitative measures to gain complete insight into the data. When following the purposes of Venkatesh et al. (2013), this case aligns with the three purposes of complementarity, completeness, and compensation (Venkatesh et al., 2013). The purpose of complementarity is given as the qualitative measures are used to extend the findings from the quantitative analysis. The completeness aspect follows a similar direction as the quantitative aspect, which can only cover parts of the phenomena. The compensation aspect is given since the amount of data is large, and only applying qualitative measures would exceed the scope of the research project due to the large amount of manual effort required. Research examining the benefits of combining these methods showed they can uncover new insights by leveraging computational methods while grounding them in a theoretical base (Berente et al., 2019; Miranda et al., 2022). While the potential of leveraging digital traces is excellent, it requires careful implementation and should be a complementing methodology that is combined with robust operationalized constructs (Hüllmann, J. A. 2023). Ideally, it is used when subject matter experts can judge the output of the computational method (Hüllmann, J. A. 2023). In the context of this research, computational methods are needed due to the amount of data. However, the results of these computations will be evaluated through human judgment to ensure validity.

4.4.1 Setup of the Analysis

The quantitative analysis evolves two primary objectives that are set by the research questions. First, there will be an analysis of the patterns in the communication, and second, the created metrics will be used to predict performance. Each metric is calculated for the previously defined window of 60 seconds. First, there is the measure of speech rate, which is the number of words spoken per minute, as it can be an indicator of how effective the team's communication is (Abramov et al., 2022; Gervits et al., 2016; Tan et al., 2022). The second metric is the share of overlap, the share of two or more people talking simultaneously, i.e., interrupting each other. Speech overlap is also a disturbing factor for team communication, as shown by Hanghøj (2023). Next is the share of silence, which describes the relative amount of silence when no one is talking. As shown in the research, silence, especially in virtual teams, can be a proper measure to improve team communication and performance (Abramov et al., 2022; Lipovaya et al., 2018; Panteli & Fineman, 2005). A metric of a similar category is the average volume, which captures how loud the players are. As everybody needs to understand each other, it requires a minimum of loudness, while being too loud might disturb team communication and performance (Abramov et al., 2022; Orlova et al., 2023; Parisi & Brungart, 2005; Whitaker et al., 1993). The last metric is the share of stop words based on the nltk stop words library. Stop words are words without a semantic meaning to the information being conveyed, as esports is a fast-paced environment that requires fast and constant information sharing. Many stopwords can influence team performance (Dehghani & Manthouri, 2021; Leavitt et al., 2016; Smith et al., 2019). These metrics are calculated and then used as features in the predictive modeling.

4.4.2 Topic Model

These numerical features do not give any insight into the situation or context within the game. To cover this area, a topic model was created that analyzes the transcript of the window in scope, excluding overlap sections to prevent transcription errors, and then determines the primary topic of that window. The derived topic will feed the machine learning algorithm with information about what is happening in the game.

Multiple topic modeling libraries were tried when creating the prototype, e.g., BER Topic or scikit learn Latent Dirichlet Allocation (LDA). However, evaluating these topics provided insufficient results, especially when reviewing them with domain knowledge. This claim is also supported by Gallagher et al. (20,17), who point out that models like LDA require well-designed hyperparameters and assumptions that do not exist yet, as in the case of LoL.

Hence, a model like CorEx is more suitable as it allows for a semi-supervised approach where the topics can be defined at the beginning with keywords that belong to the topic (Gallagher et al., 2017). The model then uses these topics as a starting point and adds additional keywords that fit within the topic. The model yields low-level topics (Appendix B) that are applied first. These low-level concepts were derived through domain knowledge as an expert of the game with close to ten years of experience in playing at a high level (top 5%). Suitable keywords were extracted from a LoL terminology website (*Terminology (LoL)*, 2024). While this may limit the validity of the model, it was necessary as there is currently no other topic model available that could be used for this research. Afterward, these topics are aggregated to a higher abstraction level by mapping them to the team process taxonomy of Marks et al. (2001) (See Table 3).

Team Process Taxonomy	**Low-Level Concept**
Affect Management	Farming/Economy
Affect Management	Game Phases/Status
Conflict Management	Agreement/Confirmation
Conflict Management	Mistakes
Coordination	Objectives
Coordination	Information Sharing
Coordination	Location Specification
Coordination	Roles/Positions
Coordination	Objective Control
Motivation and Confidence Building	Encouragement
Motivation and Confidence Building	Game Conclusion/Results
Strategy Formulation	Gameplay Strategy
Strategy Formulation	Types of Engagements
Strategy Formulation	Game Updates
Strategy Formulation	Champions and Abilities
Strategy Formulation	Combat Strategies
Strategy Formulation	Macro Strategies
Strategy Formulation	Tactical Moves
Team Monitoring and Backup Behavior	Vision Control
Team Monitoring and Backup Behavior	Defensive Actions

Table 3 Mapping of low-level concepts to high-level team taxonomies (Marks et al., 2001) (

Average Relevance Score	3.74
Median Relevance Score	4.00
Minimum Relevance Score	2.00
Maximum Relevance Score	5.00
Standard Deviation of Relevance Scores	0.79

Table 4 Relevance score results of the automated topic model evaluation of ChatGPT ((Source: own creation))

Validation is required to ensure the relevance and quality of the topics generated by the CorEx model. Current research on topic model validation states that while advances in automated evaluation are being made there is still no full consent to their quality as some researchers validate the idea while others still argue , hence human judgment is still required (Chuang et al., n.d.; Hoyle et al., 2021; Rathje et al., 2024).
Due to the amount of data, a complete evaluation via human judgment was not feasible; hence, a mixed approach was used. First, an evaluation using the GPT-4 model is conducted. This evaluation involves scoring the relevance of the topics assigned to a sample of 100 transcripts from the dataset, with each transcript rated on a scale from 1 to 5, where 1 indicated complete irrelevance, and 5 indicated high relevance. Then, the evaluation of the automated sample is validated by applying human judgment in a binary form, stating whether the observer agrees with ChatGPT's judgment.

The automated evaluation (See Table 4) yielded an average relevance score of 3.74, a median score of 4.00, a minimum score of 2.00, a maximum score of 5.00, and a standard deviation of 0.79. The histogram in Figure 4 of relevance scores demonstrates that most scores are clustered around 3, 4, and 5, indicating that the topics are generally perceived as moderately to highly relevant. Specifically, almost all evaluated topics received a relevance score of 3 or higher, reinforcing the model's consistent performance. These results suggest that the topics generated by our CorEx model are consistently relevant across the dataset, with room for minor improvements. Consequently, we can confidently use the generated topics in subsequent stages of our analysis, as the evaluation supports the robustness of the CorEx model in capturing meaningful topics from the data. Hence the model was perceived as performant and used for the analysis.

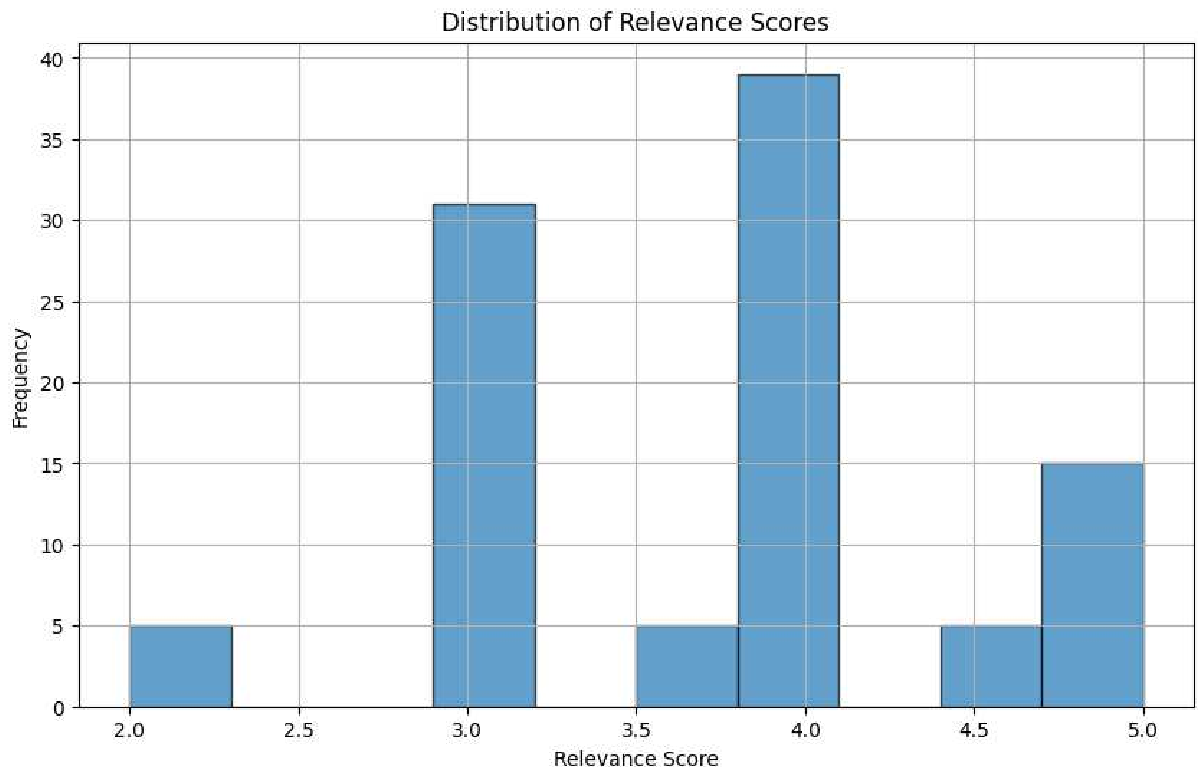


Figure 4 Visualization of the automated topic model evaluation of ChatGPT ((Source: own creation))

4.4.3 Pattern Analysis

The first part of the quantitative analysis focuses on gaining insight into the communication of professional esports teams and determining relationships between metrics, topics, and game outcomes. Initially, the analysis will be descriptive and observational, later exploring the relationships between different parameters and their influence on game outcomes.

4.4.4 Communication Metrics and Game Performance

Investigating the first relationship involves various communication metrics and sequence outcomes (win/loss). The analysis examines how metrics such as share of overlap, share of silence, and fill words change over time and across different game states, such as transitioning from winning to losing and vice versa. Statistical tests will identify significant differences between winning and losing sequences and explore how these metrics correlate with overall game outcomes. Special attention will be given to the temporal dynamics of these metrics to understand their role in critical phases of the game.

4.4.5 Distribution of Communication Topics by Game Outcomes

The analysis will explore the distribution of higher-level communication categories and dominant topics across match outcomes. The analysis will reveal how teams' communication topics vary in these scenarios by categorizing the games into wins and losses. Insights from this analysis will highlight which topics are more prevalent in successful teams and how strategic communication differs between winning and losing teams.

4.4.6 Temporal Sequences of Communication Topics

Following the approach of Tan et al. (2022), the study analyzes the compilation and sequences of topics throughout an entire game. This provides deeper insight into how communication concepts are used and their relation to the game's state. The research aims to uncover strategic patterns that differentiate winning teams from losing ones by analyzing the temporal sequences of communication topics. This section emphasizes the importance of structured and purposeful communication in achieving favorable game outcomes and identifying key sequences contributing to team success.

4.4.7 Correlation Between Communication and Game Outcomes

The research investigates the correlation between communication sequences and match outcomes. This involves statistically testing the significance of various communication patterns and their impact on game performance. By understanding which sequences are strongly associated with wins or losses, teams can refine their communication strategies to enhance performance.

4.4.8 Predictive Modelling

The performance prediction uses the previously defined metrics as features to predict the outcome of a game sequence (the previously defined 60-second windows), i.e., did the team win or lose the sequence? The prediction leverages many different machine-learning algorithms to find the best model. These models are Logistic Regression, Decision Tree, Random Forrest, XGBoost, Support Vector Machine (SVM), Convolutional Neural Network (CNN) and a Deep Feedforwarded Neural Network. These algorithms were selected because they tend to do well on smaller datasets, and as the dataset only contains 1946 rows, it is unfeasible for more advanced methods (Bhatt et al., 2023; Chaurasia & Pal, 2020). The dataset is then split into a train and test set in an 80/20 ratio. For each model, the hyperparameters are dynamically fine-tuned using Bayes Search. Bayes Search was used because other algorithms, such as grid search, are more computationally heavy and do not apply the learning of previous iterations to find the best parameter (Bergstra & Bengio, 2012; Joy et al., 2019). This was important here as the computation resources were limited. The criteria to determine the win or loss of a sequence is the gold difference compared to the previous section, i.e., the positive or negative gain achieved by the team. This value is converted to a binary scale where zero represents losses and one wins. Once the predictions are made, they are evaluated by their accuracy, precision, recall, ROC AUC and f1 score. While accuracy will be the primary criterion to evaluate model performance, the others are important to get a holistic view of the model, considering positive and negative classes and their balance (Yadavendra, 2020). Also, the importance of the individual features was calculated to gain insight into what features hold information about the team's performance, as this can give valuable knowledge for further research and teams.

4.4.9 Emotion Detection

As pointed out in previous research that already incorporated game state variables into their project, emotion plays a vital role in predicting the outcome (Abramov et al., 2022; Orlova et al., 2023). Hence it was also attempted to implement a dimension that is concerned with the emotional state of the players by analyzing the audio and predicting the emotion using an emotion classifier. However, while creating a classifier with 97% accuracy was successful, the prediction with the research data set was not as it predicted the same class for 99% of the data, creating a homogenous feature that would not add any value to the machine learning classifier in the later stage.

The paper of Abramov et al. (2022) served as the guideline here since they produced a very potent model for an esports emotion classification. At first, it served as the primary orientation in preprocessing the audio and creating the audio features that could indicate emotion. Following the structure of Abramov et al. (2022), the Mel-Frequency Cepstral Coefficients (MFCC) and the Log Mel Spectogram were the primary features. Both were extracted from the audio, and then the mean and the standard deviation were calculated (Abramov et al., 2022). With the recent developments in AI and the fact that training a classifier can consume much time, the initial idea was to find a pre-trained model for Speech-Emotion Recognition (SER) and benchmark them against an existing labeled dataset. Based on the benchmark, the best performing model would be selected for the prediction task on the dataset of this research project. The labeled dataset for testing the model here was analog to Abramov et al. (2022). The RAVDESS data set is a labeled dataset of actors speaking or singing in a range of 8 different emotions. After some research on SER models, the models or libraries SpeechBrain, pyAudioAnalysis, and WAV2VEC were chosen. However, they were not pursued due to technical incompatibilities or poor performance. Therefore, it was necessary to train a classifier from scratch. Since many models can do this task, they were selected by referencing the models tried by Abramov et al. (2022) since they could produce a performant classifier. In this case, the models selected were DecisionTree, RandomForest, Gradient Boosting, Multilayer Perceptron (MLP), LSTM, and Convolutional Neural Network (CNN). Initially, the models were run once with random parameters to understand their performance on the dataset (See Table 5). While some models performed relatively poorly, CNN and MLP had great accuracy in RAVDESS. However, since RAVDESS is relatively small, there was still the risk of an overfitted model that would perform poorly on the new data. Due to this, it was decided to extend the dataset to eliminate the overfitting. The CREMA-D dataset seemed suitable, with its six emotions overlapping with RAVDESS (Cao et al., 2014).

Classifier	Accuracy on RAVDESS	Accuracy on RAVDESS + CREMA-D with filtered emotion
Logistic Regression	0.63	58
Decision Tree	0.38	0.35
Random Forest	0.53	0.52
Gradient Boosting	0.58	0.49
SVM	0.57	0,58
MLP	0.94	0.96
CNN	0.90	0.97
LSTM	0.23	0.38

Table 5 Model performance on the emotion classification task on the training dataset ((Source: own creation))

After combining the datasets by remapping the CREMA-D labels to fit the RAVDESS dataset's labels, there was an imbalance in emotion volume. As a result, the emotions calm and surprised were highly under presented; hence, it was decided to drop them for a better class balance. This also improved the results for most classifiers with MLP and CNN, which still provided the best results at 95% and 97% accuracy. Therefore, these models are used for predicting on the data set of interest. This prediction resulted in a homogenous classification, with 99% of the classification being "fearful". Possible reasons for this lie could be that the dataset is still too small for the model to learn enough to reliably predict emotion, a highly complex phenomenon. This is particularly true for deep learning models like LSTM, which explains its poor performance (Meng et al., 2023). Another reason could be the lack of quality of the case data in either the recorded voice or possible noise in the background (Ma et al., 2019; Shi & Chen, 2022). While noise reduction was applied using the Wiener filter, which should help the classifier, it remains possible that there was still too much noise (Meng et al., 2023). The feature selection plays a vital role in the model's ability to generalize as features that work well on one data set might not work well on the next, which is why research suggests combining audio features with visual or text features (Meng et al., 2023). A particular explanation for the bad performance of CNN is that particularly CNNs tend to have an insufficient receptive field by being either too large or too small, hindering them from being able to generalize well (Koutini et al., 2021).

5 Results

This section will present the research results of this thesis. It will start by investigating how the derived audio features express them selves amongs the dataset and how those features are statistically connected to performance. In the second step the content of the communication is anaylzed using word counts first and evolving into more complex analysis using the created topic model. In the last step the results of the predicitve modelling results are presented. This section will serve as the basis for the discussion and ultimately answering the research questions.

5.1 Audio Feature Analysis

This first section of the results is concerned with investigating the relationships of the defined metrics and the performance by exploring the relationship of these variables in different context such as frequency, sequences and temporary occurences. It will yield insight into how communication differes in different stages of the match and how it differs in winning or losing teams.

5.1.1 Descriptive Statistics of Audio Communication Features

When starting the results of the pattern analysis, it appeals that getting a general insight into the metrics is essential to understand how the data is compiled and what possible questions are there to ask. Since one of the gaps is the lack of game state variables, this will be the primary focus of all questions. Hence, one of the first steps is to see what the created metrics look like on a broad scale by looking at their means in general and also for wins or losses.

Metric	Overall Mean	Mean for Wins	Mean for Loses
Average Volume (dBFS)	-30.626826	-30.189556	-31.334933
Share of Overlap (%)	11.85	12.09	11.46
Speech Rate (WPM)	186.06	189.75	180.06
Share of Silence	25.89	24.95	27.40
Share of Fillwords	40.24	40.48	39.85

Table 6 Results of mean analysis of the communication metrics ((Source: own creation))

Table 6 shows the mean of the metrics for different match outcomes. Overall, the metrics are very close to each other regardless of the match outcome. A few slight but notable differences are that in matches that were won the speech rate is slightly higher by nine words per minute. In the same notion, the share of silence is higher for losses, which is logical since the amount of speaking is more while the time interval is the same. The only exception could be if the players speak faster when winning, allowing them to put more information into the same time interval. Also, the share of overlap is higher in won matches than in lost matches. A possible conclusion could be that the teams are more interactive when performing well but also more chaotic. Combined with the lower share of silence and a higher number of words per minute, it could indicate that there is a tendency for players to be more willing to communicate when things are going well.

5.1.2 Statistical Relationships Between Audio Metrics and Performance

To validate that these observations are robust, a t-test was conducted. The table (7) below shows the results.

Metric	T-Statistic	P-Value
Average Volume	2.1507	0.1931
Share of Overlap	1.8734	0.0612
Speech Rate	-3.4049	0.0664
Share of Silence	1.8370	0.0007
Share of Fillwords	1.3018	0.0316

Table 7 Statistical evaluation of the communication metrics related to match outcomes (win/loss) ((Source: own creation))

Based on these tests, the following conclusions can be drawn: First, the significant differences in the share of fill words and share of silence suggest that winning teams are more active by using more fill words and having fewer silent periods. With the p-values of speech rate and share of overlap being marginally significant at 0.6, further research could be required to understand them fully.

5.1.3 Correlation Between Sequence Communication and Match Outcomes

With this new knowledge, it seems logical to investigate the relationship between the metrics and the match outcomes. Hence, the correlation between the metrics and a sequence outcome was calculated.

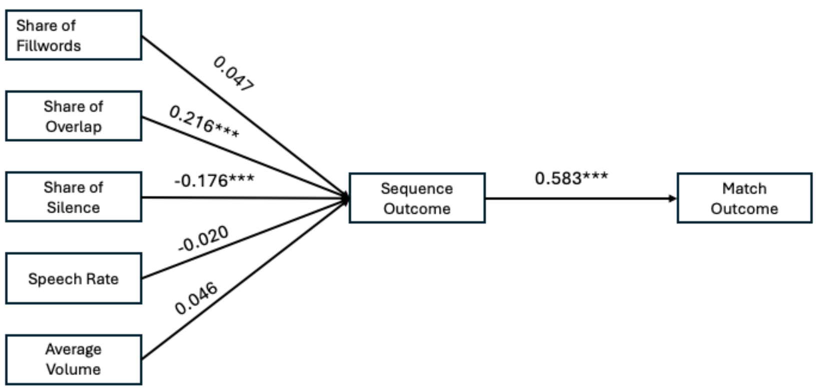


Figure 5 Relationship between metrics and sequence and match outcome (Source: own creation)

The correlations in Figure 5 allow for the following conclusions. First, having a higher overlap in a sequence will likely lead to a better outcome. Second, having a higher share of silence, i.e., less communication, will lead to worse outcomes. Third, having more fill words and talking slightly louder leads to better sequence outcomes. A louder average volume might indicate more confident communication that could improve team performance. Next, speech rate seems to be unrelated to sequence outcomes. Lastly, the significant relationship between lower silence and better match outcomes implies that consistent and ongoing communication is crucial. This suggests that teams who engage in regular, continuous communication, rather than simply speaking quickly or conveying a lot of information in bursts, tend to perform better. On the other hand, prolonged silences might indicate confusion, lack of coordination, or hesitation, which negatively impacts performance.

Since the first set of metrics with its mean was related to the overall match outcomes and the second part was concerned with sequence outcomes, it is essential to know if sequence and match outcomes are related, as this would allow to connect the knowledge. In the first step a chi square test between the two variables was conducted which resulted in a statistic of 248.01 with a p-value significantly less than 0.05 ($p = 7.05e-56$) strongly indicating a statistically significant association between the sequence outcomes and final match results. The sequence outcomes were summarized and average on a per game basis to determine the strength of the relationship, and the correlation between this value and the match result was calculated. This correlation between sequence and match outcome results in 0.583*** , indicating a moderately strong relationship between sequence outcomes and match outcomes (See Figure 5). More generally, this means that if a team wins more sequences, it is more likely to win the match which appears logical as won sequences result in more gold than the opponent making the team stronger and increasing their advantage.

5.1.4 Temporal Dynamics of Communication During Matches

The following section will explore this phenomenon by inspecting how the metrics express themselves throughout matches to find possible explanations. Therefore, the metrics will be grouped into averages per time sequence for all matches. Figure 6 shows how the metrics behave throughout the match. The following observations can be made. The share of fillwords appears to be relatively constant at a level of close to 50%. A similar but less intense consistency can be seen for the share of silence and share of overlap. However, they behave slightly differently as the share of silence tends to be higher at the beginning of matches, then drops by a bit, and then stays consistent from minute ten. For the share of overlap, it acts the other way around, where it is slightly less at the beginning of the match and marginally increases toward sequence 37. The speech rate is predominantly above 150 WPM and even hovers close to 200 while, in a few cases, exceeding 200. It has to be noted that the plot's reliability towards the later game times is less reliable as the games tend to be shorter, with an average of around 30 minutes, reducing the number of matches with that length.

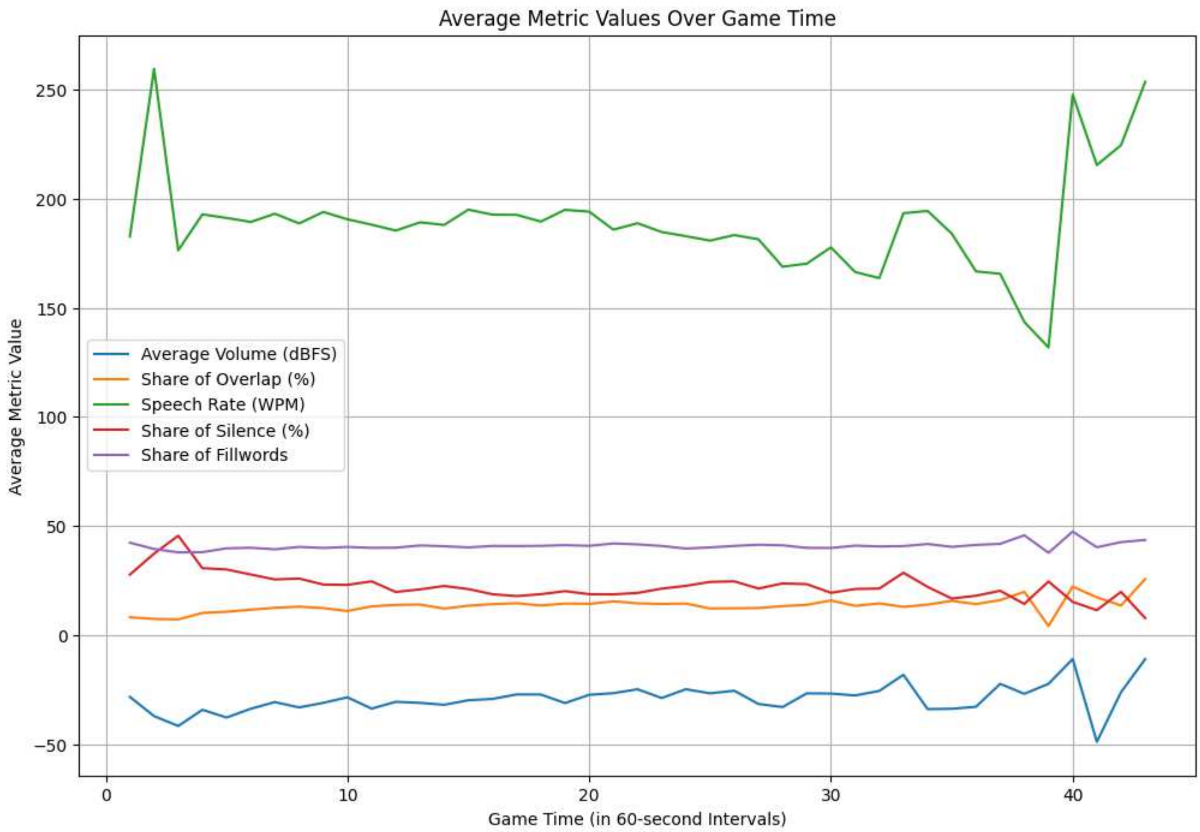


Figure 6 Visualization of the average communication metrics throughout all matches (Source: own creation)

5.1.5 Comparative Temporal Patterns in Wins vs. Losses

While these insights already provide knowledge about how esports teams communicate, seeing how they behave for won and lost matches is more interesting, as this research focuses on incorporating game state variables. Therefore, the next section will compare the metrics and their average individually over time but filtered for wins and losses.

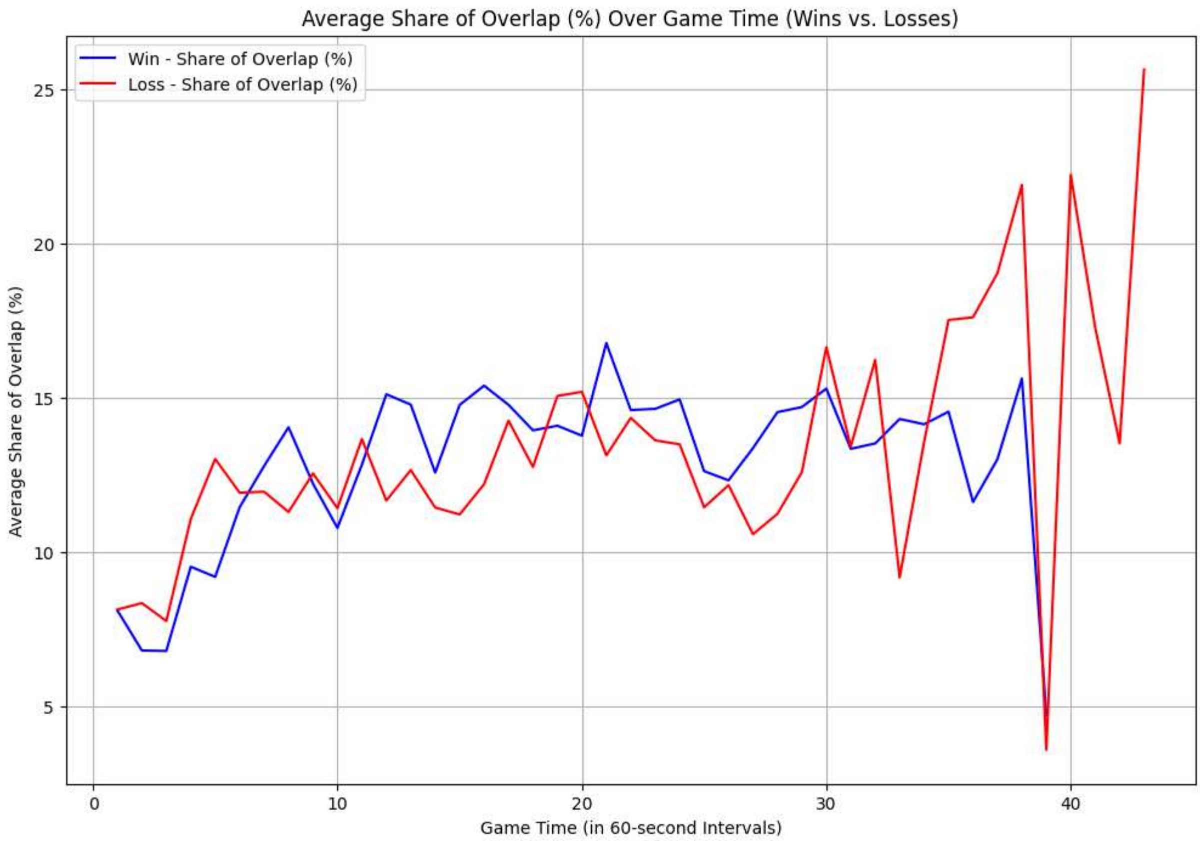


Figure 7 Comparison of the average share of overlap for wins and losses throughout all matches (Source: own creation)

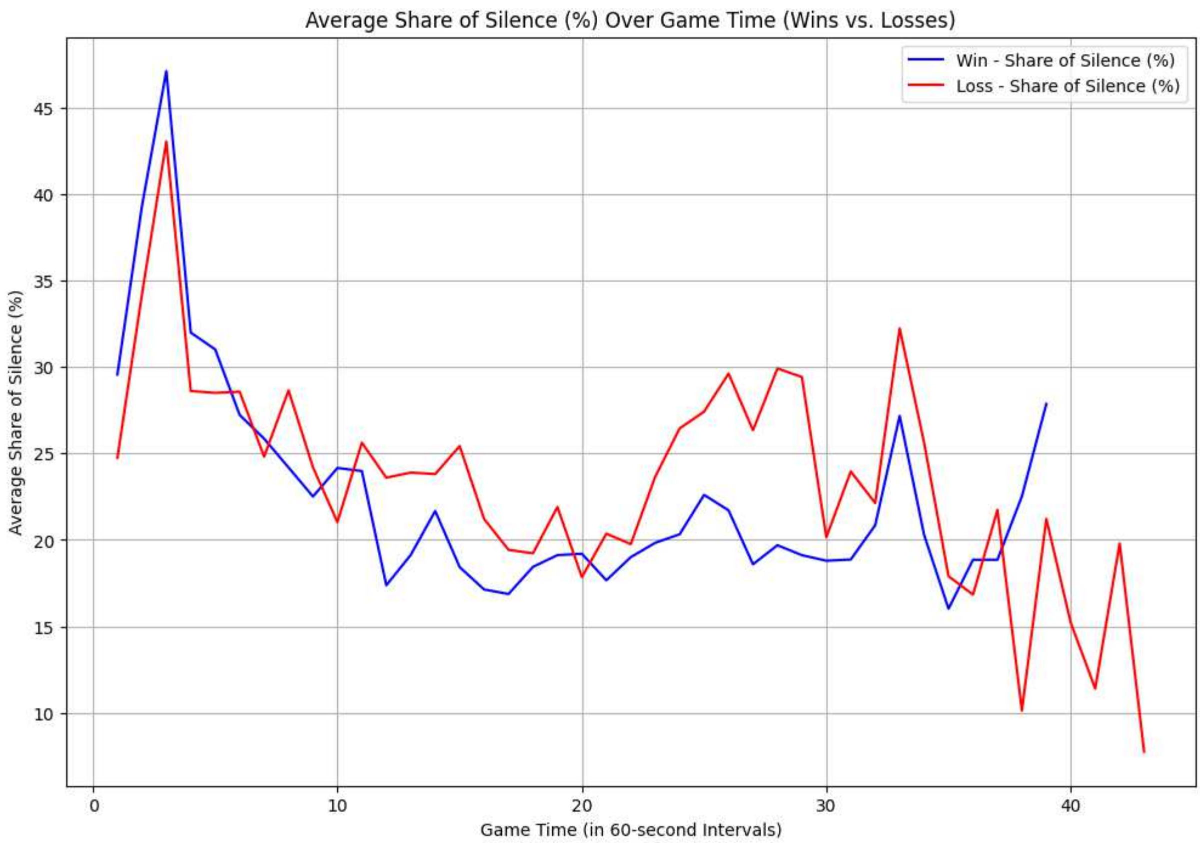


Figure 8 Comparison of the average share of silence for wins and losses throughout all matches (Source: own creation)

When looking at the overlapped charts (Figures 7 and 8), new observations can be made that show that communication differs not only over time but also between won and lost matches.
The share of overlap rapidly picks up shortly before the 10th minute for wins and losses and then reaches its peak for wins at the 22nd minute and the 30th minute for losses. For the 20th minute, it is at a new peak for both and then slightly drops afterward. This indicates that the game becomes more chaotic around minute eight as more things happen. Furthermore, winning teams might communicate more intensely early on to establish strategies and game plans that pay off later. To validate this, one could observe the gold differences and their values as higher gold differences indicate more actions taking place, which could explain this spike.
Looking at the share of silence, it peaks in the first 3 minutes of the match and then drops heavily from there, continuing to fall until reaching its first minimum at approximately the 20th minute for both match outcomes. While it slowly increases from there again, the increase in losses is significantly higher. Connecting this to the share of overlap from before, it appears that the teams, while having more chaotic conversations, tend to have more periods of silence during this sequence. The knowledge that most games in this dataset end around the 30th minute could indicate that the players already know they will likely lose the match and stop communicating due to demoralization. It could also mean that the teams are less decisive in losses as they might be unsettled about the best strategy to continue.
While the average volume tends to be higher for won matches, it shows that in losing matches, the team talks louder, that there is a shift around the 20-minute mark where the team in won matches increases their loudness and keeps increasing (See Appendix B). While this also happens for lost matches, it is still in lower volume. This could indicate that winning teams become more confident over time, and this expresses itself through louder and more assertive communication. A similar trend can be seen for speech rate with slightly lower WPM in the first ten minutes for lost matches (See Appendix B). From there until approximately the 33rd minute, the team maintains a higher WPM in won matches. This is interesting as it indicates a relation between WPM and performance which contradicts the previous correlation analysis as it showed a negative correlation of WPM and match outcomes at a marginal significance. Hence, it should be further analyzed in new research as the WPM might be more important during particular match phases. For the share of fill words, the use of fill words is higher in the first twenty minutes of the won matches and then drops by quite a margin around the 25th minute, while the share of fill words tends to only increase in lost matches (See Appendix B). This could indicate that losing sequences within the matches affects how the players articulate themselves, resulting in more fill words and less efficient communication.
Taking the observations into a more holistic consideration shows that many metrics and communication change around the 20th minute of matches. This indicates that this phase is critical in LoL, resulting in pivotal moments where key strategic decisions are made that lead to decisive moments such as fights being picked. In terms of practical implications, this could help coaches and teams understand the importance of that phase and acknowledge that it also affects their communication. This knowledge

enables them to create strategies and mechanisms to enhance communication, increasing their chances of winning.

5.2 Content Analysis

The previous sections already provided insight into how the teams communicate and how these changes are based on the state of the game. However, the content is currently missing, i.e., what the teams discuss. The following section will add this dimension by analyzing the content of the conversations and relating it to the state of the game. Starting with the pure content and then aggregating the content to topics utilizing the topic model.

5.2.1 Word Count and Sentiment Analysis

Moving towards the content of the conversations, the following analysis will inspect the spoken content by summarizing the most reoccurring words and then further analyzing them through sentiment analysis. Figure 9 shows the most used words for matches separated for wins and losses. When analyzing the 20 most common words in those sets, they overlap by 81%. This shows that there seem to be some prioritized words that are used regardless of game state or outcome. When looking at these words in detail, they are primarily concerned with confirmation such. as “yeah” or” okay”, action formulation like “go”, “look”, or “going,” or location specifications such as the different areas in Lol such as “mid”,” top” or “bot”.

Figure 9 Comparison of the 20 most common words separated for wins and losses (Source: own creation)

When comparing the occurrences of these shared words, it can be seen that, on average, they are used 40% more in wins than losses. This supports the assumption of higher communication frequency from the previous section. However, this is limited by the balance of class as 61% of the watches are wins, and 39% of the matches are losses; hence, the shared words should also occur more often however, as the average usage is still higher than the difference of the class imbalance the hypothesis stands to an extent.

Figure 10 Wordcloud representing the words associated with negative and positive sentiment (Source: own creation)

Emotion plays a vital role in esports communication, according to the current state of research. Since the audio-based emotion detection was not functional, a text-based analysis will be used to gain some insight. Figure 10 shows word clouds for the most frequent words and their association with positive or negative sentiment. It becomes apparent that both sentiments share many of the most common words. This shows that analysis on a by-word level cannot grasp the context due to its complexity and, hence, the actual sentiment. For example, the word "yeah" can be used in both a negative and positive context as it can be a positive form in an agreement and negative when acknowledging a mistake. As a result, a more sophisticated approach is required to analyze the content on the phrase level to allow for context consideration. For that reason, the results of the topic model will be analyzed next as it can account for context and even game-specific context.

5.2.2 Distribution of Communication Topics

This section will analyze the predictions made by the topic model, see how the topics are distributed, and present themselves with the game state. It will start by getting an overview of the overall distribution to understand which topics are the most dominant in LoL communication before exploring how they relate to the game states. In the final step, it will be analyzed if there are specific patterns in how the topics are connected, like the work of Tan et al. (2022).

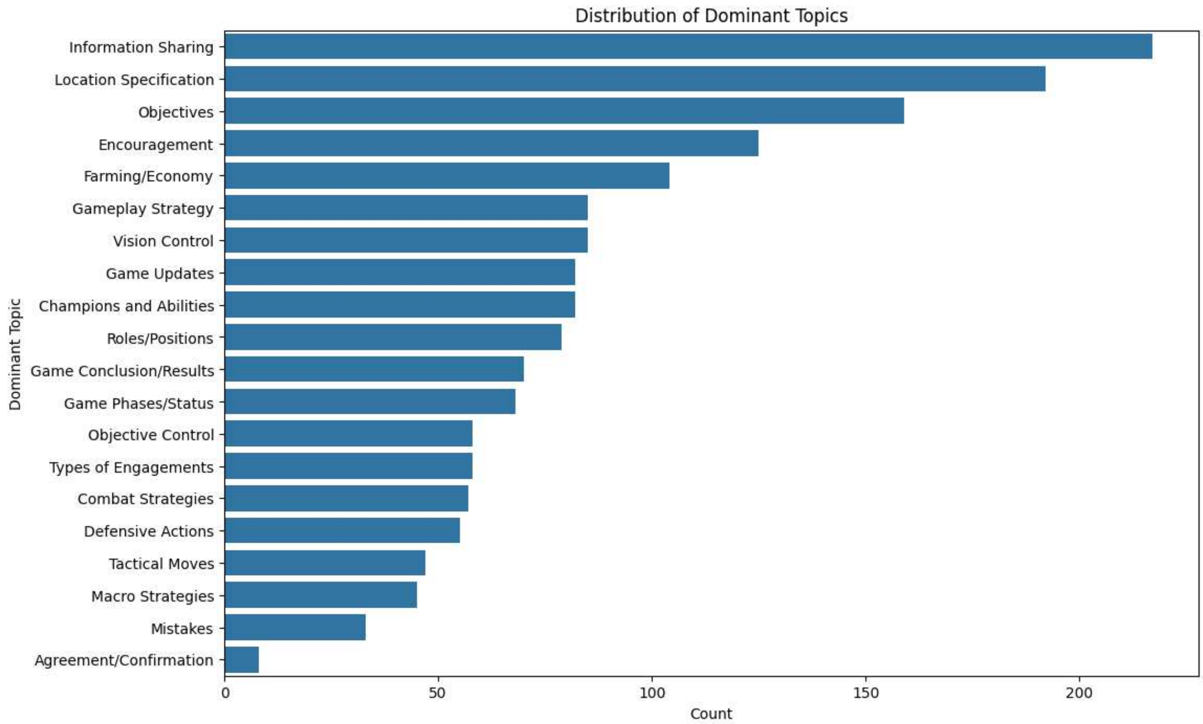


Figure 11 Count of the game-specific topics in all matches (Source: own creation)

Starting with the game-specific topics and their distribution (See Figure 11), the most occurring topics are information sharing, location specification, objectives, encouragement, and farming/economy with counts of 100 and more. The high frequency of information sharing and location specification aligns with the necessity for constant situational awareness as players need to share their positions, enemy positions, and more to make decisions individually or as a team. Additionally, the high frequency of objectives highlights their importance in the context of playing the game and makes them a strategic target that teams focus on.

A few topics are less gameplay specific, such as agreement/confirmation and mistakes, which place at the lower end but notably encouragement, which could be seen as similar ranks that are very high. This indicates that encouragement plays a vital role for the teams and suggests a positive team culture.

The aggregated version of this maps the game-specific topics to the team process taxonomy (Figure 12). It highlights that the two most important aspects of professional esports communication, coordination and strategy formulation, are closely connected to the game and its actions. This shows that esports communication is dominantly concerned with discussing relevant matters to play and, ideally, winning the match. This is supported by other topics, such as affect or conflict management, which rank relatively low—indicating that the teams barely talk about such topics. This allows the assumption that these topics are discussed outside of the game. With Motivation and Confidence Building ranking third, it suggests that maintaining team morale and confidence is essential beyond tactical discussions. This supports the high frequency of encouragement observed in the game-specific topics.

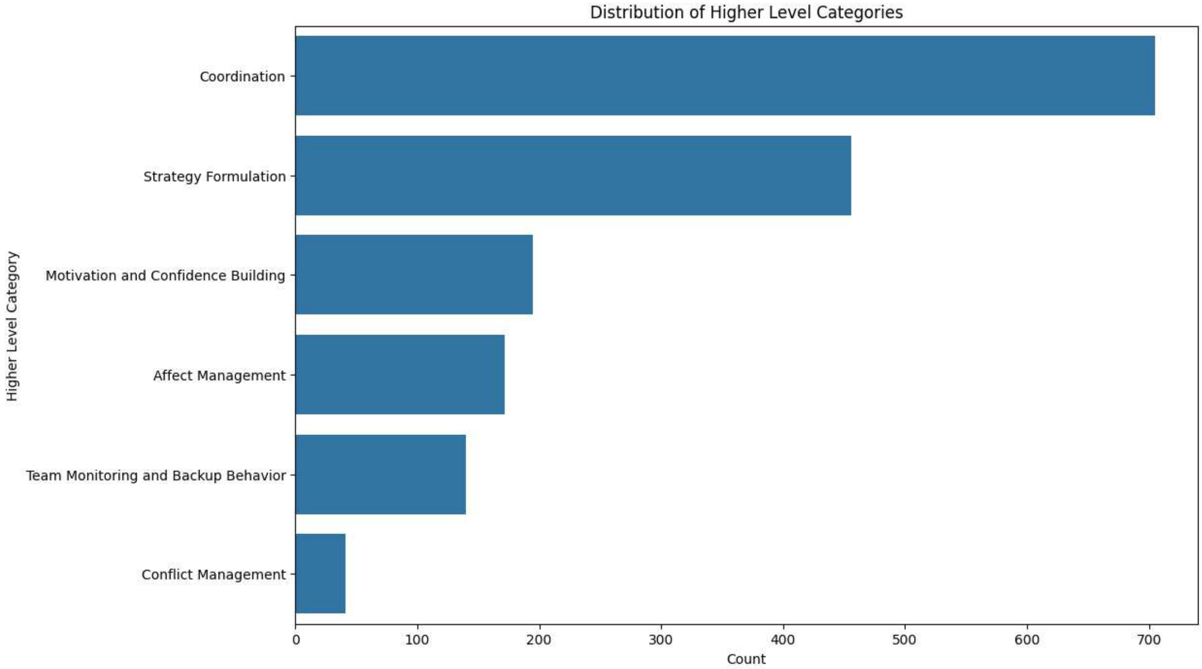


Figure 12 Distribution of the absolute number of team processes over all matches (Source: own creation)

5.2.3 Impact of Communication Topics on Game Outcomes

Following the previous structure, the game state variable will be added to find patterns specific to match outcomes. Since there is an imbalance of wins and losses, it was normalized to make it more representative.

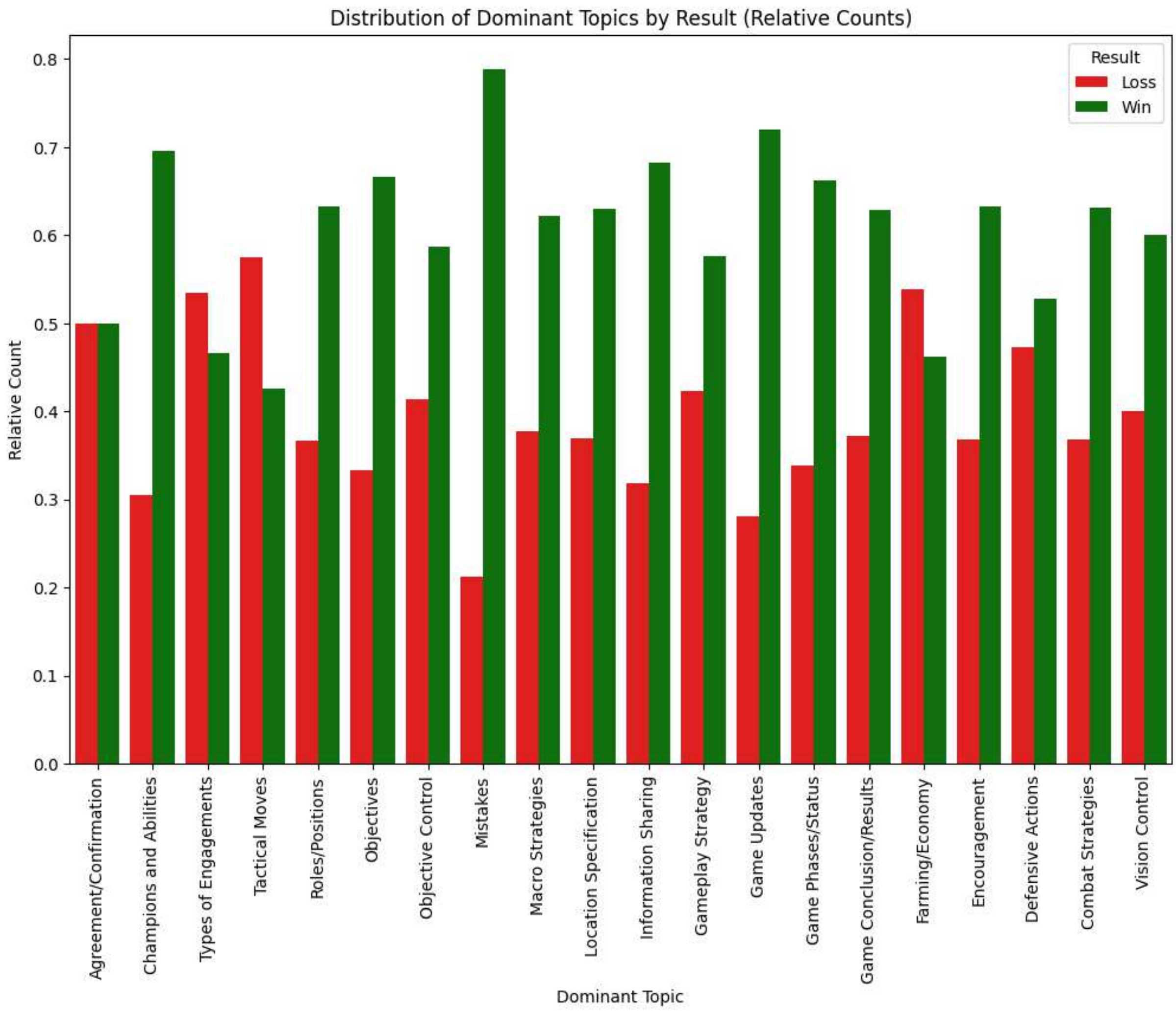


Figure 13 Distribution of game-specific topics by match result (Source: own creation)

The following observations can be made on the game-specific graph (See Figure 13). First, most topics are more present in wins than losses, except tactical moves, farming/economy, and types of engagements. They indicate that well-rounded communication is required that involves all aspects. Some areas have a significant difference in proportion, such as objectives, champions and abilities, macro strategies, information sharing, and game updates. It indicates that they are strong points of communication. Conversely, with farming/economy and game conclusion/results showing a higher proportion in losses, they might need attention to uncovering their full impact. Lastly, mistakes have a significant difference in proportion for wins and losses, which means when connecting it to the previous total occurrences, if players talk about mistakes, it would instead happen in matches that they end up winning rather than losing. This indicates that even though it happens infrequently, it could have a significant impact.

If looking at the more aggregated view (Figure 14), the trend of all topics being more present in wins than in losses even expands as this now holds true for every single topic. The ratio of conflict management is very similar to the ratio of mistakes from the previous topics. Overall, it reinforces previous observations that coordination and strategy formulation remain essential for winning, and well-coordinated teams with a clear goal seem to perform better. Motivation and confidence building are essential for creating a winning mindset and positive team dynamics.

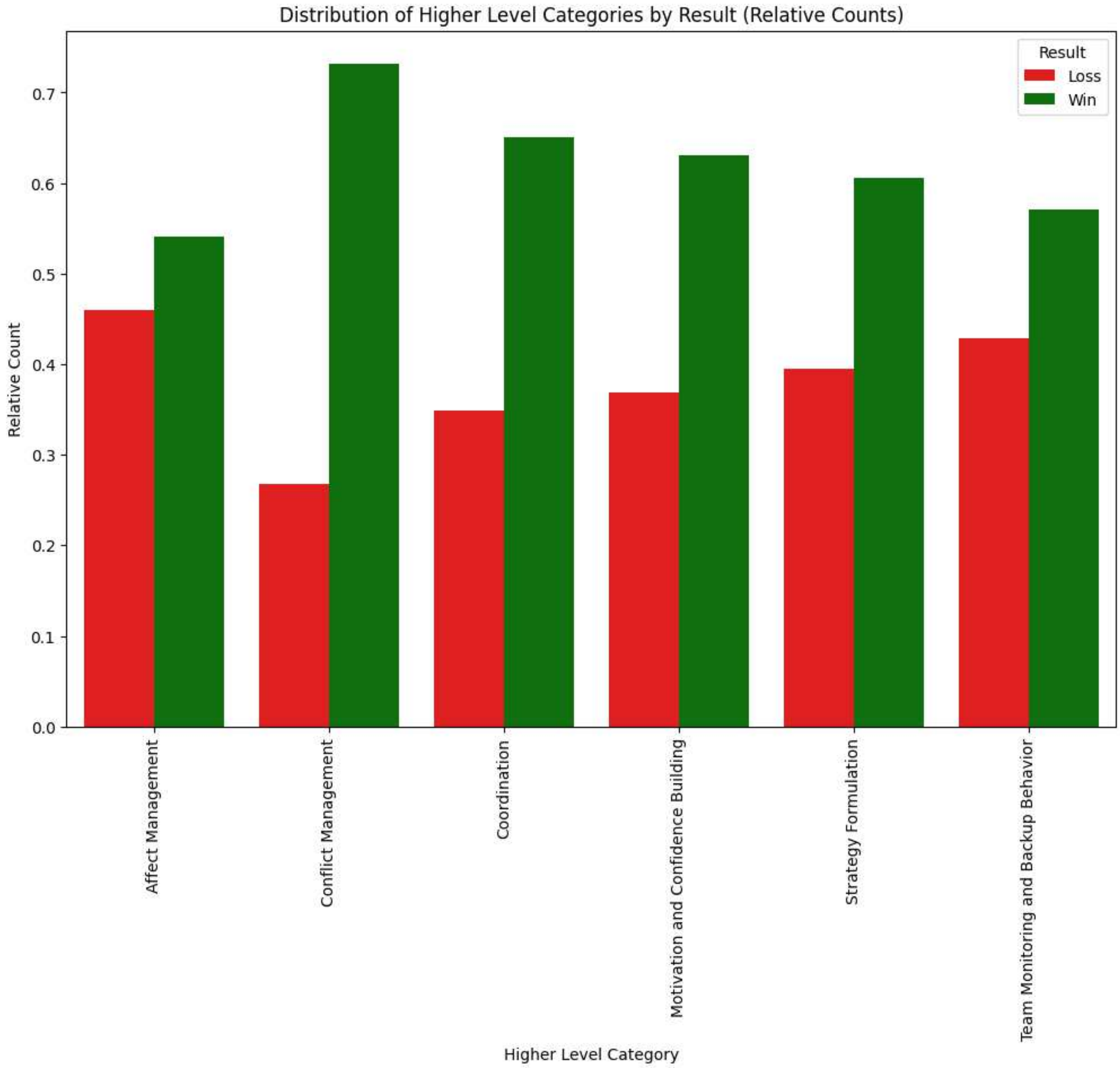


Figure 14 Distribution of team processes by match result (Source: own creation)

Overall, all of the previous observations show that the content of the conversation impacts the team's performance. To validate this in general, the statistical significance of the topics itself was tested first using chi-square tests.

Variable tested	**Chi Square Stat**	**P-Value**
Game Specific Topic	43.288	0.001
Team Process	11.573	0.041

Table 8 Statistical evaluation results of the relation between game-specific topics, team processes, and match results (Source: own creation)

Table 8 shows the results of the statistical testing. It confirms that there is indeed a statistically significant connection between the topics and the outcome of matches. For the dominant (game-specific) topic, there is a strong association of high significance with a moderate connection between the team process of significance. To gain further insights, the individual topics will now be analyzed to understand which topics are meaningful in the context of team performance and which are not (See Appendix D). This analysis extended the statistical tests performed before and calculated the standardized residuals.

The results show that the game-specific topics of champions and abilities, game updates, information, sharing, mistakes, and objectives are strongly associated with wins. In contrast, defensive actions, farming/economy, tactical moves, and types of engagements are strongly associated with losses. This suggests that focusing on these specific topics will increase the team's chances of winning, whereas focusing on other topics increases the chances of losing. Hence, teams should review both areas and find ways of enhancing the areas already working for them and finding ways to improve in the other areas. As previously observed, mistakes are more present in wins, and it is confirmed that addressing and discussing mistakes increases the team's likelihood of winning. It indicates that the teams can learn from their mistakes and immediately improve.

For the team processes, coordination and conflict management are crucial for winning, while affect management team monitoring and backup behavior are more associated with losses. Concerning the previous sections about the occurrences of topics, it can be observed that "Affect Management" and "Team Monitoring and Backup Behavior" are frequently discussed in winning matches but show a stronger negative association with losses, indicating potential issues or reactive measures. In contrast, "Conflict Management" and "Coordination" consistently show a positive association with wins in both frequency and statistical significance, highlighting their crucial role in successful outcomes.

Since it was established in the metrics section that sequence outcomes are associated with match outcomes, it will now be analyzed what connection the topics have with sequence outcomes. Therefore, the chi-square test is performed to observe if there is a connection and if it is significant (See Table 9).

Variable tested	**Chi Square Stat**	**P-Value**
Game Specific Topic	21.033	0.335
Team Process	12.288	0.003

Table 9 Statistical evaluation results of the relation between game-specific topics, team processes, and sequence outcomes (Source: own creation)

The results show no association between the game-specific topic and the sequence outcome, but a moderate association exists between the team process and the sequence outcome. Since there is an association, the residuals are calculated for the team processes to identify which topic influences performance. The following observations can be made from these residuals (see Table 10). Affect management, Team Monitoring, and Back Up Behavior are more associated with sequence losses, and Coordination is more associated with sequence wins. The other processes, such as "Strategy Formulation", "Conflict Management" and "Motivation and Confidence Building" show less association with either outcome.

Team Process	Residual for Losses (0.0)	Residual for Wins (1.0)
Affect Management	2.018	-1.765
Conflict Management	0.053	-0.046
Coordination	-1.354	1.185
Motivation and Confidence Building	-0.386	0.338
Strategy Formulation	0.162	-0.142
Team Monitoring and Backup Behavior	0.937	-0.820

Table 10 Residual analysis for team processes per sequence outcome (Source: own creation)

Comparing the standardized residuals to the relative counts graph for team processes (Table 10) reveals contradictions. For example, Affect Management shows a higher relative count in wins in the graph, yet the standardized residuals indicate it is more associated with losses. This suggests that while Affect Management is frequently discussed in winning matches, its presence in losing matches has a more substantial impact, potentially reflecting problematic situations that need addressing. Similarly, according to the graph, Team Monitoring and Backup Behavior is more frequent in wins. However, the residuals show a stronger association with losses, implying that this topic might often be a reactive measure to issues rather than a proactive strategy for success. These contradictions highlight the complexity of team dynamics, where the frequency of discussion does not always align with the impact on outcomes, underscoring the importance of context in interpreting these results.

5.2.4 Sequence Analysis of Communication Topics

Following the example of Tan et al. (2022), the topic sequences will be analyzed next. First, there will be an overview of the most occurring sequences before splitting them into the most occurring sequences for wins and losses.

Game Specific Sequences	**Count**
Objectives, Objectives, Objectives	15
Objectives, Information Sharing, Information Sharing	13
Information Sharing, Objectives, Information Sharing	11
Information Sharing, Information Sharing, Information Sharing	10
Information Sharing, Information Sharing, Objectives	10
Combat Strategies, Combat Strategies, Combat Strategies	10
Information Sharing, Objectives, Objectives	9
Objectives, Objectives, Information Sharing	9
Objectives, Information Sharing, Objectives	9
Information Sharing, Location Specification, Information Sharing	7

Table 11 Most present game-specific sequences in all matches (Source: own creation)

Table 11 shows that information sharing is present in eight out of ten sequences, reinforcing its importance. Another highly present topic is objectives, which is often paired with information sharing. This suggests that discussions about objectives are often accompanied by information sharing, indicating that teams frequently discuss objectives while updating or clarifying information. Next, the repetitive nature indicates that teams often emphasize specific topics during critical phases. This phenomenon can be observed for objectives as well as combat strategies. Teams heavily emphasize discussing objectives and sharing information, indicating that clear communication regarding objectives is critical for successful gameplay. The repetitive mention of specific topics like objectives and information sharing highlights their importance in maintaining team coordination and focus. Such repetitions could be strategies to reinforce key points and ensure all team members are aligned. Combining different topics, such as objectives with information sharing or location specification, suggests that teams dynamically adjust their strategies by frequently updating and discussing crucial aspects. The presence of combat strategies in the common sequences indicates their role in game success, albeit less frequently than objectives and information sharing. Next, the most frequent team processes will be analyzed (See Table 12).

Sequence	Count
Coordination, Coordination, Coordination	196
Strategy Formulation, Coordination, Coordination	83
Coordination, Coordination, Strategy Formulation	76
Coordination, Strategy Formulation, Coordination	60
Strategy Formulation, Strategy Formulation, Coordination	52
Strategy Formulation, Strategy Formulation, Strategy Formulation	50
Coordination, Strategy Formulation, Strategy Formulation	46
Strategy Formulation, Coordination, Strategy Formulation	45
Motivation and Confidence Building, Coordination, Coordination	36
Coordination, Coordination, Motivation and Confidence Building	35

Table 12 Most present team processes in all matches (Source: own creation)

Regarding team processes coordination dominates the sequences with 90% presence in the top 10 sequences. Strategy formulation itself is the second most present team process. The frequent combinations of "Coordination" and "Strategy Formulation" indicate that teams dynamically adjust their strategies while ensuring effective execution. Additionally, "Motivation and Confidence Building" in some sequences underscores the importance of maintaining morale and confidence during gameplay. These findings align with the previous insights regarding the general occurrence of topics where coordination and strategy formulation were identified as vital elements in team communication. The statistical relevance of these topics, confirmed through significant residuals, further supports their importance in successful outcomes. The frequent mention and combination of these topics in sequences suggest that effective team communication is characterized by continuous coordination, strategic adjustments, and morale-boosting, which are crucial for achieving better performance and match outcomes.

5.2.5 Topic Sequence Analysis by Match Outcome

Following the established structure, the next section will collect the sequences based on the game state and then analyze differences (See Table 13).

Rank	Sequence Wins	Sequence Losses
1	Combat Strategies, Combat Strategies, Combat Strategies	Objectives, Objectives, Objectives
2	Objectives, Information Sharing, Information Sharing	Objectives, Objectives, Information Sharing
3	Information Sharing, Information Sharing, Information Sharing	Objectives, Information Sharing, Objectives
4	Information Sharing, Objectives, Information Sharing	Information Sharing, Information Sharing, Objectives
5	Information Sharing, Objectives, Objectives	Information Sharing, Objectives, Objectives
6	Information Sharing, Information Sharing, Objectives	Objectives, Information Sharing, Information Sharing
7	Information Sharing, Location Specification, Information Sharing	Encouragement, Location Specification, Information Sharing
8	Farming/Economy, Information Sharing, Objectives	Information Sharing, Objectives, Information Sharing
9	Objectives, Objectives, Objectives	Encouragement, Information Sharing, Information Sharing
10	Objectives, Objectives, Information Sharing	Location Specification, Encouragement, Objective Control

Table 13 Most common sequences for wins and losses (Source: own creation)

The sequence " Combat Strategies, Combat Strategies, Combat Strategies, Combat Strategies" appears as the top sequence in wins but not in the loss sequences. This highlights its strong association with winning matches. Wins and losses feature sequences involving "Objectives" and "Information Sharing," but their contexts differ. In wins, these sequences are more varied and often include combinations with other topics like "Information Sharing, Objectives, Information Sharing. Sequences combining "Information Sharing" with "Location Specification" appear in both wins and losses, indicating their nuanced role in different match outcomes. Sequences involving "Encouragement" and "Location Specification" are more prevalent in losses, suggesting that they may not contribute effectively to successful outcomes while these topics are discussed. Next, the shared sequences of wins and losses will be analyzed to determine their association with match outcomes and if they are statistically relevant (See Table 14).

Sequence	Chi Square Statistic	P-Value
Combat Strategies, Combat Strategies, Combat Strategies	6.25	0.01
Objectives, Objectives, Objectives	5.51	0.02
Information Sharing, Information Sharing, Information Sharing	5.40	0.02
Objectives, Information Sharing, Objectives	4.91	0.03
Information Sharing, Location Specification, Information Sharing	2.23	0.14
Encouragement, Location Specification, Information Sharing	2.14	0.14
Encouragement, Information Sharing, Information Sharing	2.14	0.14
Location Specification, Encouragement, Objective Control	2.14	0.14
Farming/Economy, Information Sharing, Objectives	1.50	0.22
Information Sharing, Objectives, Information Sharing	0.54	0.46
Objectives, Information Sharing, Information Sharing	0.35	0.56
Objectives, Objectives, Information Sharing	0.24	0.62
Information Sharing, Information Sharing, Objectives	0.04	0.85
Information Sharing, Objectives, Objectives	0.00	1.00

Table 14 Statistical evaluation of the game-specific sequences related to match outcomes (Source: own creation)

The analysis of communication sequences and their impact on match outcomes reveals several key insights. Sequences like "Combat Strategies, Combat Strategies, Combat Strategies" and "Information Sharing, Information Sharing, Information Sharing" are significantly associated with winning outcomes, evidenced by high win counts (10 and 9, respectively) and statistically significant chi-square values (6.247 and 5.401). This suggests that repeated focus on combat strategies and continuous information sharing are strong indicators of a winning match. Conversely, the sequence "Objectives, Objectives, Objectives" shows a significant association with losing outcomes and a chi-square value of 5.510. This implies overemphasizing objectives without incorporating other strategic elements may harm match success. Other sequences, such as "Information Sharing, Location Specification, Information Sharing" and "Encouragement, Location Specification, Information Sharing," do not show a statistically significant association with match outcomes, indicating these patterns are less predictive. Balanced sequences like "Information Sharing, Objectives, Information Sharing" do not exhibit substantial predictive value for match outcomes. These findings suggest that focusing on combat strategies and continuous information sharing could benefit teams, while overemphasizing objectives might hinder performance. Further research could explore the qualitative aspects of these communication patterns to refine these insights.

5.2.6 Impact of Team Processes on Match Outcomes

Next, the procedure is repeated for the team processes by testing their statistical significance (See Table 16).

Team Process Sequence	**Chi Square Statistic**	**P-Value**
Coordination, Motivation and Confidence Building, Coordination	22.58	0.000002
Coordination, Coordination, Motivation and Confidence Building	12.46	0.000416
Coordination, Strategy Formulation, Coordination	1.18	0.277477
Strategy Formulation, Coordination, Strategy Formulation	1.10	0.293800
Strategy Formulation, Coordination, Coordination	0.70	0.401675
Coordination, Coordination, Coordination	0.32	0.573097
Strategy Formulation, Strategy Formulation, Strategy Formulation	0.22	0.638597
Coordination, Strategy Formulation, Strategy Formulation	0.08	0.772904
Coordination, Coordination, Strategy Formulation	0.00	1.000000
Strategy Formulation, Strategy Formulation, Coordination	0.00	1.000000
Motivation and Confidence Building, Coordination, Coordination	0.00	1.000000

Table 15 Statistical evaluation of team processes related to match outcomes (Source: own creation)

Analyzing the team process sequences in-game communication reveals several key insights into the patterns associated with winning and losing matches. Notably, "Coordination, Motivation and Confidence Building, Coordination" stands out with a highly significant Chi Square value of 22.58 and a highly significant p-value, occurring exclusively in losses. This suggests that this particular combination of topics is strongly linked with unsuccessful outcomes. Similarly, the sequence "Coordination, Coordination, Motivation, and Confidence Building" shows significant results (Chi Square = 12.46, P-value = 0.0004) and occurs only in wins, indicating a strong correlation with successful outcomes. In contrast, some sequences do not show significant differences between wins and losses. For instance, "Coordination, Strategy Formulation, Coordination" and "Strategy Formulation, Coordination, Strategy Formulation" have Chi Square values around 1.1, with P-values above 0.27, suggesting these topic combinations are equally likely in both scenarios. The sequences "Coordination, Coordination, Strategy Formulation" and "Strategy Formulation, Strategy Formulation, Coordination" have Chi Square values of 0.0 with a P-value of 1.0, indicating no difference in their distribution between wins and losses. Interestingly, "Coordination, Coordination, Coordination" is the most common sequence, appearing 129 times in wins and 67 times in losses, but with a non-significant P-value of 0.573. This implies that while coordination is a frequent focus, it does not differentiate between winning and losing outcomes. The sequence "Strategy Formulation, Strategy Formulation, Strategy Formulation" occurs frequently in wins (34) compared to losses (16), but the P-value of 0.639 indicates this difference is not statistically significant. Overall, the findings highlight the importance of coordination in successful gameplay strategies. At the same time, the role of motivation and confidence building appears dual-faceted, associated with both wins and losses depending on its context within the sequence. Strategy formulation, though critical, does not significantly distinguish between match outcomes, suggesting it is a universal focus in professional esports communication. These insights underscore the complex dynamics of in-game communication and the varying impact of different topics on match success. Further analysis with additional context would provide a deeper understanding of these relationships.

5.2.7 Summary of Findings

The analysis of communication metrics across all matches, wins, and losses revealed that higher communication activity, indicated by fewer silent periods and a higher speech rate, is associated with better performance. T-tests confirmed significant differences in the share of silence and fill words, suggesting that winning teams communicate more actively. Correlation analysis showed that higher overlap and fewer silent periods positively correlate with better sequence outcomes, highlighting the importance of interactive and continuous communication. The significant correlation between sequence and match outcomes indicates that consistent performance throughout the game increases the likelihood of winning. Temporal analysis revealed that communication patterns change significantly around the 20th-minute mark, with intensified communication in critical phases. Content analysis showed that information sharing, location specification, and objectives are the most discussed topics, emphasizing their importance in gameplay. Encouragement also ranked high, suggesting a positive team culture. The aggregated analysis identified coordination and strategy formulation as crucial elements in successful communication, while affect and conflict management were less discussed, implying they might be handled outside the game. Comparing topic distributions in wins and losses revealed that most topics are more prevalent in wins, reinforcing their importance. Statistical tests confirmed strong associations between specific topics and match outcomes, with champions and abilities, information sharing, and objectives strongly associated with wins. Sequence analysis showed that repeated combat strategies and information-sharing sequences are significantly associated with wins, while sequences focused solely on objectives are linked to losses. This suggests that a balanced approach involving various strategic elements is more effective. The analysis underscores that active, interactive, and confident communication correlates with better performance, providing valuable insights for teams to refine their strategies and communication practices for improved performance.

5.3 Predictive Modelling

The following section will present the result of the predictive modeling. It will give an overview of the different models used, their performance, the features dominantly contributing when applicable, and some explanation about the performance (See Table 16). The models were optimized using Bayesian optimization. After an initial run, the model was retrained with slightly different features by adding the rolling averages of the previous three sequences to give more information to the model. In each trial, the feature importance was measured, and non-contributing features were removed to reduce noise.

Model	Accuracy	F1 Score	Recall	Precision	ROC AUC
Logistic Regression	0.665	0.631	0.609	0.641	0.67
Decision Tree	0.628	0.629	0.628	0.642	0.64
Random Forest	0.680	0.676	0.680	0.678	0.72
XGBoost	0.666	0.664	0.666	0.664	0.72
SVM	0.659	0.656	0.659	0.657	0.68
Deep Forwarded Neural Network	0.624	0.711	0.832	0.621	0.67
CNN	0.649	0.708	0.765	0.659	0.67

Table 16 Overview of best model performance from best iteration selected by accuracy (Source: own creation)

5.3.1 Logistic Regression

When using the model to predict sequence outcomes, it performed best using the parameters C=0.0348, penalty='l1', and solver='liblinear'. These parameters use the moderate regularization of L1 for feature selection. In terms of performance, the model reached an accuracy of 60.7%, an F1 score of 58.4%, and an ROC AUC of 0.65 in the initial fine-tuning process.

After adding the rolling features, the best parameters slightly changed to C=0.0370, penalty='l1', and solver='liblinear overall improving the model performance for all metrics with a cross-validation accuracy of 65.5%, and test accuracy, F1 score, and precision and ROC AUC values of 64.3%, 63.1%, 64.1% and 0.67, respectively. In the third iteration, the importance of the features was analyzed, and only the most essential features remained as input. While the accuracy increased to 66.5%, the test accuracy, F1 Score, precision, and recall decreased to 60.9%, 60.4%, 60.5%, and 60.9%, indicating potential overfitting on the training data. The ROC AUC remained at 0.67. Overall, the model underlined the importance of the share of overlap and share of silence as they showed the most impact on model performance.

5.3.2 Decision Tree

The decision tree was trained and optimized analog to the procedure used for logistic regression, resulting in a starting accuracy of with a cross-validation accuracy of 62.7%, test accuracy of 62.8%, an F1 score of 62.9%, precision of 64.2%, and recall of 62.8% These values remained the same in the second iteration but changed in the third. The cross-validation accuracy increased to 63.4%, but the F1 score, precision, and recall decreased. The ROC AUC was consistent for the first two iterations at 0.64 and then decreased to 0.62 in the last iteration. This consistency suggests that the model's performance plateaued. Notably, the feature importance analysis revealed that the share of silence and share of overlap were the most significant predictors at 0.25 and 0.61. This consistency in model performance and feature importance indicates a robust relationship between the selected features and the target outcome, once again validating the importance of share of overlap and share of silence.

5.3.3 Random Forest

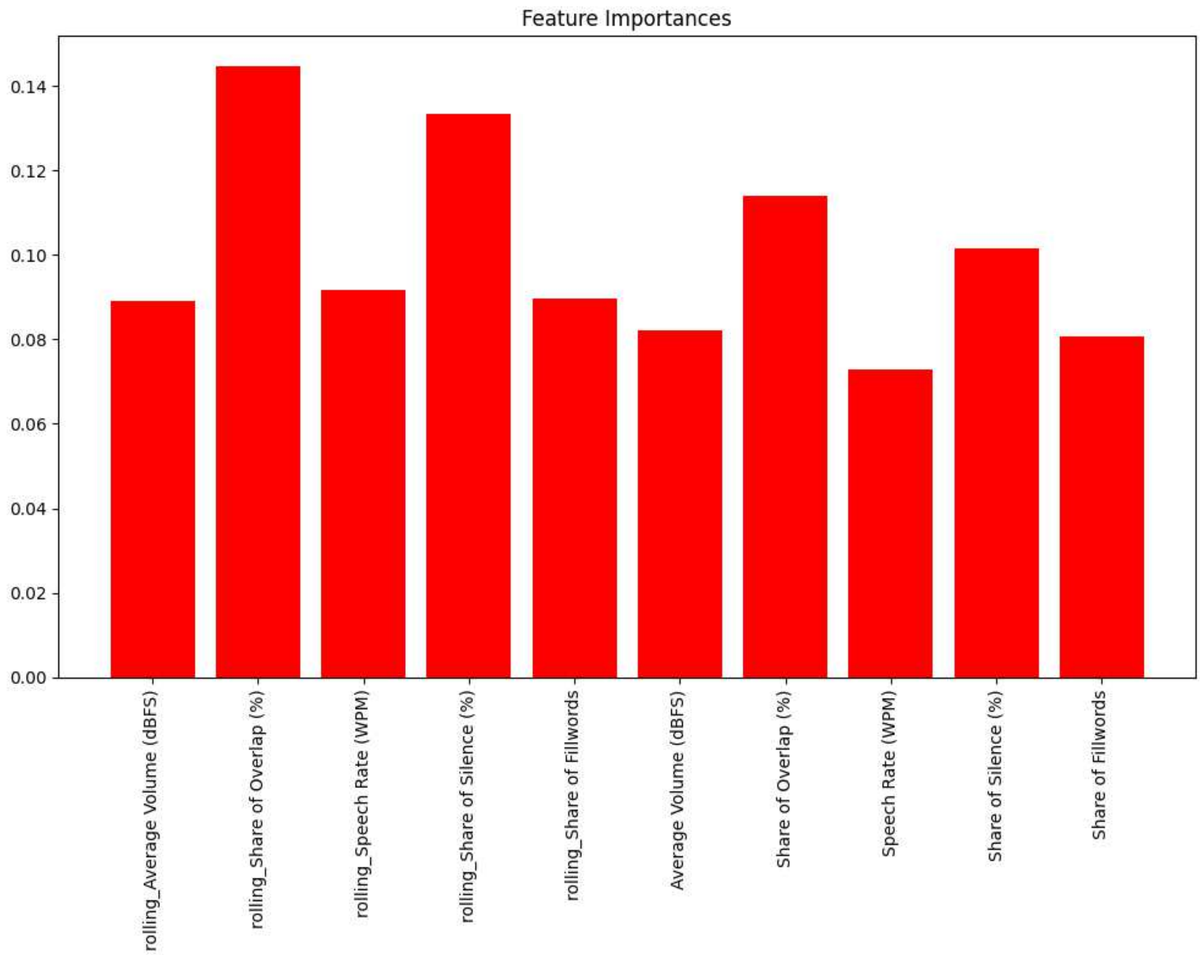


Figure 15 Feature importances for the random forest classifier (Source: own creation)

Random forest performed better than the two previous algorithms, achieving a cross-validation accuracy of 67.79%, a test accuracy of 66.4%, an F1 score of 65.9%, a precision of 66.1%, a recall of 66.4%, and an AUC of 0.70 in the first iteration. After adding the new features, the cross-validation accuracy decreased to 64.7%, and the other metrics were also lower, with only the ROC AUC remaining at 0.7. Overall, it appeared that all features had a positive contribution when looking at the importance of the features in Figure 15. In the third iteration, the parameters were optimized to include a maximum depth of 11 and 200 estimators, resulting in an improved cross-validation AUC of 0.72. The model achieved a test accuracy of 68%, an F1 score of 67.6%, a recall of 68%, and a precision of 67.8%. Feature importances confirmed the dominance of rolling metrics, particularly "rolling_Share of Overlap (%)" and "rolling_Share of Silence (%)", highlighting their consistent contribution to model performance across all iterations. The incremental tuning of parameters such as depth and estimator count enhanced the model's predictive capabilities.

5.3.4 XGBoost

The last tree method used was XGBoosting, which performed better than the decision tree but was worse than the random forest. The first iteration yielded a cross-validation accuracy of 63.4%, test accuracy of 61.2%, F1 score of 59.7%, recall of 61.2%, and precision of 61.5%. The performance was improved when adding the rolling features, resulting in a cross-validation accuracy of 65.5%, with a test accuracy of 66.6%, an F1 score of 66.4%, a recall of 66.6%, and a precision of 66.4%. In this step, the feature importance highlighted "rolling_Share of Overlap (%)" and "rolling_Share of Silence (%)" as key predictors. Using the feature importance insights in the third iteration the cross-validation accuracy remained at 65.5%, with identical performance metrics to the second iteration: a test accuracy of 66.6%, an F1 score of 66.4%, a recall of 66.6%, and a precision of 66.4%. Feature importances consistently pointed to "rolling_Share of Overlap (%)" and "rolling_Share of Silence (%)" as the most influential features, underlining the robustness of the model across iterations. The AUC values for the three iterations were 0.70, 0.70, and 0.72, respectively.

SVM

Next up was the kernel method in the SVM. Since not every kernel supports feature importance and only the best model was tracked, this algorithm will have no feature importance. Hence, the number of iterations was reduced to two. In the first iteration of the SVM model, the chosen parameters included a C value of approximately 2.21, the 'scale' gamma, and an RBF kernel. This setup resulted in a cross-validation accuracy of 67.3%, but the test accuracy was lower at 59.1%, with an F1 score of 59.0%, a recall of 59.1%, and a precision of 59.3%. Optimizing the parameters to a C value of approximately 0.92 in the second iteration, with the same gamma and kernel, improved the cross-validation accuracy to 68.0%. The test accuracy increased to 65.9%, with an F1 score of 65.6%, a recall of 65.9%, and a precision of 65.7%. This shows that parameter tuning significantly impacted model performance.

5.3.5 Deep Forwarded Neural Network

In the first iteration of the DFNN model, the test accuracy was relatively low at 57.71%, with a precision of 57.29% and a high recall of 94.12%. The F1 score was 71.22%, indicating a good balance between precision and recall for class 1 but poor performance for class 0. The classification report showed a significant imbalance, with the model performing well in detecting the positive class (class 1) but poorly for the negative class (class 0). This is reflected in the low F1 score of 20% for class 0 compared to 71% for class 1. The model's high recall suggests it predicts the positive class frequently but at the expense of precision. In the second iteration, the DFNN model marked improvement in all metrics. The test accuracy increased to 62.38%, and precision rose to 62.07%. The recall decreased slightly to 83.19%, leading to a more balanced F1 score of 71.09%. The classification report highlighted a better balance between class 0 and class 1, with the F1 score for class 0 improving to 46% and for class 1 slightly decreasing to 71%. The improved metrics indicate that the model tuning helped achieve better overall performance and balance between precision and recall.

5.3.6 CNN

The performance metrics were mixed in the first iteration of the CNN model. The test accuracy was 60.75%, and the precision was 59.83%. The recall was notably high at 89.50%, indicating that the model was quite sensitive in detecting the positive class. However, this came at the cost of precision, leading to a moderate F1 score of 71.71%. The classification report showed that the model struggled with the negative class, achieving only a 36% F1 score for class 0, while it performed better for class 1 with a 72% F1 score. The model's performance was characterized by a high recall but lower precision, suggesting it tended to predict the positive class more often. In the second iteration, the CNN model showed improvement across several metrics. The test accuracy increased to 64.95%, and the precision rose to 65.94%. The recall for class 1 decreased slightly to 76.47%, resulting in a more balanced performance with an improved F1 score of 70.82%. The classification report highlighted a better balance between precision and recall than the first iteration. The F1 score for class 0 improved to 56%, and for class 1, it slightly decreased to 71%, indicating a more even performance across both classes. This iteration showed that tuning the model parameters helped achieve better overall accuracy and balanced the precision-recall trade-off more effectively.

When summarizing the predictive modeling results, the following conclusions can be drawn. First, most models showed overfitting, indicating that the training data was not representative enough for the models to learn the patterns. Another reason could be that the phenomenon is too complex to capture in the dataset size. Additionally, the class imbalance of wins and losses likely impacted model performance as more matches were won. The models also tended to be better suited to predict won matches. Even though many features were available, only the share of overlap and the share of silence seemed to be considered relevant by the models. The same accounted for the rolling features of these two. While hyperparameter tuning improved performance, the gains were only marginal. The XGBoost model showed the best performance in terms of ROC AUC at 0.72, indicating some potential but inability to create reliable results. These points indicate the requirement for more comprehensive data and perhaps different modeling strategies. It is impossible to predict a sequence's outcome reliably with the given communication metrics. Nevertheless, it reinforced the narrative that the share of overlap and the share of silence are highly relevant features.

6 Discussion

When discussing this research's results, the following dimensions are of interest. First, how do these results compare to the current state of research, and how they answer the research questions. Second, it will be explored how reliable these results are and what possible limitations there might be. Lastly, it will evaluate what these results mean for action teams and how this knowledge could be used.

Overall, this research supports the claim from previous research that communication is vital in esports and statistically proves that there is a connection between how teams communicate and the content of that communication matter in the context of performance. This research followed a more holistic approach than previous research by combining different dimensions in the form of timing, content, and mode of conversation, allowing for a deeper insight into communication and its influence on performance in esports, allowing for detailed insight into how communication differs for winning and losing teams. Furthermore, it is shown that the outcomes of 60-second sequences correlate with the outcomes of matches. Since communication also impacts the outcomes of these sequences, optimizing communication increases the chances of winning a sequence, ultimately increasing the chances of winning a match.
As initially stated, there is currently no consensus in research on how speech rate relates to the performance of esports teams. As Tan et al. (2022) claim, there is a clear connection between word frequency and performance, and others, such as Lipovaya et al. (2018) and Musick et al. (2021), state the opposite, with performing teams requiring less communication. The results of this research could not identify a significant relationship between speech rate measured in words per minute and the game outcome as the dimension of performance. However, there was a significant relationship between the share of overlap, the share of silence, and the performance. The findings for the share of silence with its negative impact on performance contradict the results of Abramov et al. (202,2), who stated the opposite. This also counted for the rolling averages of these features. These findings suggest that only a high frequency of communication does not enable teams to win; instead, teams require a constant flow of information via continuous communication to perform better. In essence, teams need a good balance of communication volume for better performance. This hypothesis is supported by Leavitt et al. (2016), who, in their analysis of non-verbal communication, found that a high volume of pings is connected to better-performing teams but that excessive use does not improve performance. The same logic seems to be applicable when discussing verbal communication in LoL. The mentioned share of overlap is denoted as a negative phenomenon that should hinder teams from performing well, according to Hanghøj (2023). This research challenges this claim as the results show a positive relationship between overlapping speech and match outcomes. When approaching this phenomenon from a game-based perspective by thinking where the overlap could occur and why it does, the scenario of quickly collecting agreement or confirmation from the team comes to mind, e.g., when deciding whether to

contest or forfeit an objective in-game. However, this was not analyzed; hence, this theory only requires further study through additional research. Other findings new to the research that this project presents are the relationship between the average volume and share of fill words with sequence outcomes. First, it is shown that a slightly higher average volume positively influences sequence outcomes. Possible explanations here could be that the loudness represents confidence, as players talking louder might have more confidence and are perceived by their teammates as having more confidence, which could help decision-making. This theory is also supported by linguistic research, as confident humans talk louder and faster and are perceived as more confident simultaneously (Jiang & Pell, 2015; Kimble & Seidel, 1991; Scherer et al., 1973).

Regarding the topics the teams discuss, the results align well with the research of von Gillern (2022), as the primary communication is concerned with coordination, strategy, and encouragement, whereas the latter two are an exact match. Commentary on how von Gillern described it could be compared to the information coordination in this research. Overall, this validates the claim that these are the primary topics esports players discuss via verbal communication. Furthermore, it provides statistical evidence that communication content is directly related to the outcome of matches, at least on a team process level. Teams should identify these topics for them as they could be highly individual per team or video game, as Lipoyava et al. (2018) pointed out. Then, they could try to steer their communication to evolve around the positively contributing topics. When considering the emotional aspect, which was identified as highly important by Abramov et al. (2022) and Orlova et al. (2023), it appears that there are helpful mechanisms in place to handle their emotion during games, keeping them in control of them which aligns with Orlova et al. (2023). This expresses itself in two ways. First, the topic of mistakes is more present in wins, suggesting that the players can quickly and objectively discuss mistakes and learn from them. If the players are not in control of their emotions, this could lead to irritation during such a process influencing performance. However, it appears that while it works for mistakes, it is not yet consistent. Since the topic of affect management, i.e., handling emotion, is very present in winning matches, its impact is more prominent in losses, suggesting that its impact is higher in losses, which indicates that the players can lose control of their emotions in matches where they are losing impacting their performance. Hence, teams should pay close attention to this and find solutions for reliable affect management if they discover that it does not always work. This research also explains how this negative emotion in losses expresses itself. The data shows that the average share of silence deviates in losses the most from around the 20th minute. So, the state of the game influences emotion, which influences communication, resulting in less information being shared. In the case of this data set, most matches were around 30 minutes long, which aligns with the average length of matches in LoL (Eaton et al., 2018). This suggests that the players may already know they are very likely to lose the game and see no point in keeping up their communication efforts. Furthermore, the 20th-minute mark seems to be a critical phase in LoL matches. All communication metrics, especially the most relevant ones in the share of overlap and silence, showed more considerable differences for wins and losses.

In the sequence analysis that was inspired by the research of Tan et al. (2022), it is shown that there are sequences of game-specific topics or team processes that are more likely to appear as wins or losses. For example, the sequence of “Combat Strategies”, “Combat Strategies”, “Combat Strategies” is only present in wins, while the sequences of “Objectives”, “Objectives”, “Objectives” correlates more with losses. This highlights that overemphasis can have positive as well as negative impacts and that it is highly context-specific. Another finding is that in most sequences for either outcome, “Information Sharing” is highly present, highlighting that information sharing alone does not have an impact, but the strategic use of it creates the difference. Lastly, the combination of “Coordination” and “Strategy formulation” is very dominant in wins, underscoring the importance of dynamic strategic planning and execution, which are directly connected to outcomes in games.

Regarding using communication as a feature for predictive modeling, this research shows that the concept has potential, with some models being able to pick up on patterns that indicate game states. The modeling process yielded feature importances that reinforced the importance of share of overlap and share of silence as the most informative metrics. The content related features in the form of the dominant topic or the team primary team process did not have a meaningful value to the algorithms. With the XGBoost showing the most potential currently, further research could aim to identify new modeling approaches that yield more reliable predictions. Possible adjustments evolve around using a more balanced dataset as this data set contained more wins than losses. This explains the tendency of overfitting and the model's tendency to have many false positives for wins where they were actually losses.
Furthermore, the range of features was limited because the audio was mono, and all players were on the same audio track, which did not allow to get rid of overlapped speech. In this case, it would have falsified the results. In a new setup, the players could all individually record their audio, allowing for more detailed insights into turn-taking share of speech distribution for players and then combining it with metadata such as roles to explore which roles tend to contribute to communication. Overall, slightly better audio quality would also improve the transcription, giving even more insight into the topics discussed and possibly allowing for emotion classification. Emotion classification should provide a lot of information about the game, as it was already established that emotion is tightly connected to performance, as identified by Abramov et al. (2022) and Orlova et al. (2023).

The following arguments can be presented when critically evaluating the relevancy and reliability of these results. First, esports is a highly complex environment, and communication is only a subpart. In terms of LoL, other aspects such as the actual gameplay in the form of mouse clicks and keyboard strokes, the decision-making of the individual player, team cohesion, player health and well-being, and many more factors influence the performance. Hence, the minor differences in the metrics might not have a noticeable impact. Furthermore, the metrics in the form of a share of overlap, etc., only provide a quantitative look at communication and might not be able to provide complete insight into performance and how it is influenced. These metrics do not consider other influences, such as content, timing, and context, such as game state. However, this research analyzed communication more holistically, and the content and the timings were analyzed, making it a more reliable metric when put into a broader context. Arguments that underline the value of the results are relevant, such as the high level of play in LoL or the high level of performance in any other sports. In such environments, minor things can decide outcomes. Hence, athletes try to optimize all parts of their craft to achieve small advantages that can help them succeed. There are examples from different sports, such as cycling or race walking, with further studies suggesting that the concept can be applied in many more sports and also applicable in esports (Cazzola et al., 2016; McParland et al., 2020; Patel, 2016; Pentecost et al., 2018). Additionally, improved communication might have other positive side effects, such as better team cohesion, leading to better performance (Rambusch et al., 2007; Tan et al., 2022).

When considering the generalizability of the derived insights, a few generally qualify for application in other action teams that shared traits with esport teams. In high-performing action teams in time-critical operations, the following insights should also apply. They should prioritize a consistent information flow by minimizing episodes of silence. Also, they should explore intentional speech overlap in scenarios where it can be beneficial, e.g., confirming a decision or acknowledging information. This could help in speeding up the decision-making process. However, each team needs to identify if such a strategy fits the conditions under which they operate and what scenarios suit such a utilization. It requires extensive validation and testing of these findings as for other action teams the consequences of bad communication can be more severe than they are for LoL.

6.1 Theoretical Implications

This research contributes to the current knowledge in esports research by validating existing knowledge, challenging the current status quo, and opening new discussions for phenomena that have not been discovered yet. First, this research shows that communication can be quantified and that these quantified metrics allow communication and match outcomes to connect. This presents a new perspective for future research, as this has not been performed yet. These quantified metrics open a new discussion on overlapped speech as it is presented as a positive phenomenon. The same accounts for silent episodes in esports communication as they are related to negative outcomes. These new insights allow for a discussion of whether they are generally applicable or specific to LoL or even just the teams that were part of this project. Similar to the identified relationship between communication metrics and game outcomes, it was shown that the content of discussion amongst the players also matters, with specific topics being very informative about the game state. Next, it gives rare insight into the communication of professional teams, providing an opportunity for comparison with amateurs. In terms of existing research, it validated existing knowledge about the topics of esports communication, sequences, and modes. Overall, it creates new impulses that can spark new discussions, resulting in new research by either researching different games to determine generalizability across the same domain or cross-validating it in different domains of similar characteristics, ultimately generating new knowledge. But not only the generalizability and validation offers new research opportunity, the results also offer the opportunity to dive deeper into things such as communication in relation to game state connected to location within the game. The failed emotion classification also provides additional possibilities to extend the current research to see how sequences, or topics are tied to communication or game states or both at the same time.

6.2 Practical Implications

This research highlights the crucial role of communication in esports team performance. Teams are encouraged to actively engage in refining their communication strategies. A key aspect is acknowledging the importance of seamless communication, which is as vital as gameplay skills. Teams should work on enforcing positive overlap in conversations during strategic planning to ensure a quick and efficient exchange of information. Minimizing silent intervals to maintain a steady flow of critical updates among team members is equally important. Notably, the findings pinpoint the 20th-minute mark as pivotal in matches. Teams can benefit from scrutinizing communication patterns during this period to adjust and optimize their strategies, improving their chances of success in crucial game phases. By implementing these targeted communication practices, teams can enhance their coordination and overall game performance.

6.3 Limitations

This research navigates several constraints that could impact the interpretation and applicability of its findings. One significant limitation stems from the relatively small dataset used, which exhibited signs of overfitting, potentially limiting the generalizability of our predictive models. The data quality also restricted the number of features we could accurately analyze, such as speaker diarization and turn-taking, due to overlapping speech and the absence of emotion classification. These issues challenge the depth of our communication analysis. Furthermore, the marginal differences in metrics between winning and losing sessions raise questions about the practical impact of our findings. There is also a concern that the insights may be specific to LoL, as prior research indicates that communication strategies might not be universally applicable across different games (Lipovaya et al., 2018). Additionally, the analysis of WPM was hindered by overlapping speech, affecting the accuracy of this metric's correlation with team performance. Aside from the content related limitations there are also technical limitations to be considered. While the evaluation via large language models is seen as potent it is not fully sufficient yet and resaerch still lacks consensus on its quality. Additionally, as pointed out in the data collection chapter the pyannote library used for overlapping speech has its limiations that could partially falsify the results of the transcription as a consequence impact the conclusions drawn from the data. These limitations highlight the need for a cautious approach in applying these results beyond the specific context of this study

7 Conclusion

This research has contributed to understanding communication within esports, particularly in the context of professional LoL teams. In regards to the first research question:

- **How do communication metrics such as speech rate, share of silence, average volumne, share of fillwords and share of overlap relate to team performance in professional esports, and how can these metrics inform strategies for optimizing team coordination and success?**

This study has validated and extended existing knowledge in esports research by incorporating a multifaceted approach that analyzed communication sequences, timing, and content. Firstly, the findings of this study have underscored the critical role of communication dynamics in influencing team performance. Notably, aspects such as the share of overlap and silence within team communication have shown substantial implications for match outcomes, suggesting that effective communication is just as critical as strategic gameplay. These results resonate with the high-performance standards seen in other sports and highlight unique elements pertinent to esports.

Moreover, this research has challenged existing paradigms by providing new insights into the effects of speech volume and overlap, suggesting that louder, more confident communication may positively affect team performance. This aligns with linguistic research supporting that speech characteristics can influence perceptions of confidence and leadership within teams. Furhtermore, it challenged existing findings that suggest that silence and less communciation is favorable while this reasearch showed that increased amount of silence is bad for performance. The analysis of communication sequences provided novel insights into the strategic use of information sharing and coordination, especially in the patterns that differentiate winning from losing scenarios. This adds a layer of strategic depth to communication studies in esports, illustrating that the amount and type of communication matters critically in high-stakes matches. The practical implications of this research are profound for esports teams and coaches. The study offers concrete strategies to optimize communication—focusing on critical match moments like the 20th minute, enhancing information flow, and strategically utilizing overlaps in speech to enhance team cohesion and response times.

When answering the second research question

- **How can metrics such as speech rate, share of silence, average volumne, share of fillwords, share of overlap paired with content topics be used to predict match outcomes in professional esports, and what communication patterns are most indicative of a team's likelihood to win or lose?**

The the following conclusions can be made. This research demonstrates the potential of using communication for predictive modeling, with certain models identifying patterns indicative of game states. Feature importances highlighted the significance of share of overlap and share of silence as the most informative metrics. However, content-related features like the dominant topic or primary team process were not valuable to the algorithms. XGBoost showed the most promise, suggesting further research should explore new modeling approaches for more reliable predictions. Adjustments could include using a more balanced dataset, as the current one had more wins than losses, leading to overfitting and false positives. The range of features was limited by mono audio, with all players on the same track, which prevented accurate separation of overlapped speech. Future setups could involve individual audio recordings for players, providing detailed insights into turn-taking and speech distribution, combined with metadata such as roles to explore communication contributions. Improved audio quality would enhance transcription accuracy, offering deeper insights into discussed topics and enabling emotion classification. The latter one was recognized as important feature in performance prediction in previous research.

Finally, the limitations noted, such as the dataset size and its specific focus on LoL—highlight the necessity for further research to generalize these findings across different games and larger sample sizes. This research paves the way for future investigations into the intricate balance of communication and game strategy, potentially influencing training routines and competitive tactics in the professional esports industry. Overall, this thesis not only extends the academic understanding of communication's role in esports but also provides practical frameworks that can be applied to enhance team performance across competitive gaming environments.

8 Bibliography

Abramov, S., Korotin, A., Somov, A., Burnaev, E., Stepanov, A., Nikolaev, D., & Titova, M. A. (2022). Analysis of Video Game Players' Emotions and Team Performance: An Esports Tournament Case Study. *IEEE Journal of Biomedical and Health Informatics*, *26*(8), 3597–3606. IEEE Journal of Biomedical and Health Informatics. https://doi.org/10.1109/JBHI.2021.3119202

Agarwal, A., Priyadarshi, P., Sinha, S., Gupta, S., Jangra, H., Kumaraguru, P., & Garimella, K. (2024). Television Discourse Decoded: Comprehensive Multimodal Analytics at Scale. *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 4752–4763. https://doi.org/10.1145/3637528.3671532

Bányai, F., Griffiths, M. D., Király, O., & Demetrovics, Z. (2019). The Psychology of Esports: A Systematic Literature Review. *Journal of Gambling Studies*, *35*(2), 351–365. https://doi.org/10.1007/s10899-018-9763-1

Berente, N., Seidel, S., & Safadi, H. (2019). Research Commentary—Data-Driven Computationally Intensive Theory Development. *Information Systems Research*, *30*(1), 50–64. https://doi.org/10.1287/isre.2018.0774

Bergstra, J., & Bengio, Y. (2012). Random Search for Hyper-Parameter Optimization. *J. Mach. Learn. Res.*, *13*, 281–305. https://doi.org/10.5555/2503308.2188395

Bhatt, C. M., Patel, P., Ghetia, T., & Mazzeo, P. (2023). Effective Heart Disease Prediction Using Machine Learning Techniques. *Algorithms*, *16*. https://doi.org/10.3390/a16020088

Bredin, H., Yin, R., Coria, J. M., Gelly, G., Korshunov, P., Lavechin, M., Fustes, D., Titeux, H., Bouaziz, W., & Gill, M.-P. (2020). Pyannote.Audio: Neural Building Blocks for Speaker Diarization. *ICASSP 2020 - 2020 IEEE International Conference on Acoustics,* *Speech and Signal Processing (ICASSP)*, 7124–7128. https://doi.org/10.1109/ICASSP40776.2020.9052974

Cantallops, M. M., & Sicilia, M. (2018). Exploring player experience in ranked LoL. *Behaviour & Information Technology*, *37*, 1224–1236. https://doi.org/10.1080/0144929X.2018.1492631

Cao, H., Cooper, D. G., Keutmann, M. K., Gur, R. C., Nenkova, A., & Verma, R. (2014). CREMA-D: Crowd-sourced Emotional Multimodal Actors Dataset. *IEEE Transactions on Affective Computing*, *5*(4), 377. https://doi.org/10.1109/TAFFC.2014.2336244

Cazzola, D., Pavei, G., & Preatoni, E. (2016). Can coordination variability identify performance factors and skill level in competitive sport? The case of race walking. *Journal of Sport and Health Science*, *5*, 35–43. https://doi.org/10.1016/j.jshs.2015.11.005

Chaurasia, V., & Pal, S. (2020). Applications of Machine Learning Techniques to Predict Diagnostic Breast Cancer. *SN Computer Science*, *1*. https://doi.org/10.1007/s42979-020-00296-8

Cheung, V., Chang, Y.-L. B., & Scott, S. D. (2012). Communication channels and awareness cues in collocated collaborative time-critical gaming. *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, 569–578. https://doi.org/10.1145/2145204.2145291

Chuang, J., Gupta, S., Manning, C. D., & Heer, J. (n.d.). *Topic Model Diagnostics:Assessing Domain Relevance via Topical Alignment*.

Dehghani, M., & Manthouri, M. (2021). Semi-automatic Detection of Persian Stopwords using FastText Library. *2021 11th International Conference on Computer Engineering and Knowledge (ICCKE)*, 267–271. https://doi.org/10.1109/ICCKE54056.2021.9721519

Dulebohn, J. H., & Hoch, J. E. (2017). Virtual teams in organizations. *Human Resource Management Review*, *27*(4), 569–574. https://doi.org/10.1016/j.hrmr.2016.12.004

Eaton, J., Mendonça, D., & Sangster, M.-D. D. (2018). Attack, Damage and Carry: Role Familiarity and Team Performance in LoL. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *62*, 130–134. https://doi.org/10.1177/1541931218621030

Ebrahimi, H., Yarahmadi, R., Moghadam, S. M. K., Malekpour, F., Nasezadeh, Z., Taheri, E., & Mohammadian, Y. (2020). Investigating the status of prevention of coronavirus in industries. *Salāmat-i Kār-i Īrān*, *17*(1), 1–8.

Esports Charts. (n.d.). *LoL Esports Tournaments Statistics for 2023*. Retrieved December 12, 2023, from https://escharts.com/tournaments/lol

Ferraro, A., Galli, A., Gatta, V. L., & Postiglione, M. (2023). Benchmarking open source and paid services for speech to text: An analysis of quality and input variety. *Frontiers in Big Data*, *6*. https://doi.org/10.3389/fdata.2023.1210559

Freeman, G., & Wohn, D. Y. (2019). Understanding eSports Team Formation and Coordination. *Computer Supported Cooperative Work (CSCW)*, *28*(1), 95–126. https://doi.org/10.1007/s10606-017-9299-4

Gallagher, R. J., Reing, K., Kale, D., & Ver Steeg, G. (2017). Anchored Correlation Explanation: Topic Modeling with Minimal Domain Knowledge. *Transactions of the Association for Computational Linguistics*, *5*, 529–542. https://doi.org/10.1162/tacl_a_00078

Gervits, F., Eberhard, K., & Scheutz, M. (2016). Team Communication as a Collaborative Process. *Frontiers in Robotics and AI*, *3*. https://www.frontiersin.org/articles/10.3389/frobt.2016.00062

Hanghøj, T., Höper, R., Rudberg, T., & Steensen, E. (2023). *Pre-print draft "We have to talk together": Addressing communicative challenges among amateur esport players*.

Heller, R. (2010). *A Cost-Benefit Analysis of Face-to-Face and Virtual Communication: Overcoming the Challenges*. https://hdl.handle.net/1813/73711

Hollenbeck, J. R., Beersma, B., & Schouten, M. E. (2012). Beyond Team Types and Taxonomies: A Dimensional Scaling Conceptualization for Team Description. *Academy of Management Review*, *37*(1), 82–106. https://doi.org/10.5465/amr.2010.0181

Hoyle, A., Goel, P., Hian-Cheong, A., Peskov, D., Boyd-Graber, J., & Resnik, P. (2021). Is Automated Topic Model Evaluation Broken? The Incoherence of Coherence. *Advances in Neural Information Processing Systems*, *34*, 2018–2033. https://proceedings.neurips.cc/paper/2021/hash/0f83556a305d789b1d71815e8ea4f4b0-Abstract.html

Hüllmann, J. A. (2023). Digital Traces as Measurement Instruments for Variance Theoretic Research in Information Systems. In Wurm, B., & Mendling, J. (Eds.), Digital Trace Data Research in Information Systems: Foundations, Methods, and Applications.

Ishak, A. W., & Ballard, D. I. (2012). Time to Re-Group: A Typology and Nested Phase Model for Action Teams. *Small Group Research*, *43*(1), 3–29. https://doi.org/10.1177/1046496411425250

Jiang, X., & Pell, M. (2015). On how the brain decodes vocal cues about speaker confidence. *Cortex*, *66*, 9–34. https://doi.org/10.1016/j.cortex.2015.02.002

Joy, T. T., Rana, S., Gupta, S., & Venkatesh, S. (2019). A flexible transfer learning framework for Bayesian optimization with convergence guarantee. *Expert Syst. Appl.*, *115*, 656–672. https://doi.org/10.1016/j.eswa.2018.08.023

Karakuş, K. (2022). Espor Oyuncularının Sporcu Kimlikleri ile Etkili İletişim Düzeyleri Arasındaki İlişkinin İncelenmesi. *Akdeniz Spor Bilimleri Dergisi*, *5*(2), Article 2. https://doi.org/10.38021/asbid.1117316

Kim, Y. J., Engel, D., Woolley, A. W., Lin, J. Y.-T., McArthur, N., & Malone, T. W. (2017). What Makes a Strong Team? Using Collective Intelligence to Predict Team Performance in LoL. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 2316–2329. https://doi.org/10.1145/2998181.2998185

Kimble, C., & Seidel, S. (1991). Vocal signs of confidence. *Journal of Nonverbal Behavior*, *15*, 99–105. https://doi.org/10.1007/BF00998265

Klein, K. J., Ziegert, J. C., Knight, A. P., & Xiao, Y. (2006). Dynamic Delegation: Shared, Hierarchical, and Deindividualized Leadership in Extreme Action Teams. *Administrative Science Quarterly*, *51*(4), 590–621. https://doi.org/10.2189/asqu.51.4.590

Kokkinakis, A., Demediuk, S., Nölle, I., Olarewaju, O., Patra, S., Robertson, J., York, P., Chitayat, A., Coates, A., Slawson, D., Hughes, P., Hardie, N., Kirman, B., Hook, J., Drachen, A., Ursu, M., & Block, F. (2020). DAX: Data-Driven Audience Experiences in Esports. *ACM International Conference on Interactive Media Experiences*. https://doi.org/10.1145/3391614.3393659

Koutini, K., Eghbalzadeh, H., & Widmer, G. (2021). Receptive Field Regularization Techniques for Audio Classification and Tagging With Deep Convolutional Neural Networks. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *29*, 1987–2000. https://doi.org/10.1109/TASLP.2021.3082307

Krenz, H. L., & Burtscher, M. J. (2021). Investigating voice in action teams: A critical review. *Cognition, Technology & Work*, *23*(3), 605–624. https://doi.org/10.1007/s10111-020-00646-9

Leavitt, A., Keegan, B., & Clark, J. A. (2016). Ping to Win?: Non-Verbal Communication and Team Performance in Competitive Online Multiplayer Games. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/2858036.2858132

Lipovaya, V., Lima, Y., Grillo, P., Barbosa, C. E., de Souza, J. M., & Duarte, F. J. de C. M. (2018). *Coordination, Communication, and Competition in eSports: A Comparative Analysis of Teams in Two Action Games*. https://doi.org/10.18420/ECSCW2018_11

Ma, Y., Hao, Y., Chen, M., Chen, J., Lu, P., & Košir, A. (2019). Audio-visual emotion fusion (AVEF): A deep efficient weighted approach. *Inf. Fusion*, *46*, 184–192. https://doi.org/10.1016/j.inffus.2018.06.003

Mahlmann, T., Schubert, M., & Drachen, A. (2016). *Esports Analytics Through Encounter Detection*.

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A Temporally Based Framework and Taxonomy of Team Processes. *Academy of Management Review*, *26*(3), 356–376. https://doi.org/10.5465/amr.2001.4845785

McParland, A., Ackery, A., & Detsky, A. (2020). Advanced analytics to improve performance: Can healthcare replicate the success of professional sports? *BMJ Quality & Safety*, *29*, 405–408. https://doi.org/10.1136/bmjqs-2019-010415

Meng, T., Shou, Y., Ai, W., Yin, N., & Li, K. (2023). *Deep Imbalanced Learning for Multimodal Emotion Recognition in Conversations* (arXiv:2312.06337). arXiv. https://doi.org/10.48550/arXiv.2312.06337

Miranda, S., Berente, N., Seidel, S., Safadi, H., & Burton-Jones, A. (2022). Computationally Intensive Theory Construction: A Primer for Authors and Reviewers. *MIS Quarterly*, *46*.

Musick, G., Zhang, R., McNeese, N. J., Freeman, G., & Hridi, A. P. (2021). Leveling Up Teamwork in Esports: Understanding Team Cognition in a Dynamic Virtual Environment. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW1), 49:1-49:30. https://doi.org/10.1145/3449123

Neus, F., Nimmermann, F., Wagner, K., & Schramm-Klein, H. (2019). *Differences and Similarities in Motivation for Offline and Online eSports Event Consumption*. 1–10. https://doi.org/10.1007/978-3-658-29262-1_6

Orlova, J., Stepanov, A., Vinogradov, A., Orlova, L., Baldycheva, A., & Somov, A. (2023). Analysis of Latent Factors Affecting Video Game Performance Using Machine Learning Methods. *2023 IEEE 32nd International Symposium on Industrial Electronics (ISIE)*, 1–6. https://doi.org/10.1109/ISIE51358.2023.10228159

Panteli, N., & Fineman, S. (2005). The sound of silence: The case of virtual team organising. *Behaviour & Information Technology*, *24*(5), 347–352. https://doi.org/10.1080/01449290512331335618

Parisi, J. A., & Brungart, D. S. (2005). *Evaluating communication effectiveness in team collaboration*. 1569–1572. https://doi.org/10.21437/Interspeech.2005-459

Patel, R. (2016). When I say … aggregation of marginal gains. *Medical Education*, *50*, 709–710. https://doi.org/10.1111/medu.12970

Pentecost, C., Richards, D. A., & Frost, J. (2018). Amalgamation of Marginal Gains (AMG) as a potential system to deliver high-quality fundamental nursing care: A qualitative analysis of interviews from high-performance AMG sports and healthcare practitioners.

Journal of Clinical Nursing, *27*(11–12), 2387–2402. https://doi.org/10.1111/jocn.14186

Precedence Research. (2023, January 8). *Video Game Market Size To Attain USD 610.6 Billion By 2032*. https://www.precedenceresearch.com/video-game-market

Railsback, D., & Caporusso, N. (2018). Investigating the Human Factors in eSports Performance. *Advances in Human Factors in Wearable Technologies and Game Design*. https://doi.org/10.1007/978-3-319-94619-1_32

Rambusch, J., Jakobsson, P., & Pargman, D. (2007). *Exploring E-sports: A case study of game play in Counter-strike*. *4*, 157–164. https://urn.kb.se/resolve?urn=urn:nbn:se:his:diva-1463

Rathje, S., Mirea, D.-M., Sucholutsky, I., Marjieh, R., Robertson, C. E., & Van Bavel, J. J. (2024). GPT is an effective tool for multilingual psychological text analysis. *Proceedings of the National Academy of Sciences*, *121*(34), e2308950121. https://doi.org/10.1073/pnas.2308950121

Reitman, J. (2018). Distributed Cognition and Temporal Knowledge in LoL. *International Journal of Gaming and Computer-Mediated Simulations*, *10*, 23–41. https://doi.org/10.4018/IJGCMS.2018010102

Reitman, J. G., & Steinkuehler, C. (2021). *Esports and Domain General Research for High Performance Teams*. https://doi.org/10.31219/osf.io/zd9wq

Ryu, Y., Hwang, H., Jeong, J., Jang, W., Lee, G., & Pyun, H. (2023). Missed a live match? Determinants of LoL Champions Korea highlights viewership. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1213600

Sapienza, A., Zeng, Y., Bessi, A., Lerman, K., & Ferrara, E. (2018). Individual performance in team-based online games. *Royal Society Open Science*, *5*. https://doi.org/10.1098/rsos.180329

Scherer, K., London, H., & Wolf, J. (1973). The voice of confidence: Paralinguistic cues and audience evaluation. *Journal of Research in Personality*, *7*, 31–44. https://doi.org/10.1016/0092-6566(73)90030-5

Shi, R., & Chen, T. (2022). Emotion Detection with Deep Neural Network and Contrastive Learning. *2022 14th International Conference on Computer Research and Development (ICCRD)*, 83–93. https://doi.org/10.1109/ICCRD54409.2022.9730257

Smith, M. J., Birch, P. D. J., & Bright, D. (2019). Identifying Stressors and Coping Strategies of Elite Esports Competitors. *International Journal of Gaming and Computer-Mediated Simulations (IJGCMS)*, *11*(2), 22–39. https://doi.org/10.4018/IJGCMS.2019040102

Talafha, B., Waheed, A., & Abdul-Mageed, M. (2023). N-Shot Benchmarking of Whisper on Diverse Arabic Speech Recognition. *ArXiv*, *abs/2306.02902*. https://doi.org/10.48550/arXiv.2306.02902

Tan, E. T. S., Rogers, K., Nacke, L. E., Drachen, A., & Wade, A. (2022). Communication Sequences Indicate Team Cohesion: A Mixed-Methods Study of Ad Hoc LoL Teams. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CHI PLAY), 225:1-225:27. https://doi.org/10.1145/3549488

Terminology (LoL). (2024, June 7). LoL Wiki. https://leagueoflegends.fandom.com/wiki/Terminology_(League_of_Legends)

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the Qualitative-Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems. *MIS Quarterly*, *37*(1), 21–54.

von Gillern, S. (2021). *Communication, Cooperation, and Competition: Examining the Literacy Practices of Esports Teams* (pp. 148–167). https://doi.org/10.4018/978-1-7998-7069-2.ch009

Whitaker, L. A., Fox, S. L., & Peters, L. J. (1993). Communication between Crews: The Effects of Speech Intelligibility on Team Performance. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *37*(9), 630–634. https://doi.org/10.1177/154193129303700925

Xu, B., Tao, C., Feng, Z., Raqui, Y., & Ranwez, S. (2021). A Benchmarking on Cloud based Speech-To-Text Services for French Speech and Background Noise Effect. *ArXiv*, *abs/2105.03409*. https://consensus.app/papers/benchmarking-cloud-based-speechtotext-services-french-xu/0e393830d7b455cd9bbd1caa3726afc1/

Xu, D., & Jaggars, S. S. (2014). Performance Gaps between Online and Face-to-Face Courses: Differences across Types of Students and Academic Subject Areas. *The Journal of Higher Education*, *85*(5), 633–659. https://doi.org/10.1080/00221546.2014.11777343

Yadavendra, S. C. (2020). A comparative study of breast cancer tumor classification by classical machine learning methods and deep learning method. *Machine Vision and Applications*, *31*. https://doi.org/10.1007/s00138-020-01094-1

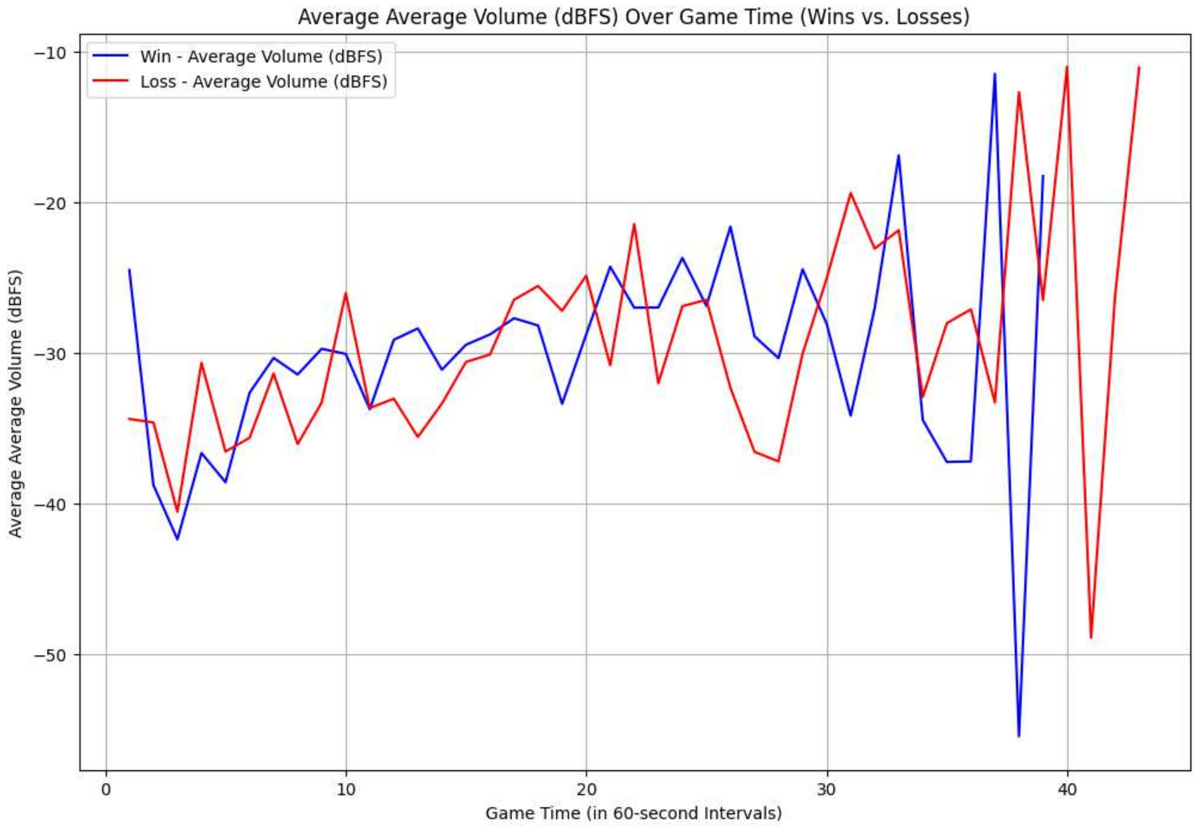
9 Appendix

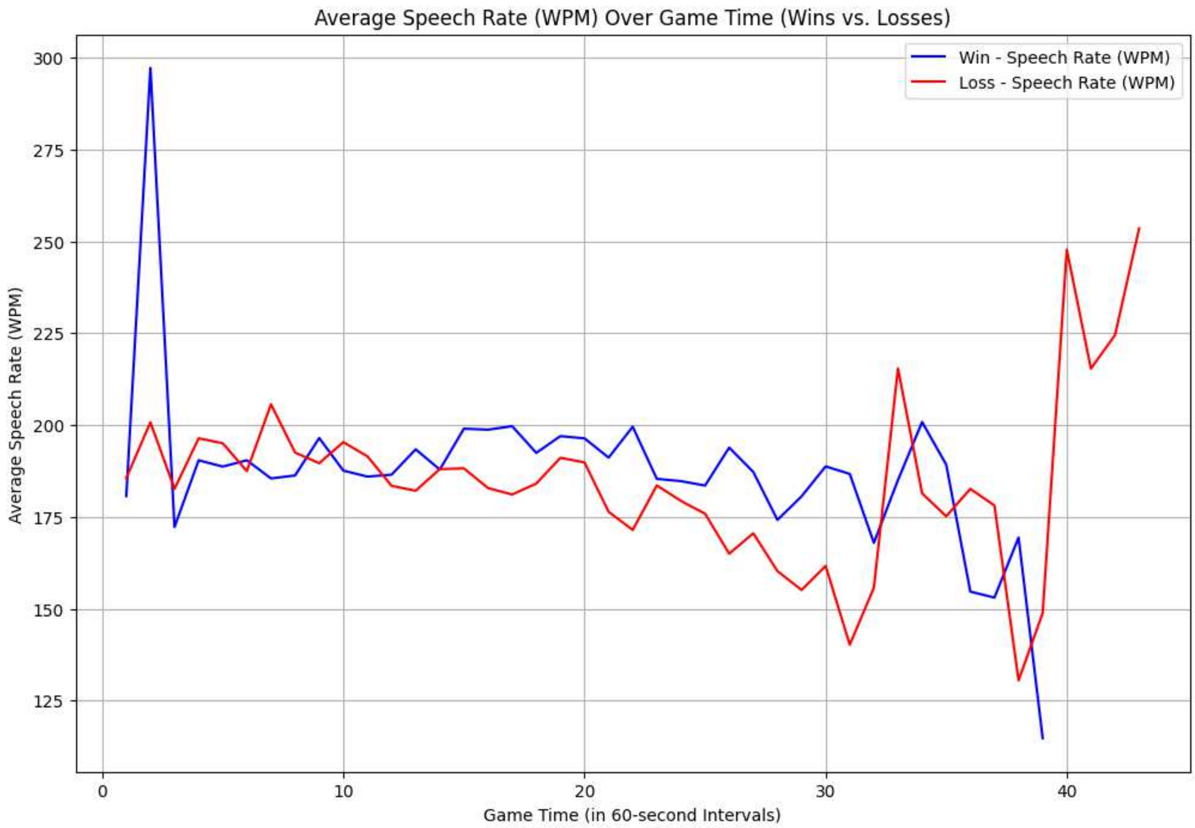
Appendix A

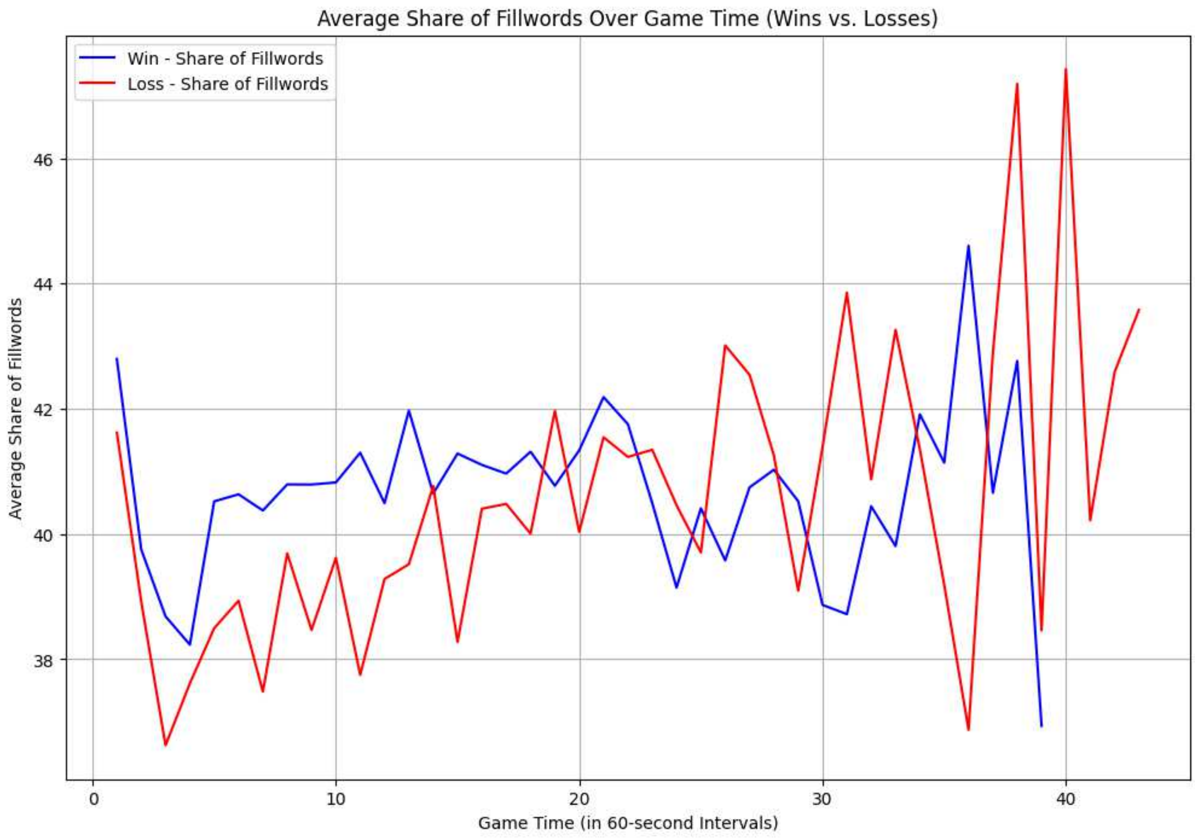
Category	Keywords
Agreement/Confirmation	yeah, yes, okay, alright, sure, right, exactly, absolutely, definitely, of_course
Objectives	dragon, tower, baron, nashor, herald, inhibitor, turret, base, objective, buff
Information Sharing	base, wave, ult, flash, cooldown, back, recall, push, rotate, gank
Encouragement	good, nice, well_done, great, awesome, excellent, fantastic, amazing, well_played, superb
Location Specification	bot, top, mid, jungle, lane, river, bush, ward, blue side, red side
Gameplay Strategy	gank, engage, disengage, fight, battle, skirmish, contest, invade, dive, peel
Farming/Economy	cs, farm, gold, item, build, minions, jungle camps, last hit, economy, scaling
Vision Control	ward, vision, sight, reveal, map, deward, sweeper, pink ward, trinket, fog of war
Types of Engagements	teamfight, duel, clash, engage, disengage, poke, all_in, trade, burst, combo
Roles/Positions	adc, support, jungler, mid_laner, top_laner, carry, tank, assassin, mage, bruiser
Game Updates	nerf, buff, patch, update, balance, rework, meta, tier_list, viable, op
Game Conclusion	gg, wp, next, rematch, defeat, victory, lose, win, surrender, ff
Champion and Abilities	champion, ability, skill, passive, active, cooldown, ultimate, q ability, w ability, e ability
Combat Strategies	poke, harass, all in, trade, burst, zone, kite, cc, root, stun
Defensive Actions	save, peel, protect, heal, shield, rescue, sustain, buff, revive, disengage

Mistakes	mistake, error, blunder, throw, caught, overextend, misplay, fault, punish, capitalize
Objective Control	steal, secure, contest, deny, capture, baron steal, smite fight, objective control, dragon steal, nashor secure
Macro Strategies	split push, siege, backdoor, stall, freeze, slow push, lane swap, 1 3 1, 4 1, pressure
Tactical Moves	flank, dive, collapse, cut_off, surround, pinch, engage, backstab, ambush, pincer
Game Phases/Status	carry, fed, scaling, snowball, late game, early game, mid game, power spike, item power, level advantage

Appendix B


Average Average Volume (dBFS) Over Game Time (Wins vs. Losses)
Win - Average Volume (dBFS)
Loss - Average Volume (dBFS)
Average Average Volume (dBFS)
−10
−20
−30
−40
−50
0
10
20
30
40
Game Time (in 60-second Intervals)


Average Speech Rate (WPM) Over Game Time (Wins vs. Losses)
Win - Speech Rate (WPM)
Loss - Speech Rate (WPM)
Average Speech Rate (WPM)
300
275
250
225
200
175
150
125
0
10
20
30
40
Game Time (in 60-second Intervals)


Average Share of Fillwords Over Game Time (Wins vs. Losses)
Win - Share of Fillwords
Loss - Share of Fillwords
Average Share of Fillwords
Game Time (in 60-second Intervals)
46
44
42
40
38
0
10
20
30
40

Appendix C

Category	Topic/Category	Wins (Residual)	Losses (Residual)	Association with Outcome
Dominant_Topic	Agreement/Confirmation	-0.434	0.555	Slightly more with Losses
	Champions and Abilities	0.854	-1.093	Strongly with Wins
	Combat Strategies	0.103	-0.132	No strong association
	Defensive Actions	-0.881	1.127	Strongly with Losses
	Encouragement	0.158	-0.203	No strong association
	Farming/Economy	-2.062	2.638	Strongly with Losses
	Game Conclusion/Results	0.082	-0.105	No strong association
	Game Phases/Status	0.428	-0.548	No strong association
	Game Updates	1.134	-1.451	Strongly with Wins
	Gameplay Strategy	-0.519	0.664	No strong association
	Information Sharing	1.144	-1.464	Strongly with Wins
	Location Specification	0.165	-0.211	No strong association
	Macro Strategies	0.012	-0.015	No strong association
	Mistakes	1.218	-1.558	Strongly with Wins
	Objective Control	-0.335	0.428	No strong association

	Objectives	0.734	-0.939	Strongly with Wins
	Roles/Positions	0.136	-0.174	No strong association
	Tactical Moves	-1.699	2.174	Strongly with Losses
	Types of Engagements	-1.501	1.921	Strongly with Losses
	Vision Control	-0.244	0.312	No strong association
Higher_Level_Category	Affect Management	-1.334	1.707	Strongly with Losses
	Conflict Management	0.901	-1.153	Strongly with Wins
	Coordination	1.019	-1.304	Strongly with Wins
	Motivation and Confidence Building	0.176	-0.225	No strong association
	Strategy Formulation	-0.422	0.540	No strong association
	Team Monitoring and Backup Behavior	-0.742	0.949	Strongly with Losses