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Measuring the Performance of MOBA players through their in-game tasks

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"A true master is an eternal student."
- Master Yi, League of Legends

Abstract

The research in the MOBA gaming field has expanded alongside the genre's growing popularity. This growth is driven by the increasing availability of data and the capabilities of analyzing complex and unique gaming scenarios. These developments are particularly pronounced in the eSports domain, where data undergoes rigorous scrutiny by the gaming community.

In MOBA games, players are characterized by their roles, each with specific tasks that are expected to be fulfilled. However, the performance analysis of MOBA players often relies on generic metrics that are universally applied across all player-roles and weighted equally. This omission can lead to an incomplete or potentially unfair evaluation of performance, as these actions' unique contributions and impacts on match outcomes are not adequately accounted for.

To address this limitation, this study aims to analyze players' behavior by focusing on specific tasks in their designated roles. By examining both Commitment and Compliance, this approach enables a more nuanced observation of individual gameplay aspects and facilitates a detailed assessment of player performance.

Commitment is a metric designed to measure a player's engagement with the game. The metric is determined through a multi-stage process, utilizing unsupervised and supervised machine learning approaches to determine the Commitment levels to respective data groups. Compliance, on the other hand, considers the Commitment levels obtained from player data, along with the team's strategy, to calculate the assertiveness of players' and team performance.

The obtained results validate the use of Commitment per Task metric as an evaluation of player engagement, as well as the effectiveness of Commitment levels and Compliance in assessing performance, predicting match outcomes, and providing gameplay improvement suggestions.

Key-words: MOBA, League of Legends, Player Commitment, Player Compliance Player Performance, Player-Role, Data Science, Machine Learning, eSports, Game Analytics

Resumo

A pesquisa no campo dos jogos MOBA tem se expandido juntamente com a crescente popularidade do gênero. Esse crescimento é impulsionado pela maior disponibilidade de dados e pela capacidade de analisar cenários de jogo complexos e singulares. Esses avanços são particularmente evidentes no domínio dos eSports, onde os dados são submetidos a análises rigorosas pela comunidade de jogadores.

Nos jogos MOBA, os jogadores são caracterizados por suas funções, cada uma com tarefas específicas a serem cumpridas. No entanto, a análise de desempenho dos jogadores de MOBA frequentemente se baseia em métricas genéricas, aplicadas universalmente a todas as funções e ponderadas igualmente. Essa omissão pode resultar em uma avaliação incompleta ou potencialmente injusta do desempenho, pois as contribuições e os impactos únicos dessas ações no desfecho da partida não são devidamente considerados.

Para solucionar essa limitação, este estudo busca analisar o comportamento dos jogadores com foco em tarefas específicas de suas funções designadas. Ao examinar tanto o Comprometimento quanto a Conformidade, essa abordagem permite uma observação mais detalhada dos aspectos individuais do jogo e viabiliza uma avaliação mais precisa do desempenho dos jogadores.

O Comprometimento é uma métrica desenvolvida para medir o engajamento do jogador com o jogo. Sua determinação ocorre por meio de um processo em múltiplas etapas, utilizando abordagens de aprendizado de máquina supervisionado e não-supervisionado para definir os níveis de Comprometimento em relação aos respectivos grupos de dados. A Conformidade, por outro lado, considera os níveis de Comprometimento obtidos a partir dos dados dos jogadores, juntamente com a estratégia da equipe, para calcular a assertividade do desempenho individual e coletivo.

Os resultados obtidos validam o uso da métrica de Comprometimento por tarefa como uma avaliação do engajamento do jogador, além da eficácia dos níveis de Comprometimento e da Conformidade na análise de desempenho, na previsão dos resultados das partidas e na geração de sugestões para a melhoria do jogo.

Palavras-chave: MOBA, League of Legends, Comprometimento do Jogador, Conformidade do Jogador, Papel do Jogador, Ciência de Dados, Aprendizado de Máquina, eSports, Análise de Jogos

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List of Acronyms

ADC Attack Damage Carry

AD Attack Damage

AFK Away from Keyboard

AI Artificial Intelligence

AIIDE Artificial Intelligence in Interactive Digital Entertainment

AoS Aeon of Strife

AP Ability Power

API Application Programming Interface

ARAM All Random All Mid

AUC Area Under the Curve

CAPES Coordenação de Aperfeiçoamento de Pessoal de Nível Superior

CBLOL Campeonato Brasileiro de League of Legends

CNN Convolutional Neural Network

COG IEEE Conference on Games

CS:GO Counter Strike: Global Offensive

DNN Deep Neural Network

DotA Defense of the Ancients

eSports Eletronic Sports

FN False Negative

FP False Positive

FPS First-Person Shooter

FUR FURIA

FX Fluxo

GCN-WP Graph Convolution Networks for Win Prediction

GradB Gradient Boosting Regressor

GVGAI General Video Game AI framework

HFN Hero-Featured Network

HoK Honor of Kings

IBA Interactive Behavior Analytics

ITZ INTZ

JGL Jungle

KBM KaBuM! Esports

KDA Kills, deaths and assists

LBR Liberty

LLL LOUD

LoL League of Legends

LOS Los Grandes

LSTM Long Short-Term Memory

MEC Ministério da Educação

MID Middle

ML Machine Learning

MMORPG Massive Multiplayer Online Role-Playing Game

MOBA Multiplayer Online Battle Arena

NICE Neural Individualized Context-Aware Embeddings

NNLM Neural Network Language Model

NPC Non-Playable Character

PCA Principal Components Analysis

PNG paiN Gaming

PPGIa Graduate Program in Informatics

PUBG PlayerUnknown's Battlegrounds

PUCPR Pontifícia Universidade Católica do Paraná

PUUID Player Universally Unique Identifiers

PvE Player versus Environment

PvP Player versus Player

RED RED Canids Kalunga

RFE Recursive Feature Elimination

RTS Real-Time Strategy

SBGames Brazilian Symposium of Game and Digital Entertainment

SUP Support

SVM Support Vector Machine

TFT Teamfight Tatics

TN True Negative

TOP Top

TP True Positive

U&G Uses and Gratifications

VKS Vivo Keyd Stars

1

Introduction

In 1998, Blizzard Entertainment[1] released the successful real-time strategy (RTS) game StarCraft (THAVAMUNI; KHALID; IIDA, 2023; BASSI et al., 2018). The game included an editing tool that allowed players to modify maps and share them, creating opportunities for new game genres to emerge, such as the Multiplayer Online Battle Arena (MOBA) (WU; XIONG; IIDA, 2016). One StarCraft player, known as Aeon64, created a map titled Aeon of Strife (AoS), featuring three lanes and a single objective: to destroy the opposing team's base. This map set the foundational standards for MOBA games (THAVAMUNI; KHALID; IIDA, 2023). However, the genre only firmly established itself after the release of Defense of the Ancients (DotA) (MORA-CANTALLOPS; SICILIA, 2018a; COSTA et al., 2023).

MOBA games have become highly popular in recent years, attracting interest not only from players but also from researchers, professional championship (eSports) organizers, and sponsors (BASSI et al., 2018; ANI et al., 2019). With millions of players worldwide (TENG et al., 2022) and numerous matches occurring simultaneously, MOBA games generate diverse data that is valuable for research, such as for outcome prediction, champion recommendations, and player behavior studies (MORA-CANTALLOPS; SICILIA, 2018b; COSTA et al., 2023).

One area of interest in the field has been the enhancement of player perfor-

[1]https://www.blizzard.com/en-us/

mance (BASSI et al., 2018), both within eSports (COSTA et al., 2023) and among non-professional (casual) players. MOBA games feature a competitive structure where two teams face each other, with player rankings determined by match outcomes — positive for wins and negative for losses (MORA-CANTALLOPS; SICILIA, 2018a). However, the success of a team is not solely reliant on the performance of an individual player; rather, it requires collaboration among all team members (BASSI et al., 2018) and strategic decision-making. This includes choices related to role assignment and champion selection (TENG et al., 2022).

In many studies, the kills, deaths, and assists (KDA) ratio is often used to measure player performance, as it serves as a strong indicator of general player behavior (ZENG; SAPIENZA; FERRARA, 2019; MOURA et al., 2019). When a player dies, they are forced to wait to respawn, incurring a time penalty. This temporarily weakens the ally team for teamfights and leaves parts of the map unprotected, allowing the enemy team to capture objectives — sometimes a decisive factor in determining match outcomes. However, while the KDA ratio significantly impacts both player and team performance, MOBAs require players to perform a wide range of actions beyond kills that are also crucial and should be considered in performance evaluations. Each in-game action is commonly associated with a specific role, which is often expected to fulfill particular tasks based on its defined attributes and responsibilities. These games feature five primary roles, distinguished by the player's position on the game map (e.g., lane or jungle) and the selected champion. Players choose a role to leverage its unique skills, contributing to the team's efforts to secure victory (GAINA; NORDMOEN, 2018; DEMEDIUK et al., 2019). Additionally, MOBA games include champion class roles, such as assassin, mage, and tank (ZHOU; CHU; HE, 2021), as well as roles indicating the champion's gameplay style, including Ability Power (AP) and Attack Damage (AD) (CHOI, 2022).

Due to the multiple types of roles associated with MOBA games, this study will focus on a specific category referred to as the player-role. The player-role is defined by the player's placement on the map and their chosen champion. The five player-roles are: Top, Middle, Attack Damage Carry (ADC), Support, and Jungle. For example, a player positioned in the bottom lane who selects a shooter-type champion typically assumes the ADC role. Conversely, selecting a support-type champion in the same lane corresponds to fulfilling the Support role.

In this study, we aim to measure the engagement of MOBA players with their assigned roles by employing the Commitment metric through Machine

Learning methods. Unlike general metrics such as KDA, the Commitment metric (KUMMER; NIEVOLA; PARAISO, 2017; KUMMER; NIEVOLA; PARAISO, 2018) focuses on a more descriptive aspect: the in-game actions associated with specific player-roles. For this purpose, we refer to these in-game actions as tasks, emphasizing their connotation of obligation and responsibility.

Since a skilled player may perform poorly in a structured team scenario (THAVAMUNI; KHALID; IIDA, 2023), such as in eSports, it is essential to define team-specific expectations for each member. These expectations are determined by the team's strategy rather than individual preferences and specify what players must achieve to fulfill their roles in a match. This study addresses these expectations through descriptions and associations from the literature, complemented by strategies developed in collaboration with an eSports team, called Liberty.

Liberty eSports[2], commonly referred to as Liberty (LBR), was a Brazilian LoL team that competed in the Brazilian Championship of League of Legends (CBLOL). Liberty actively participated in each stage of this research, contributing to the validation of results and the relevance of the proposed metrics. However, due to the restructuring of the championship, the proposed method could not be tested with the players. Given the importance of understanding player behavior and performance in structured team environments, such as those in eSports, this study benefits from the Commitment and Compliance metrics.

The Commitment metric was developed to measure how attached a player is to a game, considering the time spent playing and obtained scores. Initially, it was designed for analyzing Massive Multiplayer Online Role-Playing Games (MMORPGs) (KUMMER; NIEVOLA; PARAISO, 2017; KUMMER; NIEVOLA; PARAISO, 2018), with the aim of predicting player churn — the likelihood of a player abandoning the game — and identifying the game's stage within its lifecycle. Subsequently, the metric was adapted for MOBA games by Mazeto, Kummer, and Paraiso (MAZETO; KUMMER; PARAISO, 2018) and Humenhuk, Kummer, and Paraiso (HUMENHUK; KUMMER; PARAISO, 2021). In this context, the gameplay dynamics shift from continuous progression, characteristic of MMORPGs, to discrete, match-based gameplay in MOBAs.

However, when applied to MOBAs, certain elements of the Commitment

[2]https://lol.fandom.com/wiki/Liberty

metric are influenced, particularly in the eSports domain. These adaptations will be examined in detail in Chapters 2 and 4. This study aims to evaluate the use of the Commitment metric in MOBAs by focusing on three primary factors: the temporal structure of MOBA gameplay, the distinction between player-roles, and the specific tasks associated with each role.

After measuring the Commitment, it is essential to compare the results with the expected scores for each task to analyze the players' performance. The Compliance metric was developed to assess the degree of alignment between the player's actions and the team's strategic objectives. This metric was tested considering the expectations of the analysts of the eSports team regarding their players, as well as by referencing literature descriptions of each player-role. Although the expectations of this specific team may differ from those of others, the metric was applied to evaluate the Compliance of all players from the championship. Through this investigation, the study aims to determine whether the proposed strategy was applicable or if it diverged significantly from the actual results observed.

In recent years, MOBA games have gained significant popularity, with League of Legends (LoL)[3] standing out as one of the most prominent titles (VILLA et al., 2020). The LoL developer, Riot Games, provides access to matches and player data through its Application Programming Interface (API)[4]. Due to these factors, LoL has been selected as the primary focus of this study. The proposed methodologies can be extended to other MOBA games and even other game genres that have a similar structure of player-roles. The outcomes of this research include match outcome prediction, player performance evaluation aimed at achieving favorable results, and insights for structuring optimal MOBA teams.

Ultimately, this work contributes to the field of Game Analytics by offering a novel approach to understanding player behavior through a new application of the previously proposed Commitment metric, and a new proposed metric called Compliance.

[3]https://www.leagueoflegends.com/en-us/

[4]https://developer.riotgames.com/apis,mora2018player

1.1 Motivation

In MOBA games, particularly LoL, two distinct gameplay scenarios emerge: the casual and the professional. While players in both scenarios strive to improve their performance, the associated risk factors differ significantly between these contexts.

The game ranks players based on match outcomes using a skill-based classification system, specifically an ELO-based system (AUNG et al., 2018; MORA-CANTALLOPS; SICILIA, 2018a). Prior to the realization of this work, ELO rankings were divided into increasing tiers: Iron, Bronze, Silver, Gold, Platinum, Emerald, Diamond, Master, Grand Master, and Challenger.

LoL operates in an ultra-competitive environment, where climbing the ranking ladder provides players with a strong sense of accomplishment (KUMMER; NIEVOLA; PARAISO, 2021). A player's position within the ELO system depends on match results, which affect the entire team regardless of individual contributions (JANG; WOO; KIM, 2022). Consequently, the match outcome depends on the performance of each player in their respective role, with each contribution being vital to overall team success. This is particularly relevant in MOBAs, where the correlation between team members' performances and the match outcome has been well-documented, especially when roles are considered separately (MONDAL et al., 2022). Transitions between ELO tiers often trigger both positive and negative emotional responses, which are integral to the player experience. The competitive nature and achievement-driven aspects of the game enhance player satisfaction, ultimately increasing engagement and time spent playing (TENG et al., 2022). In conclusion, improving a player's performance and rank is crucial for maintaining engagement and ensuring long-term participation in casual gameplay scenarios.

In the context of eSports, teams frequently replace players — even during championship phases. The primary reason for this is the need to maintain a balance among team members. Players' strengths and weaknesses can complement one another, leading to improved overall performance (SABTAN; CAO; PAUL, 2022). If a player underperforms and jeopardizes the team's success, the organization may choose to replace them. Consequently, professional players are constantly striving to improve — not only to achieve higher rankings (GAINA; NORDMOEN, 2018) but also to secure their positions within their current teams or to receive offers from other organizations.

As Costa *et al.* (COSTA et al., 2023) highlight, a common research focus in MOBA games is the improvement of player and team performance. Some studies emphasize the importance of communication between team members as a key influencing factor, while others focus on recommending champions that align with players' preferences. However, prior to these factors, it is crucial to investigate the player's familiarity with the role's tasks and the scores they achieve. By analyzing fundamental elements of performance — such as task execution and the roles linked to them — researchers can outline a developmental path for players, where their skills will be considered as a sum of the responsibilities they hold within the team. As this perspective moves from individual tasks to overall player influence on the team, it can be considered a holistic approach.

1.2 Objectives

The primary objective of this study is to develop a computational method that uses Commitment and Compliance metrics to assess MOBA players' performance based on their execution of in-game tasks.

To achieve this goal, the study followed these steps:

- **Definition of player-roles and task attributions:** Identified and categorized in-game tasks associated with each player-role.
- **Development of a data extraction algorithm:** Implemented an automated pipeline to collect structured data from the League of Legends API.
- **Commitment metric computation:** Evaluated player engagement in role-specific tasks using clustering, classification, and ensemble machine learning techniques.
- **Adaptation of the Commitment vector:** Refined the metric to more accurately reflect MOBA dynamics and eSports-specific contexts.
- **Compliance metric computation:** Developed a metric to quantify individual performance in alignment with the team's strategic expectations.
- **Match outcome prediction:** Built a classification model to predict match results based on Commitment and Compliance scores.
- **Gameplay optimization suggestions:** Analyzed the impact of tasks on match outcomes and individual performance, offering data-driven recommendations for skill improvement.

1.3 Hypotheses

The raised hypotheses of this work are:

H1 The Commitment metric can be used to measure the engagement of players per role's associated tasks.

H2 The Commitment metric can be used without the temporal element in an eSports situation.

H3 The player-roles associated tasks can be used as predictive features in a classification model to determine match outcomes, considering its results with the Commitment and Compliance metrics.

H4 The player-roles associated tasks can be used to suggest strategies by analyzing their influence on match outcomes, considering its results with the Commitment and Compliance metrics.

1.4 Contributions

The contributions of this work are as follows:

- Created and publicly released a large-scale dataset containing gameplay data from 502,472 players over 40 weeks of 2023. This dataset provides a valuable resource for future research on MOBA game analysis.
- Extended the Commitment metric to new contexts by adapting it to the eSports scenario. These adaptations account for the sporadic nature of championships, which produce fewer matches and, therefore, limited data.
- Developed a new metric, called Commitment per Task, based on the original Commitment concept. This metric evaluates how engaged players are in completing tasks specific to their roles during a match. Insights from this metric enabled the assessment of another gameplay dimension: how well players align with their team's strategic goals. This led to the introduction of a second metric, named Compliance.
- Demonstrated the applicability of the Commitment and Compliance metrics in player performance assessment, match outcome prediction, and gameplay optimization. The results support future research in player behavior analysis, including recommendations (e.g., champion and item selection), predictive modeling, and the design of improved team matchmaking strategies.

1.5 Scope

The scope of this research includes the development of an algorithm to extract data from the LoL API and the measurement of Commitment and Compliance metrics based on role-specific tasks for each player. Additionally, the study aims to predict match outcomes and identify tasks that players need to improve, enabling the construction of personalized training plans based on each player's weaknesses as indicated by their role-specific metrics.

This study does not test the proposed approach in other MOBA games or game genres. Instead, it focuses exclusively on LoL due to its widespread popularity and the large amount of available gameplay data. Nevertheless, the proposed method can be applied to any game that features a clear structure of roles and tasks.

1.6 Grammar Corrections

English grammar corrections were made using a software tool called *Grammarly*[5], specifically the free web-based version. All suggestions were reviewed before being applied to this document.

1.7 Overview

This project is organized into eight chapters. Chapter 2 introduces the core concepts and theoretical framework that support the research. Chapter 3 presents the state of the art. Chapter 4 outlines the methodological procedures used to develop the proposed approach. Chapter 5 describes how the dataset was obtained and processed. Chapter 6 details the proposed method, including its structure and steps. Chapter 7 presents the results. Finally, Chapter 8 concludes the work and discusses the challenges encountered and modifications made during the project's development.

[5] https://app.grammarly.com

2

Theoretical Grounding

This chapter will explain all referenced concepts related to the objects of study, the proposed approaches to solve the presented problem, and the domain this research fits in.

2.1 Eletronic Sports (eSports)

Electronic Sports, commonly referred to as eSports (SEO, 2013), encompasses the competitive environment of digital games (AESCHBACH et al., 2023). Unlike traditional games, which primarily focus on providing entertainment, eSports emphasize the development and refinement of players' skills. For a game to be considered suitable for eSports, it must incorporate specific parameters that allow for the evaluation and measurement of player performance. These parameters vary depending on the game and its respective winning criteria (SEO, 2013).

As highlighted by Sabtan, Cao, and Paul (SABTAN; CAO; PAUL, 2022), the most popular game genres in eSports include:

- Real-Time Strategy (RTS).
- First-Person Shooter (FPS).
- Multiplayer Online Battle Arena (MOBA).

In eSports, professional players compete against each other both online and offline (BLOCK; HAACK, 2021). Offline competitions typically take place in traditional sports stadiums, where players are positioned at the center of the venue, surrounded by the audience (SABTAN; CAO; PAUL, 2022).

The first eSport game to engage players worldwide was *StarCraft: Brood War* (1998), developed by Blizzard Entertainment. Today, broadcasters stream eSports events online to millions of spectators, including individuals who do not actively play the games themselves (HOWARD, 2018).

Due to its growing popularity, a discourse has emerged regarding the classification of eSports as a form of sport. A distinction is often drawn between eSports and traditional sports, particularly concerning the aspect of physical effort (HOWARD, 2018). eSports players engage in repetitive physical actions, such as clicking hundreds of times per minute, and utilize cognitive functions that traditional sports do not typically require (BLOCK; HAACK, 2021). Nevertheless, eSports have become increasingly similar to traditional sports in terms of how their championships are organized. Another crucial parallel between eSports and traditional sports is the role of the coach. eSports coaches play a fundamental role in team strategy, player development, and performance optimization. They analyze in-game data, design training regimens, and refine team compositions to maximize efficiency in different scenarios. Additionally, they act as a bridge between the analyst team and the players, ensuring that data-driven insights are effectively translated into practical improvements and strategic adjustments.

Research in the eSports field has expanded due to the unique complexities inherent in gameplay, as well as the variety and abundance of data available for analysis (COSTA et al., 2023). Today, players have access to their own match data, which they can use to analyze their performance. However, how they utilize this data to improve in an eSports context remains unclear in academic research (KLEINMAN; EL-NASR, 2021).

2.2 Multiplayer Online Battle Arena

Derived from an RTS game, the MOBA genre emerged in the early 2000s. Typically, MOBAs are played by 10 players divided into two teams, each controlling a unit of Non-Playable Characters (NPCs) with the objective of destroying the enemy's structures. Each team has a main structure (e.g., Nexus, Ancient, Crystal) located in their base, which they must protect while attempting to destroy the enemy's main structure to secure victory (THAVAMUNI; KHALID; IIDA, 2023).

MOBAs are played in discrete matches rather than a continuous scenario, allowing players to adopt various gameplay styles. Players select a virtual character, often referred to as a champion, hero, or similar, and choose a specific part of the map to defend or attack, known as a lane or jungle — the area between lanes. Team composition also plays a critical role in shaping gameplay. At the start of each match, all players begin on equal footing, as any advantages gained during the match, such as items or character levels, are reset at the end of each game.

2.3 League of Legends

One of the most popular MOBA games is League of Legends (commonly known as LoL), developed by Riot Games (VILLA et al., 2020; KOU et al., 2018). LoL has established itself as a major player in the eSports industry (JIANG et al., 2021), generating millions of dollars in revenue (KOU et al., 2018; HE et al., 2021).

LoL matches typically last between 20 minutes to nearly an hour (KOU et al., 2018; JIANG et al., 2021). In each match, players must select a champion from a roster of over 140 options to represent them, depending on the type of match. Players also choose a specific lane to battle in (VILLA et al., 2020; JIANG et al., 2021; HE et al., 2021).

At the time of this study, League of Legends featured four primary types of matches: Summoner's Rift, All Random All Mid (ARAM), Teamfight Tactics (TFT), and Arena.

The most prominent type of match, used in championships and following the structure of AoS and DotA — the pioneers of the MOBA genre — is Summoner's Rift. In this mode, two teams of five players, the red team and the blue team, compete on a mirrored map, see Figure 2.1. The map is divided by a river, with three towers and an inhibitor per lane, and a Nexus for each team. Destroying the enemy Nexus is the ultimate objective, securing victory for the team.

Figure 2.1: League of Legends game map, called Summoner's Rift, with the indication of the structural objectives: towers, inhibitors, and nexus; and lanes: top, middle, bottom and jungle

Hordes of NPCs called minions support each team, which assist in conquering objectives and engaging the enemy team. Players earn experience and gold by eliminating these minions. Experience allows players to strengthen their champions, enabling them to level up their skills, while gold can be used to purchase items that enhance their champion's performance, such as those that increase health, speed, or resistance to enemy attacks. Additional in-game actions also reward players with experience and gold, including destroying objectives, eliminating opposing players (RIJNDERS; WALLNER; BERNHAUPT, 2022), defeating neutral monsters, or securing special objectives such as Dragons, Baron Nashor, and the Rift Herald.

The LoL game map features a fog-of-war mechanic that limits players' visibility. To counteract this, players can purchase an item called a vision ward to expand their team's field of view. As Gaina, and Nordmoen (GAINA; NORDMOEN, 2018) explains, this task is typically assigned to a specific player-role, with each role having distinct responsibilities that the team expects to be fulfilled.

LoL features a vast array of content, making it challenging for beginners to learn how to play. Mastering the game — or even a single champion — can take years, as some champions are highly complex. For instance, in 2018, only 200 players achieved the Challenger rank, the highest tier in the ELO-based ranking system used to classify players (MORA-CANTALLOPS; SICILIA, 2018b). This represents an exceptionally small percentage, given that LoL boasts millions of players worldwide (TENG et al., 2022).

To maintain player engagement and recognize their in-game efforts, LoL organizes the year into seasons, during which players can earn limited rewards. However, not all rewards are obtained solely through gameplay; some require in-game purchases to unlock additional content. These purchases are a key monetization strategy for free-to-play games like LoL, which do not require an upfront payment to play but generate revenue through such microtransactions (DEMEDIUK et al., 2018).

A player account will eventually level up, granting access to additional content, such as a game mode called Ranked (RIJNDERS; WALLNER; BERNHAUPT, 2022). To encourage continued engagement, the game rewards players with achievements upon reaching specific levels. A player's position on the public rank can increase or decrease, significantly influencing their motivation and engagement. This dynamic remains a critical factor in player behavior (JANG; WOO; KIM, 2022). Ranks are reset or adjusted each season, reflecting variations in player performance across games. Rank is determined by match outcome statistics (MORA-CANTALLOPS; SICILIA, 2018b), which are influenced by team performance rather than individual player contributions. This differs from the Commitment per Task approach, which evaluates player performance based on role-specific tasks fulfilled during a match. Specifically, this approach compares a player's performance in their chosen role to that of an opposing player in the same role classification.

In this study, Summoner's Rift data was selected for analysis due to its relevance to player-roles, champion and lane selection, and map objectives. The remaining three match types were excluded from the analysis because they do not align with the core characteristics of a MOBA game:

- **Aram**[1]: This game mode features a single-lane map where ten players (five per team) are assigned random champions. The focus is on team fights, and player-roles are less emphasized compared to other match types. However, players must still destroy enemy towers and the nexus to win the match. Minions spawn periodically to assist teams in conquering objectives and leveling up. ARAM retains the core structure of a traditional MOBA but is simplified and faster-paced.

- **TFT**[2]: This auto-battler game mode is similar to auto-chess games. Players select champions to compose their team and strategically position them on a board. The objective is to build the strongest team and defeat opponents in rounds. Initially, players face AI-controlled enemies, but later phases involve battles against other players' teams. Unlike traditional MOBAs, TFT diverges significantly in gameplay mechanics, existing primarily within the League of Legends universe through shared champion designs.

- **Arena**[3]: This mode takes place on a circular map with four teams, each composed of two players. Matches are divided into rounds, where two teams face off in direct combat. The primary objective is to eliminate the opposing team. Unlike traditional MOBAs, Arena lacks side objectives such as structures to destroy or NPCs to assist players. The mode is entirely focused on team fights and player-versus-player combat.

Summoner's Rift supports multiple gameplay modes, which can be divided into two principal categories: Player versus Player (PvP) and Player versus Environment (PvE). In PvP, ten players compete against each other in teams of five. In PvE, five players face a team of five AI-controlled characters, a mode also known as COOP vs AI.

PvE mode is divided into three levels of difficulty:

- Intro.
- Beginner.
- Intermediary.

PvP mode features different compositions that are unlocked based on the player's level:

- Blind Pick.

[1]https://support-leagueoflegends.riotgames.com/hc/en-us/articles/201752854-Howling-Abyss-ARAM-FAQ

[2]https://www.leagueoflegends.com/en-au/news/game-updates/what-is-teamfight-tactics/

[3]https://support-leagueoflegends.riotgames.com/hc/en-us/articles/17211075407635-League-of-Legends-Arena-Game-Mode

- Draft Pick.
- Ranked Solo/Duo.
- Ranked Flex.

The LoL API does not differentiate between the types of modes, levels, or compositions of matches. Instead, matches are categorized into four main types: Summoner's Rift, ARAM, TFT, and Arena. This limitation, however, does not affect the applicability of the proposed method. The rationale for selecting specific match types for analysis in this work will be elaborated in Chapter 5.

2.4 Player-Roles

Since our work is based on the concept of player-roles, it is essential to describe each role and outline the tasks they are expected to fulfill. This framework can be adapted to other game scenarios, provided there is a clear division of players into roles with associated responsibilities. In LoL and most MOBA games, there are five primary player-roles, defined by their lane and champion: Top, Middle, Attack Damage Carry (ADC), Support, and Jungle. Each role requires distinct skills, utilizes specific sets of items, and is responsible for different tasks. For this description, we draw on the works of Gaina, and Nordmoen (GAINA; NORDMOEN, 2018) and Jang, Woo, and Kim (JANG; WOO; KIM, 2022) as key references.

2.4.1 Top (TOP)

The top role is typically filled by a tank or fighter champion, chosen for their high resistance and health. The top laner begins the game in the top lane, which is strategically located near key jungle objectives such as the Rift Herald and Baron Nashor but is farther from the Dragons. The primary responsibilities of the top laner include initiating team fights and absorbing the majority of the damage. The top laner often adopts a more isolated strategy, focusing on farming — gaining resources such as experience, gold, and items — primarily in their lane. They also provide assistance to the team in specific situations, such as securing their lane and applying pressure to the enemy team. This forces the enemy to defend that part of the map, creating opportunities for the allied team to advance elsewhere. In addition to general lane tasks, such as eliminating minions and destroying objectives, the top laner is responsible for dealing significant damage to enemies while also protecting allies by absorbing incoming damage.

2.4.2 Middle (MID)

Middle laners, the players who operate in the middle lane, are typically mage champions. These champions heavily rely on the mana attribute, which enables the use of spells, particularly during aggressive gameplay. The middle lane is the shortest lane on the map and is centrally located, providing easy access to other lanes and the jungle. This strategic positioning allows middle laners to assist their team effectively, especially those in the jungle and bottom lane. Middle laners are renowned for their ability to deal significant magical damage to enemies and often dictate the pace of the match. Like other primary lane players, they are responsible for eliminating minions and destroying objectives.

2.4.3 Attack Damage Carry (ADC)

The Attack Damage Carry (ADC), also referred to as AD Carry, is responsible for dealing the highest amount of damage within the team. ADCs typically choose shooter-type champions, which excel in dealing long-range damage. This choice is ideal for the role due to the champions' low health attributes. ADCs operate in the bottom lane, which is strategically located near the Dragons. They are paired with a support role player, relying on constant protection to effectively eliminate enemies. ADCs often achieve the highest Creep Scores (CS), a metric that indicates the number of NPCs eliminated. In team fights, ADCs play a crucial role in leading the engagement, leveraging their high damage output to secure multi-kills — eliminating multiple enemy players in quick succession.

2.4.4 Support (SUP)

The support role is played in the bottom lane alongside the ADC. Supports are primarily responsible for protecting the ADC and, by extension, the rest of the team. Unlike other roles, supports are not tasked with eliminating minions or destroying objectives. Instead, they typically achieve higher scores in assists — helping allies eliminate enemy players — rather than in kills, which are direct eliminations of enemy players. A critical responsibility of the support is managing vision control on the Summoner's Rift map. The map features a fog-of-war that limits players' visibility. Supports place wards to reveal areas of the map and remove enemy wards, thereby controlling vision. This vision control is crucial for tracking enemy positions and formulating both offensive and defensive strategies. The support role is challenging due to the extensive use of active items, which require quick reflexes and precise coordination to use effectively.

2.4.5 Jungle (JGL)

The jungle role is often considered the most challenging for beginners. Junglers, the players who operate in the jungle area, do not gain experience from minions or towers. Instead, they level up by defeating neutral jungle NPCs, known as monsters. There is a specific order to eliminate these monsters, and selecting the appropriate set of spells is crucial for efficient elimination. Junglers play a pivotal role in assisting all team members, as the jungle territory is situated between the three lanes. They can utilize bushes — map structures that provide concealment from enemies — to launch surprise attacks. Junglers are responsible for securing special monsters such as the Rift Herald, Baron Nashor, and Dragons. They contribute significantly to team fights by dealing substantial damage or eliminating these objectives solo. Additionally, junglers can invade the enemy's side of the map to steal neutral monsters, thereby denying the enemy team valuable rewards.

2.5 Machine Learning

Machine Learning (ML) is a field of study that focuses on developing methods to improve approaches by analyzing their intended functionality through provided examples. These methods rely on patterns and inferences derived from user behavior. ML is broadly categorized into four learning types (DIETTERICH, 2003; TELIKANI et al., 2021; SARAVANAN; SUJATHA, 2018):

- **Supervised**: This approach is applied to labeled datasets, where each data point has a specified target for the model to learn during the training phase. Labels can be binary or multiclass. Supervised methods rely on human intervention to provide ground truth labels, enabling the model to classify data or perform regression and evaluate its performance by comparing predictions against the true labels to calculate accuracy.

- **Unsupervised**: This approach is applied to both raw and pre-processed datasets, without relying on predefined targets for the model to learn. Instead, the method identifies inherent patterns or similarities within the data. Unsupervised learning does not require a training phase and operates independently of human intervention to generate outputs.
- **Semi-supervised**: This approach combines both labeled and unlabeled data during the training process. By leveraging the strengths of supervised and unsupervised methods, semi-supervised learning aims to achieve higher accuracy, particularly in scenarios where labeled data is limited or costly to obtain.
- **Reinforced**: In this approach, the model learns through interactions with an environment, guided by a set of predefined rules. The method iteratively improves by analyzing feedback in the form of errors and successes, optimizing its decision-making process over time.

ML has revolutionized the way data is processed and interpreted, finding applications across numerous domains (CHATTERJEE, 2024). Notably, ML has been extensively utilized in areas related to AI and computer systems architectures (LEWIS; DENNING, 2018). Furthermore, the adoption of ML techniques and methods has significantly increased in the analysis of player behaviors within the MOBA games domain (COSTA et al., 2023).

2.5.1 Cluster

Clustering methods, which fall under the category of unsupervised ML, do not rely on pre-labeled data. These methods group data points into clusters based on similar behaviors or patterns. In this study, the clustering process was implemented using the K-means algorithm, a technique also employed by Kummer, Nievola, and Paraiso (KUMMER; NIEVOLA; PARAISO, 2017), Mazeto, Kummer, and Paraiso (MAZETO; KUMMER; PARAISO, 2018) and Humenhuk, Kummer, and Paraiso (HUMENHUK; KUMMER; PARAISO, 2021) for measuring Commitment-related metrics.

K-means is a widely used clustering algorithm that minimizes errors during the clustering process. It is known for its computational efficiency and fast processing. However, its performance is highly dependent on the initial placement of the cluster centers, which can impact the quality of the resulting clusters (LIKAS; VLASSIS; VERBEEK, 2003).

2.5.2 Classifier

Classifiers are methods that rely on pre-defined categorical labels for their execution, categorizing them as part of supervised ML techniques. These methods are used to predict the class of a given instance by assigning it to a specific group. Additionally, the performance of a classifier can be evaluated by comparing its predictions against the ground truth labels (ALNUAIMI; ALBALDAWI, 2024).

Researchers can evaluate the classifier's predictions using metrics, which assess the model's ability to correctly predict classes. Common evaluation metrics include accuracy, precision, recall, and the F1-Score.

For this study, the *Random Forest* algorithm was selected for the analysis of data in a classification and prediction context. *Random Forest* has been identified by Costa *et al.* (COSTA et al., 2023) as one of the most widely used classifier algorithms for analyzing MOBA games. This approach has been employed in previous research, including studies by Ani *et al.* (ANI et al., 2019) and Costa *et al.* (COSTA et al., 2021a), to predict match outcomes, as well as by Jiang, Lerman, and Ferara (JIANG; LERMAN; FERRARA, 2020a) to examine differences in individual player performance. All of these studies utilized data from LoL.

The *Random Forest* algorithm offers more reliable predictions by aggregating the results of multiple *Decision Trees*, which are themselves a type of classifier algorithm. *Decision Trees* operate through a structure of nodes, where leaf nodes represent class labels, and non-leaf nodes correspond to attribute values that guide the decision-making process (ALNUAIMI; ALBALDAWI, 2024).

Another classifier utilized was *LightGBM* (LGBM), a gradient boosting framework known for its high efficiency and speed. LGBM often outperform other gradient boosting-based algorithms while requiring lower computational resources (KE et al., 2017). It is particularly suitable for handling large datasets, making it an option for the executed experiments on this study.

2.5.3 Ensemble

Ensemble methods integrate the outputs of multiple models to enhance overall performance and predictive accuracy (ALNUAIMI; ALBALDAWI, 2024). These methods can enhance the model's predictive performance; however, to maximize their effectiveness, it is essential to use classifiers with diverse approaches. Classifiers with similar methodologies may produce redundant results, offering little to no benefit for the purposes of research analysis (OPITZ; MACLIN, 1999).

2.6 Game Analytics

Game Analytics is a field focused on modeling player behavior (EL-NASR; DRACHEN; CANOSSA, 2016; KUMMER et al., 2019) and extracting actionable insights from in-game data. As a significant component of Game Data Science, it has evolved substantially over the past few decades, leveraging machine learning, statistical analysis, and data mining techniques to improve game design, balance, and player experience.

This field spans both academic and business applications, contributing to player engagement analysis, retention strategies, monetization models, and AI-driven content personalization. By analyzing in-game actions, decision-making patterns, and performance metrics, Game Analytics provides a deeper understanding of players' psychological and technical behaviors (PFAU; EL-NASR, 2023).

Given the vast amounts of data generated by digital games, the field of Game Analytics benefits from significant advantages, particularly in eSports. Researchers and developers have collaborated with the gaming community to develop and test analytics tools, offering real-time feedback, predictive modeling for player performance, and automated coaching systems. However, despite these advancements, scientific research in this area remains in its early stages, with limited exploration into the usability, interpretability, and broader impacts of these tools on players (PFAU; EL-NASR, 2023).

Future directions in Game Analytics include several key areas of research and development. One of the main focuses is match outcome prediction in eSports, ensuring that models are tailored to the competitive gaming audience. Another growing area is the identification of toxic behavior in voice channels, aiming to improve player interactions and community health. Additionally, balancing NPC AI to prevent player frustration remains a critical challenge, requiring adaptive difficulty systems that maintain engagement without making the game unfair. Team composition recommendations are also gaining attention, using data to optimize player synergies in competitive environments. The rise of Human-Centered AI has further emphasized the importance of designing systems that enhance player experiences, with particular attention to eSports players' cognitive and behavioral aspects. In this context, eSports analytics is expanding to incorporate psychological measures and behavioral profiling. Finally, game design innovations can benefit from ML for procedural and AI content generation (COSTA et al., 2023).

3

State of the Art

This chapter presents the key findings from the systematic literature review relevant to our work. The search protocol followed during this process will be detailed in Chapter 4.

3.1 Player Performance

An analysis of team composition and its impact on team performance was conducted by Cheng *et al.* (CHENG et al., 2019). The authors utilized data from Honor of Kings (HoK)[1], the largest mobile MOBA game, and examined the roles selected by players. However, the role nomenclature in HoK differs from the used in our study. In HoK, players are categorized into five roles: warrior, mage, marksman, assassin, and support. The authors proposed a winning rate metric to evaluate team performance and observed that most teams in the analyzed scenario adopted logical compositions for matches. They found that the winning rate increased when teams had a well-planned composition, attributing this to the complementary design of roles, which are intended to fulfill each other's needs. This finding underscores the importance of considering player-role dynamics for analysis and recommendations.

[1]https://www.honorofkings.com/index.html

Joshi *et al.* (JOSHI et al., 2019) conducted a study focused on improving player performance. Their research examined Destiny 2[2], a FPS game, which differs from MOBAs in terms of structure and role division. Nevertheless, the study offers valuable insights into performance evaluation in digital games and among players. The objective was to develop a recommendation system that identifies optimal areas and strategies for player training, taking into account gameplay style preferences, champion selection, and equipment choices. Additionally, the study employed win rate as a metric for performance evaluation, suggesting that players with higher win rates serve as role models to emulate. Furthermore, the authors developed player profiles, which were subsequently used to create team profiles. They emphasized that individual improvement does not guarantee team success. Players were categorized into three groups based on their preferences using a clustering method, and these groupings were incorporated into the recommendation system.

Jang, Woo, and Kim (JANG; WOO; KIM, 2022) proposed a method to evaluate all actions performed by a player during a MOBA match, specifically LoL, and their contribution to the team's success. Their approach addresses a gap in team strategy, where a player may perform actions that appear detrimental to individual performance but ultimately benefit the team by achieving strategic objectives, such as distracting opponents. Such actions are often premeditated as part of the team's coordinated strategy under the guidance of a coach. The authors analyzed data from LoL, drawing inspiration from embedding techniques used in natural language processing, specifically the Neural Network Language Model (NNLM), to develop their action evaluation method, termed score-embedding.

Dehpanah *et al.* (DEHPANAH et al., 2021) conducted an analysis of how individual player skills influence match outcomes. Their study aimed to determine whether the performance of more skilled players or less skilled players had a greater impact on results. Additionally, they examined whether each player's performance contributed equally to the match outcome. This analysis was performed across three distinct games: LoL, PlayerUnknown's Battlegrounds (PUBG)[3], and Counter-Strike: Global Offensive (CS:GO)[4]. The proposed ap-

[2]https://www.bungie.net/7/pt-br/Destiny/NewLight
[3]https://pubg.com/en-us/
[4]https://www.counter-strike.net

proaches were integrated into rating systems, with the most accurate predictions stemming from a model that emphasized the impact of highly skilled players on team performance. The study revealed that highly skilled players, through proactive leadership and strategic decision-making, exert a significant influence on the gameplay of their teammates. This underscores the importance and fairness of conducting individual performance analysis. A player may be classified as high-performing when, in reality, their success is attributable to team dynamics rather than individual skill alone. To illustrate a scenario where a player benefits from their allies' performance, consider a situation where a player achieves a positive match outcome and advances in the public ranking. However, during the match, the player may have died multiple times, which could have been avoided with more attention or skill. In MOBAs, each death results in a time penalty, forcing the player to remain inactive for several seconds. During this period, players cannot contribute to team fights, assist in securing objectives, or defend their assigned area of the map, leaving it vulnerable to enemy attacks.

3.2 Player Engagement Over Time

Río, Chen, and Periánez (RÍO; CHEN; PERIÁNEZ, 2019) investigated player engagement in relation to lifetime value, game level, and playtime predictions. Similar to Churn prediction using the Commitment metric, which also evaluates player engagement in relation to gameplay aspects, the study categorized players into short, medium, and long lifespans, as well as "loyal" players — those who exhibit no risk of disengagement. However, the analyzed game is unrelated to MOBAs; it is a card-based game where players select cards to build a team, which then competes against an opposing team composed of either other players or AI-controlled characters. The prediction values were generated using a method based on Long Short-Term Memory (LSTM) neural network.

Uysal (UYSAL, 2016) analyzed player Commitment to a game using the Investment Model, a psychological framework. This perspective states that individuals may remain committed to a game even if they are not fully satisfied, due to factors such as a lack of alternatives or the extent of their investment in the game. The study highlights that loyalty can arise from various reasons, including social factors; for instance, being part of a player group (e.g., a guild) can encourage continued participation in the community. However, the authors do not associate Commitment with the likelihood of continuing or abandoning the game, which contrasts with the approach and findings of Kummer, Nievola, and Paraiso (KUMMER; NIEVOLA; PARAISO, 2017).

Moreover, Zaib Abbasi *et al.* (Zaib Abbasi et al., 2023) applied the Uses and Gratifications (U&G) theory, a framework for measuring consumer engagement, to assess player engagement in an eSports context. This theory explains behavioral outcomes by examining the antecedents and consequences of engagement. The approach offers insights into the motivations behind engagement and how they contribute to players' reminiscence of the game. However, the study relied on a survey-based research method conducted in a highly specific setting. Since the survey included only students from three universities in Malaysia within a predetermined age group, concerns arise regarding potential bias in the dataset, despite the authors' analysis of this limitation.

3.3 Player Behavior

Ahmad *et al.* (AHMAD et al., 2019) studied individual and team behavior in multiplayer games, particularly in the context of eSports, highlighting its significance for players, and game design. The authors proposed a methodological framework, called Interactive Behavior Analytics (IBA), which incorporates visual systems to facilitate the analysis process. Two games were analyzed: BoomTown[5], developed by Gallup, and DotA 2[6], a MOBA developed by Valve Corporation. Labels were assigned based on in-game player actions and used to measure performance, classifying players as either low-performing or high-performing, without considering average performance levels. Although distinctions between certain roles were made during the analysis phase, these were not incorporated into the data extraction or segregation processes.

3.4 Player Classification in Roles

Jiang *et al.* (JIANG et al., 2021) categorized LoL players into three types:

[5] https://volunteerscience.com/extype/about/500/
[6] https://www.dota2.com/home

specialists, generalists, and mavericks. This classification is based on player behaviors related to gameplay styles, such as focusing on a limited or broad range of styles, exploring popular or unconventional strategies within the game community. The authors employed a clustering method using the K-means algorithm to group players with similar characteristics, setting the number of clusters (K) to three (K = 3) to represent the three player types. Once the types were defined, a Support Vector Machine (SVM) was utilized to classify the data accordingly. Additionally, the KDA ratio was used to analyze and characterize these player types. The study revealed distinct behavioral patterns among the types: specialists typically outperformed others, mavericks took greater risks but achieved higher rewards, and generalists demonstrated greater resilience to environmental instabilities.

A study by Mondal *et al.* (MONDAL et al., 2022) analyzed the Support role and its influence on LoL match outcomes. The authors employed a Monte Carlo Simulation; however, they were unable to draw definitive conclusions. During the research, they discovered that the influence of each player-role, rather than a single role, collectively impacted the match outcome.

3.5 Outcome Prediction

In MOBAs, as in other game genres, players are consistently concerned with the outcome of their matches. Consequently, a branch of Game Analytics focuses on developing methods to predict match outcomes by analyzing different game phases and features. This section presents the key findings related to outcome prediction.

An important factor influencing player behavior, performance, and ultimately match outcomes is champion selection. In MOBAs, champions are chosen before the match begins, and players cannot change their selection once confirmed. This constraint poses challenges related to team composition and champion skill balancing. To address this issue, Do *et al.* (DO et al., 2021) proposed a Deep Neural Network (DNN) model to predict match outcomes based solely on players' experience with their selected champions (i.e., team formation). The DNN model achieved an accuracy of 75.1%. During experiments, the authors found that a GBOOST approach yielded higher accuracy but also a greater standard error, leading them to conclude that the DNN results were more reliable. The study assessed player experience using champion mastery points, win rate, and the number of matches played with each champion.

On the other hand, Costa *et al.* (COSTA et al., 2021b) analyzed the entire picks and bans phase, considering both the champions selected by players and those banned to restrict the opposing team's choices. The proposed model employed Random Forest and Logistic Regression approaches, both achieving an Area Under the Curve (AUC) value of 0.97. The authors concluded that the most significant features for predicting match outcomes are win rate and KDA, derived from players' historical performance with the same champions.

Prakannoppakun, and Sinthupinyo (PRAKANNOPPAKUN; SINTHUPINYO, 2016) randomly selected matches and analyzed 10 champion-related features: kills, deaths, assists, hero damage, hero healing, last hits, denies on creep score, experience per minute, gold per minute, and tower damage. A neural network model was implemented using historical match data, and the authors concluded that outcome prediction based on individual skill yields better results than approaches relying on overall team composition or previous match outcomes.

However, pre-match approaches have interesting findings related to champion selection, it lacks explorations on other relevant the facts such as player-roles, gameplay styles, and other factors. For example, in LoL, playing the champion Seraphine in the middle lane may emphasize magical damage and result in a higher win rate, whereas considering the same player, champion and task as a support may lead to a lower win rate. Consequently, the experience used to train the model may not align with the data analyzed during testing or even within the training dataset itself — particularly if the dataset includes only a few or single instances for each scenario (e.g., one instance reflecting a player's experience with a champion as a jungler and another as a top laner). This variability raises concerns about the reliability of the obtained results.

Tian, Lan, and Zhang (TIAN; LAN; ZHANG, 2022) proposed a Hero-Featured Network (HFN) to enhance outcome prediction accuracy by incorporating both chosen champions and real-time data, assigning weights to different features. The model's performance was evaluated at specific time-points (0.0, 3.5, 7.0, 10.5, and 14+ minutes), with the highest accuracy of 81.8% achieved at the 7.0-minute mark. HFN outperformed Logistic Regression, SVM, LSTM, and transformer-based methods. The HFN framework consists of two spatial stages: combat space and hero space. The combat space considers three gameplay features — gold earned, kills, and towers captured. In contrast, the hero space accounts for synergy and counter relationships among champions, win rate, and respective champion identifiers.

Most studies focus on predicting outcomes before the match, which is useful in player training scenarios. However, to provide insights for eSports spectators, commentators, and suggestions for players to learn during gameplay, real-time predictions are essential. Zhao *et al.* (ZHAO et al., 2022) analyzed players' movements on the game map to assess offensive and defensive team strategies, developing a framework called Winning Tracker, which is based on a Convolutional Neural Network (CNN).

Vieira *et al.* (VIEIRA et al., 2017) also proposed a game map analysis to track players' movements and their impacts on gameplay events. The authors identified key features for game analysis, including deaths, objectives destroyed, and special monsters eliminated, as the most significant factors influencing the game outcome.

A similar approach was proposed by Drachen *et al.* (DRACHEN et al., 2014), where the authors analyzed players' movements using a heat map to track their positioning relative to allies during different periods of the game. The primary features utilized by the model are timestamps and players' coordinates on the map. In the late game, it becomes possible to distinguish the winning and losing teams based on players' distances, particularly in the eSports context.

Another important aspect of gameplay analyzed for outcome predictions is teamfights, as proposed by Ke *et al.* (KE et al., 2022). The result of a teamfight can have a significant impact on a team's standing, providing crucial rewards to the winner and leaving the losing team in a difficult position, especially if most of their players are eliminated. The outcome of a teamfight can be a decisive factor in the match's result, making it a critical concern for players. Teamfights are also among the most engaging moments for spectators and are extensively discussed by commentators and casters. Teamfights can serve as a complementary analysis of player and team performance, much like side objectives such as conquering Dragons and jungle monsters. However, one aspect that has not been fully explored is the influence of the number of players on each team during the teamfight. The timing of when a player joins the fight could also play a crucial role in its outcome. Therefore, a more comprehensive analysis must consider all the nuances of this specific objective and how these factors influence predictions.

A model called Neural Individualized Context-Aware Embeddings (NICE), designed to account for individual aspects of players' performance in relation to match outcomes, was developed by Jiang, Lerman, and Ferrara (JIANG; LERMAN; FERRARA, 2020b). NICE is capable of identifying divergent player behavior to enhance the prediction of outcomes, as well as players' performance and engagement. The features used in the model included the KDA rate and the composition of individual features — kills, deaths, and assists. The AUC value achieved by NICE surpassed those obtained in experiments with Random Forest, XGBoost, and DNN approaches.

In MOBAs, various leagues represent regions around the world where the game is played. Despite playing the same game and in similar roles, players from different regions can exhibit distinct experiences, performances, and preferences. This regional variation is often the reason why data comparisons for analysis are typically confined to a single region. However, Bisberg, and Ferrara (BISBERG; FERRARA, 2022) proposed an alternative approach to address this issue, called Graph Convolution Networks for Win Prediction (GCN-WP). The GCN-WP is a semi-supervised method that learns from all teams in a league, constructing a unique league structure that can be compared across different leagues. This approach contrasts with methods that focus solely on learning from the historical behavior of individual teams, thus generating an understanding of team structure based on player-roles. The features analyzed in the study included objectives, farming, gold and experience, fighting, and vision. As with other studies in the literature, the GCN-WP experiments did not account for the attribution of features to specific player behaviors, such as tasks associated with player-roles. All features were weighted and considered equally, and the highest accuracy obtained was 61.9%. One notable aspect of this league-based approach is the variance in performance among teams within the same league. For example, in CBLOL, some teams consistently occupy the top positions in the championship nearly every season. However, other teams can outperform and defeat these established teams, as demonstrated during the 2024 season - Split 1, when Liberty, a novice team at the time, achieved a remarkable sequence of positive match outcomes.

To avoid bias and identify risk situations that could impact match outcomes, Gaina, Lucas, and Perez-Liebana (GAINA; LUCAS; PEREZ-LIEBANA, 2018) proposed a real-time prediction model based solely on agent-based features. Using the General Video Game AI framework (GVGAI), the agents were able to recognize factors that could lead to a negative outcome and make adjustments before the game concluded. The agent-based approach, however, disregards real players' features. Nonetheless, it could be integrated into an in-game suggestion system, where the agent's adjustments can be compared with players' match histories to generate more comprehensive insights.

Riv *et al.* (R et al., 2019) investigated outcome prediction by selecting relevant features through Recursive Feature Elimination (RFE), which considers small sets of features, and applied those features to all players in the dataset. Data from pre-match and within-match phases were tested separately and combined. The highest accuracy, 99.75%, was achieved using Random Forest with the combined data. Other methods tested, including AdaBoost, Gradient Boost, and Extreme Gradient Boost, also yielded high accuracy for within-match and combined data. However, for pre-match data, the accuracy was 65.67% or lower.

Yang *et al.* (YANG et al., 2020) used Transformer and LSTM methods to explore the prediction of four in-game events, one of which referred to the match outcome. The highest accuracy obtained, 70.8%, was achieved using the Transformer approach. The study considered the following features: hero-related (i.e., champion), global features (game time, number of players alive, amount of money, and remaining towers), as well as features related to monsters, NPCs, and towers.

An outcome prediction based on player-roles was conducted by Bahrololloomi *et al.* (BAHROLOLLOOMI et al., 2023). The authors compared evaluation metrics with and without considering player-roles, finding no significant difference between the approaches, which contrasts with our results, as further explained in Chapter 7. The highest accuracy achieved was 86%, using the Gradient Boosting Regressor (GradB) method.

The expertise of commentators and casters regarding which features most affect the outcome was explored by Chitayat *et al.* (CHITAYAT et al., 2024). Among all the analyzed features, only four were actually used by these professionals to base their predictions and analyses: player experience with a champion, team composition and game patch influence, potential kills of a team, and ideal timing for a team. This study aims to leverage this knowledge to enhance spectators' experience while providing insights to improve commentators' narratives.

Using a binary replay dataset, Hodge *et al.* (HODGE et al., 2021) were able to recreate entire DotA2 matches and use live game stats to predict outcomes. The focus features analyzed included team damage dealt, team kills, team last hits, team net worth, team tower damage, and team experience gained, thereby emphasizing team performance rather than individual player performance. The authors employed the LGBM method, the same as in our study, with the goal of providing real-time data to game spectators.

A concern in game analysis is the presence of outliers in datasets, a common characteristic found in both casual and eSports player performances. Tyran, and Chomatek (TYRAN; CHOMATEK, 2021) investigated the influence of outliers on the quality of outcome predictions. The authors observed no significant difference between predictions made with and without outliers, suggesting that addressing outliers in the dataset was unnecessary.

3.6 Conclusions

The study by Bahrololloomi *et al.* (BAHROLOLLOOMI et al., 2023) shares similarities with this research, as it also incorporates player-roles to propose an outcome prediction approach. However, the algorithm employed in their study did not demonstrate significant differences between tests conducted with and without the division of player-roles. This result contrasts with our findings, and their model achieved marginally lower accuracy. Furthermore, their study lacks a clear definition of how player performance was evaluated, thereby limiting the comparability of the results.

Other studies do not integrate player-roles into their methodologies or evaluations, instead relying on generalized tasks that are applicable to some or all roles. Such approaches fail to account for the individual aspects inherent in MOBAs, potentially leading to an inaccurate or incomplete assessment of player performance.

Among the related studies, see Table 3.1, none have proposed an approach that simultaneously measures player engagement, evaluates their alignment with team strategies, and utilizes both metrics to assess player performance, predict match outcomes, and provide actionable suggestions for improving gameplay — all while considering player-roles. Existing research has only addressed partial aspects of these elements, lacking a comprehensive and integrated analysis.

Ordem cronologica

Table 3.1: A comparison among state of art and proposed method.

Study	Role	Behavior Analysis	Engagement/Commitment	Performance Measurement	Match Outcome Prediction	Gameplay Suggestions	MOBA	League of Legends
(DRACHEN et al., 2014)	-	X	-	-	X	-	X	-
(PRAKANNOPPAKUN; SINTHUPINYO, 2016)	-	-	-	-	X	-	X	-
(UYSAL, 2016)	-	X	X	-	-	-	-	-
(VIEIRA et al., 2017)	-	-	-	-	X	-	X	X
(GAINA; LUCAS; PEREZ-LIEBANA, 2018)	-	-	-	-	X	-	-	-
(AHMAD et al., 2019)	X	X	-	X	-	-	X	-
(CHENG et al., 2019)	X	-	-	X	-	-	X	-
(JOSHI et al., 2019)	-	-	-	X	-	-	-	-
(RÍO; CHEN; PERIÁNEZ, 2019)	X	X	X	-	-	-	-	-
(R et al., 2019)	-	-	-	-	X	-	X	X
(JIANG; LERMAN; FERRARA, 2020b)	-	X	X	X	X	-	X	X
(YANG et al., 2020)	-	-	-	-	X	-	X	X
(COSTA et al., 2021b)	-	-	-	X	X	-	X	X
(DEHPANAH et al., 2021)	-	X	-	X	-	-	X	X
(DO et al., 2021)	-	-	-	-	X	-	X	X
(HODGE et al., 2021)	-	-	-	-	X	-	X	-
(JIANG et al., 2021)	X	X	-	X	-	-	X	X
(TYRAN; CHOMATEK, 2021)	-	-	-	-	X	-	X	X
(BISBERG; FERRARA, 2022)	-	-	-	-	X	-	X	X
(JANG; WOO; KIM, 2022)	X	-	-	X	-	-	X	X
(KE et al., 2022)	-	-	X	-	X	-	X	-

Study	Role	Behavior Analysis	Engagement/Commitment	Performance Measurement	Match Outcome Prediction	Gameplay Suggestions	MOBA	League of Legends
(MONDAL et al., 2022)	X	-	-	X	-	-	X	X
(TIAN; LAN; ZHANG, 2022)	-	-	-	-	X	-	X	-
(ZHAO et al., 2022)	-	-	-	-	X	-	X	-
(BAHROLOLLOOMI et al., 2023)	X	-	-	X	X	-	X	X
(Zaib Abbasi et al., 2023)	X	-	X	-	-	-	-	-
(CHITAYAT et al., 2024)	-	-	-	X	X	-	X	-

4

Methodological Procedures

This chapter outlines the methodology used to conduct the systematic literature review, which was carried out to establish the state of the art and identify the research gap addressed in this study. Additionally, it details the implementation, evaluation, and experiments conducted to assess the proposed method.

4.1 State of Art Structure

A systematic literature review was conducted, focusing on two key topics to identify studies relevant to our objectives and compare the proposed approaches:

- **Match Performance**: This topic focuses on analyzing the scores achieved by players during a match. While most studies utilize general parameters, their structure, score analysis, and choice of methods — such as clustering and classification — are similar to those employed in our work.
- **Player-Role**: This topic examines team formation and composition, particularly in eSports scenarios where roles are clearly defined, and tasks are explicitly assigned to players.

An exploratory search was conducted using articles from the IEEE Conference on Games (CoG) without applying a search string. This search was limited to the specified timestamp to identify all research directions explored. This approach was applied exclusively to IEEE CoG publications because, among the three databases analyzed — IEEE, ACM, and ScienceDirect — it is the only conference dedicated solely to games. While the ACM Digital Library includes the Artificial Intelligence in Interactive Digital Entertainment (AIIDE) conference, its scope extends beyond digital games, encompassing other domains of interactive digital entertainment.

Based on these topics and the exploratory search conducted both on IEEE CoG, and furthermore on Google Scholar, the following keywords were identified for the systematic literature review:

- **String 01:** "esports players performance" AND "team composition" AND "moba".
- **String 02:** "player" AND "game" AND "moba".

Three academic databases were selected for this purpose, as outlined in Table 4.1 and 4.2: ACM Digital Library, IEEE Xplore, and ScienceDirect. These platforms were chosen because they host a wide range of publications in the field of Computer Science, including research related to games.

Table 4.1: First search string - Systematic literature review with the string ("esports players performance" AND "team composition" AND "moba") in search bases.

Search Base	Amount of articles found	Amount of articles related to this work theme
ACM Digital Library	211	47
IEEE Xplore	1	1
ScienceDirect	16	8

Table 4.2: Second search string - Systematic literature review with the string ("player" AND "game" AND "moba") in search bases.

Search Base	Amount of articles found	Amount of articles related to this work theme
ACM Digital Library	7	2
IEEE Xplore	29	18
ScienceDirect	150	21

The Brazilian Symposium on Games and Digital Entertainment (SBGames) was initially considered as a potential search source. However, its articles were already indexed in other databases, such as IEEE Xplore and ACM Digital Library, making its inclusion redundant.

A timestamp from 2009 to 2023 was selected to encompass the years preceding the start of this study, including the release year of our object of study, thereby providing a comprehensive historical overview. This timeframe accounts for frequent updates and significant gameplay modifications in the studied game, which could substantially influence the results. Furthermore, the last analyzed period (2023) corresponds to the first year of this study.

Articles focusing on the social aspects of the game environment, such as gender-related issues, toxic behaviors, or those exclusively analyzing psychological factors, were excluded from consideration. For the remaining articles, all titles and abstracts were reviewed, and works containing at least one element relevant to our study were selected for full reading.

For the second search string, only unique articles were considered, excluding those found in both the first and second searches. This explains the relatively low number of articles in the academic databases, as illustrated in Table 4.2.

The primary objectives identified in the systematic literature review, which partially align with the literature mapping conducted by Costa *et al.* (COSTA et al., 2023), are as follows:

- Match outcome prediction.
- Performance measurement.
- Recommendation of champions or items.
- Matchmaking systems, which allocate players to matches based on factors such as rank or account level.

Through this process, a research gap was identified. Most studies classify player performance based on the general context of a well-executed match, such as using metrics like the KDA ratio. Few analyses consider the player-role and its associated tasks, and among these, most focus on theoretical aspects, providing definitions and briefly mentioning some tasks. The topic with the most research leveraging player-role definitions is recommendation systems.

However, as noted by Macedo, and Falcão (MACEDO; FALCÃO, 2020), relying solely on the KDA ratio may not provide a comprehensive analysis of a match. This is because matches are composed of multiple objectives and actions, all of which should be considered. The authors also emphasized the importance of teamwork and team composition in MOBAs, highlighting their role in achieving a positive match outcome.

Despite the existence of research focused on player-related elements to improve performance and provide recommendations, most studies do not validate their proposed methods with actual players. Among those that do, few focus on how players interpret the results or utilize them in practice (KLEINMAN; EL-NASR, 2021).

Our work takes a step back by initially focusing on measuring a player's engagement with each in-game task. This approach enables an analysis of whether a player is underperforming during a specific period or if they consistently fail to fulfill a particular task. As a result, this measurement offers valuable insights into the player's Commitment to their chosen role. Each task is represented by instances of numerical scores, while categorical values denote player, champion, and match identifiers or specific game states such as *early surrender*.

Furthermore, by defining the criteria for good performance in each task, these findings can contribute to advancing eSports analysis and enhancing player-role evaluation. For instance, the performance data for each player-role combination in a match can be utilized as features for predicting match outcomes. Moreover, these insights can be applied to recommend strategies that teams can adopt to improve their chances of winning, which will be explained further in Chapter 7.

Section Commitment Vector Creation foi removida daqui

4.2 Work Procedures

This work is organized into four main steps:

- Step 01 involves obtaining and processing data. Player and match information is extracted for the casual players dataset. For the eSports scenario, a dataset is provided through a partnership with a MOBA team. Subsequently, the datasets are segmented by the chosen period, player-role, and task. During this segmentation process, only the features that contribute to the Commitment vector are considered.
- In Step 02, an unsupervised ML method, specifically clustering, is applied to the casual players dataset with the goal of grouping instances based on similarity. The results of the clustering are then labeled by considering the mean of each group to match the Commitment levels proposed in the original metric. These labels are provided as target values in supervised ML methods, classifiers, and an ensemble approach. This application of Commitment differs from the originally proposed method by incorporating player-role aspects through the association of tasks.

- Step 03 applies the same methods as Step 02, but to a different dataset — the eSports dataset — while considering the contextual characteristics specific to this scenario.
- In Step 04, the obtained Commitment levels are compared with the team's strategy, assigning a score based on the player's assertiveness. This measurement yields a Compliance value for each player in every match. Once Compliance is determined, a supervised ML method, specifically a classifier, is applied to predict match outcomes. Finally, by considering both Compliance and the relative weight (i.e., the features' contribution linked to predictions) of each task in predicting match outcomes, gameplay suggestions can be provided to enhance the likelihood of achieving a positive match result.

4.3 Experiments

This section outlines all experiments conducted to achieve the proposed objectives, as well as those intended for complementary analysis.

The algorithm developed for casual players data extraction was adapted from the work of Humenhuk, Kummer, and Paraiso (HUMENHUK; KUMMER; PARAISO, 2021), with modifications to account for updates in the API of the analyzed game. All results obtained from API requests — which returned data related to players and matches — were analyzed and filtered based on player-role descriptions established in the literature. A detailed discussion of the findings is provided in Chapter 6.

The original Commitment metric incorporates a d_i element to track the evolution of player behavior over time. To determine the most suitable timestamp granularity (e.g., daily, weekly, monthly) for the analyzed dataset, visual analyses — specifically histograms — were conducted. Based on these analyses, weekly granularity was selected for data segregation. The rationale behind this choice is discussed in detail in Chapter 5.

To analyze the evolution of Commitment per Task, line graphs were generated using casual player data, depicting the Commitment level per week for each task. A similar procedure was applied to the eSports player data, utilizing a championship round granularity. These visual analyses serve to validate H1: the Commitment metric can effectively measure player engagement in role-specific tasks. The graphs provide evidence of how closely a player adheres to the tasks associated with their role over a defined period, thereby demonstrating the utility of the metric in assessing engagement.

For each extracted player, a graph was generated for every task associated with their role. These graphs provide a detailed visualization of task-specific performance and engagement, with further analysis and discussion provided in Chapter 7.

H2 examines the application of the Commitment metric without considering the temporal element, represented by d_i. The exclusion of d_i was intended to model an eSports context, where matches are structured around championship phases and team standings. However, after analyzing the dataset from eSports players, it became possible to associate the number of matches played per championship round with the d_i element. Consequently, H2 was invalidated.

We conducted a Principal Component Analysis (PCA), see Figure 4.1, to determine the number of features required to measure Commitment. The four features — d_i, S_{i-min}, S_{i-max}, and Δ — were analyzed, and the PCA results showed no significant difference between using three or four features. Therefore, the theoretical foundation was prioritized, and all four features were retained to capture the variation among scores.

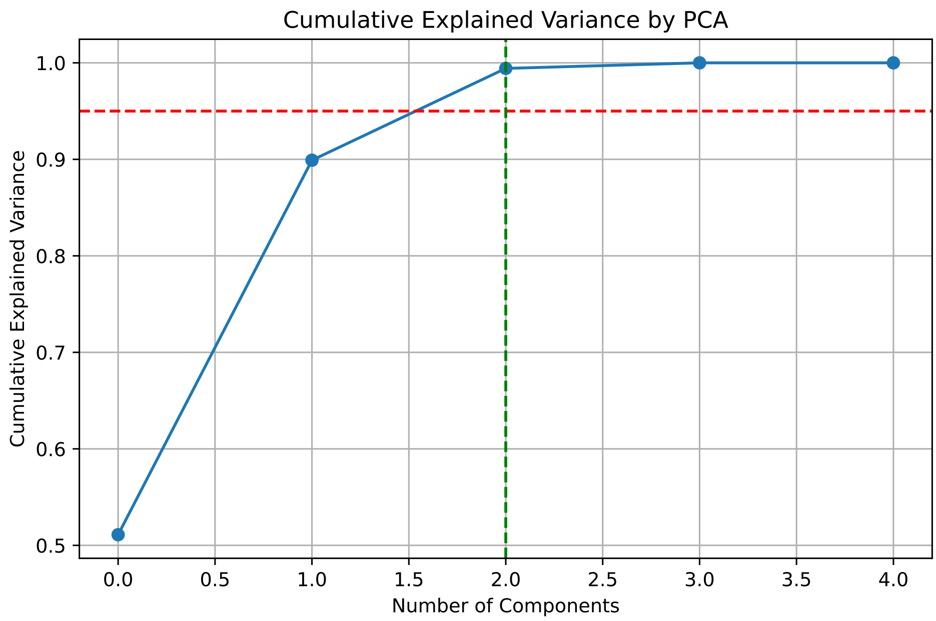

Figure 4.1: PCA results for the Commitment vector features.

The Commitment levels were compared against expectations for each player-role. This comparison was conducted by considering both the strategy defined by the eSports team and the literature, and was applied uniformly to all teams and players to assess performance in relation to the match outcome. The result of this analysis is a metric called Compliance, which indicates the assertiveness of players' performances according to teams' strategies (i.e., desired Commitment degree per task associated with a role). Compliance is used to measure player performance, predict match outcomes, and provide gameplay suggestions.

The expectations for the eSports domain were defined in collaboration with an eSports team, incorporating the insights of the team's analysts. These analysts not only associated tasks they deemed most appropriate for each role but also provided a classification — low, average, or high — of the expected level of Commitment for each player in each task. To assess the degree of alignment between the analysts' opinions, a Kappa coefficient test was conducted.

Cohen's Kappa coefficient measures the agreement rate between evaluators while accounting for the possibility of random agreement. As a result, it is considered a more robust metric compared to a simple percentage rate. The formula for Kappa, see Equation 4.1, is given as follows (VIEIRA; KAYMAK; SOUSA, 2010):

$$K = \frac{P(o) - P(e)}{1 - P(e)} \tag{4.1}$$

Here $P(o)$ represents the observed agreement, see Equation 4.2, calculated as the sum of the agreements between the evaluators divided by the total number of samples analyzed. $P(e)$ denotes the expected probability that an agreement will occur by chance.

$$P(o) = \frac{\sum_{i=1}^{k} M_{ii}}{N} \tag{4.2}$$

In which, M_{ii} represents the number of times both evaluators classified a sample in the same category i, and N is the total number of samples analyzed.

$$P(e) = \sum_{i=1}^{k} P(A_i) \times P(B_i) \tag{4.3}$$

Where $P(A_i)$ and $P(B_i)$ are the probabilities of each evaluator independently assigning a sample to category i, and k represents the total number of categories, see Equation 4.3.

As an example, consider the classification of two evaluators of 100 samples into three categories: low, average, high. These classifications were represented in Table 4.3.

Table 4.3: Classification of evaluators for the exemplification of Cohen's Kappa coefficient calculation.

	Low	**Average**	**High**
Evaluator A	20	30	50
Evaluator B	35	20	45

$P(o)$ is calculated by summing the number of agreements between evaluators. Thus, the number of samples where both evaluators agreed in each category are: 20 (Low), 20 (Average), and 45 (High).

$$P(o) = \frac{(20 + 20 + 45)}{100} = \frac{85}{100} = 0.85 \tag{4.4}$$

On the other hand, $P(e)$ is obtained by multiplying $P(A_i)$ and $P(B_i)$ for each category and then summing the results.

$$P(e) = \left(\frac{20}{100} \times \frac{35}{100}\right) + \left(\frac{30}{100} \times \frac{20}{100}\right) + \left(\frac{50}{100} \times \frac{45}{100}\right) \tag{4.5}$$

$$P(e) = (0.07) + (0.06) + (0.225) = 0.355 \tag{4.6}$$

Finally, the Kappa coefficient can be obtained as:

$$K = \frac{0.85 - 0.355}{1 - 0.355} = \frac{0.495}{0.645} \approx 0.76 \tag{4.7}$$

The Kappa coefficient ranges from -1 to 1. A value close to 1 indicates strong agreement among the evaluators, while a value of 0 or lower suggests no agreement or disagreement beyond the probability levels.

However, the obtained Kappa coefficients were too low to determine an agreement among analysts, which is further detailed in Chapter 7. Therefore, the opinion from the "most experienced" analyst — the scout analyst, according to the eSports team — was considered.

A series of supervised ML methods was tested to predict match outcomes based on the tasks fulfilled by players, taking into account their respective roles. The goal of this experiment is to identify the optimal parameters for enhancing the accuracy of this prediction model. The analysis was conducted only with eSports player data. This experiment was conducted to validate H3, which posits that the tasks associated with player-roles, along with the Commitment levels and Compliance, can be utilized to predict match outcomes.

For the experiments that depended on the relation among features, a Pearson test was made to identify highly correlated tasks, which could influence the accuracy of the ML methods. The highly correlated tasks were analyzed for exclusion, leaving only the ones that indicated an important action in the match, and could not be dismissed.

An analysis was conducted to evaluate the relationship between fulfilled tasks per player-role and match outcome prediction. This analysis aims to identify which tasks have the most significant influence on match outcomes. Besides a graphical and statistical approaches, the importance of each feature was also measured during the outcome prediction. Consequently, H4 is derived as a logical extension of the validation of H3. In both hypotheses, the Compliance metric was incorporated following the final experiments.

As highlighted by Joshi *et al.* (JOSHI et al., 2019), more experienced players and teams are generally receptive to suggestions aimed at enhancing their chances of achieving a positive match outcome. In contrast, less experienced players tend to focus on accelerating their understanding of the game's fundamental aspects.

Therefore, while it is possible to generate a set of suggestions for casual players, such recommendations may not hold the same level of relevance for them as in the eSports scenario. For this reason, we validated these suggestions through collaboration with an eSports team. By aligning the findings with their approaches, the study sought to refine gameplay strategies and, consequently, improve match outcomes.

For experiments conducted, four evaluation metrics — accuracy, precision, recall, and F1-score — were applied, when possible, and analyzed. The descriptions of these metrics were based on the work of Hossin, and Sulaiman (HOSSIN; SULAIMAN, 2015), and the mathematical formulas for each metric included the following elements:

- **True Positive** (TP): The model correctly predicts a positive outcome when the actual outcome is positive.

- **True Negative** (TN): The model correctly predicts a negative outcome when the actual outcome is negative.
- **False Positive** (FP): The model incorrectly predicts a positive outcome when the actual outcome is negative.
- **False Negative** (FN): The model incorrectly predicts a negative outcome when the actual outcome is positive.

Accuracy, see Equation 4.8, measures the proportion of correctly classified instances relative to the total number of instances analyzed. It provides an overall assessment of the method's effectiveness but may be less informative when dealing with imbalanced datasets.

$$\text{Accuracy} = \frac{TN + TP}{TN + FP + TP + FN} \tag{4.8}$$

Precision, see Equation 4.9, quantifies the proportion of correctly classified positive instances among all instances predicted as positive. A higher precision indicates fewer false positives, making it particularly important in scenarios where misclassification of negative instances as positive is costly.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.9}$$

Recall, see Equation 4.10, measures the proportion of actual positive instances correctly identified by the method. A higher recall reduces the number of false negatives, making it crucial when missing positive cases has significant consequences.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4.10}$$

F1-Score, see Equation 4.11, calculates the harmonic mean of precision and recall. It is particularly useful in scenarios with imbalanced datasets, as it balances the trade-off between precision and recall, preventing overemphasis on either metric.

$$\text{F1-Score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4.11}$$

Each evaluation metric serves a specific purpose and is essential for assessing the effectiveness of the methodologies employed. These metrics assist in identifying the most appropriate ML method for the problem at hand and provide a comprehensive evaluation of the method's overall performance (HOSSIN; SULAIMAN, 2015).

For this study, accuracy is considered as the evaluation metric for match outcome prediction, since a binary (true or false) feature is compared with continuous values and the addressed problem is inherently balanced, as each match yields one winning and one losing team. The objective is to determine which method is most effective in addressing the problem. The remaining evaluation metrics were tested for exploratory purposes.

4.4 Python Libraries

The programming language selected for this research was *Python version 3.9.13*. This choice was driven by the extensive availability of libraries tailored for machine learning applications. All code was executed in *Anaconda Spyder*, an open-source scientific environment for Python, as well as in *Google Colab* and *Anaconda Jupyter Notebook* for generating visual plots. The following libraries were utilized:

- Data extraction from the API was performed using the *Requests library*.
- In cases where errors occurred due to API limitations, the *Sys library* was employed to terminate the application, preventing the inclusion of incomplete or malformed data in the dataset.
- The *DateTime library* was utilized to convert match timestamps into a DateTime format (year, month, day). This conversion was essential for organizing data into weekly intervals and calculating the number of matches for the d_i element of the Commitment metric.
- The time spent on data extraction, as well as the sleep intervals required to comply with API limitations, were managed using the *Time library*.
- All .csv files were created, updated, and read using the *Pandas and CSV libraries*.
- The *Os* and *Shutil libraries* were used to create directories, manage file paths for saving data at each stage of the work, and retrieve or read filenames.
- The *Seaborn* and *Matplotlib libraries* were employed for generating graphical plots, such as boxplots and lineplots, to facilitate visual analysis.
- From the *Sklearn library*, the K-means clustering algorithm was used to segregate dataset into groups. Additionally, the *VotingClassifier*, an ensemble method that aggregates predictions from multiple classifiers to produce

a final output based on their averaged results, was implemented. The tested and integrated classifiers (*DecisionTree*,*RandomForest*,*MLP*) into the *VotingClassifier* were also implemented using the *Sklearn library*.

- For match outcome prediction, the *LGBM* classifier, which belongs to a distinct library, was applied.

- Pearson and Point-Biserial correlation tests were made through *SciPy library*.

5

Dataset Creation

We conducted a comprehensive search to identify a dataset with the features required for this study, focusing especially on resources available on *Kaggle*[1], a well-known ML and data science platform where users host competitions and share datasets. However, we found no dataset that included all the essential features — such as player roles, a wide range of tasks, temporal elements, and match outcomes. Moreover, most available datasets were outdated, ranging from three to seven years old, raising concerns about data depreciation or obsolescence.

Members of the Game Analytics research group at PPGIa developed two datasets that we also analyzed in this study. The first dataset, created by Mazeto, Kummer, and Paraiso (MAZETO; KUMMER; PARAISO, 2018) in 2018, comprises 146,762 instances involving 93,228 unique players. However, it lacks the dates when matches were played and includes only lane information, without specifying player roles. The second dataset, developed by Humenhuk, Kummer, and Paraiso (HUMENHUK; KUMMER; PARAISO, 2021) in 2021, provides daily login information using a numeric scale: "-1" for no login, "0" for initial login followed by absence, and "1" for confirmed login. Nonetheless, this dataset omits data about tasks, matches, chosen champions, and player roles.

Due to these limitations, we developed a new dataset tailored to the goals of this study. This chapter describes the data acquisition process, addressing the restrictions of the extraction tool and detailing the preprocessing steps applied

[1]https://www.kaggle.com

to prepare the data for analysis.

5.1 League of Legends API

We used Riot Games' League of Legends API to extract data, employing the *Spyder*[2] environment for Python. The API provides access to extensive match and player information, including scores, objectives, match outcomes, selected champions, and player regions.

To access the API, we registered a free developer account and authenticated requests using a unique, encrypted access key. This process, however, involves several constraints:

- The access key expires every 24 hours.
- The system permits 20 requests per second.
- The system limits requests to 100 every 2 minutes.

When the access key expired, we manually generated a new one, as Riot's platform includes a robot verification step that prevents full automation. We also incorporated the *sleep* method into the extraction algorithm to avoid exceeding the request limit.

5.2 Data Extraction

We initiated the extraction process in September 2023 and concluded it in February 2024. Due to API constraints, we extracted the data intermittently.

To begin, we identified players using their summoner names—the usernames used in-game and recognized by the API as unique identifiers. We selected approximately 400 summoner names with the goal of retrieving at least 20,000 player-match instances per week, ensuring diversity and adherence to our research timeline. We measured extraction time using Python's *Time* library, basing estimates on the first 100 names.The term "data" refers to the information associated with each player in a match, and it is possible to have multiple instances of match-related information per player.

[2]https://www.spyder-ide.org

Of the 400 mapped summoner names, we selected 200 from the region where the research is being conducted, Brazil. The remaining 200 were evenly distributed between the South Korea server (KR1 in the LoL API) and the server encompassing Hong Kong, Taiwan, and Macao (TW2 in the LoL API). Data from mainland China was not available during the extraction period. These regions were chosen due to their prominence in the game, characterized by larger player bases and a history of championship titles (HOWARD, 2018; SEO, 2013; SABTAN; CAO; PAUL, 2022).

We chose the first summoner name based on the player's activity level, region, and account level. At the time, the player held a Bronze ELO rank, indicating engagement in ranked matches. We found this summoner name through OP.GG[3], a platform for League of Legends match statistics. We applied the same selection criteria to subsequent names, ensuring variability in ELO ranks and account levels. We also included some summoner names believed to belong to professional eSports players. However, many of these were unofficial fan accounts, which we excluded when possible. Approximately two-thirds of the dataset includes players who had matched with previously selected players

After identifying a summoner name, we used the API to obtain the Player Universally Unique Identifier (PUUID), which can be used to retrieve a list of matches played by the corresponding player. We applied constraints aligned with the research criteria.

We focused on a 40-week period to construct the dataset. This period encompasses the first week of the year, beginning on January 2nd, and extends to the week in which the extraction process commenced, ending on October 8th. We applied this timeframe as a constraint for requesting the list of matches, with a maximum of 100 matches retrievable per week.

In 2024, significant changes were introduced to LoL, including modifications to the map, objectives, and player preferences for champions, commonly referred to as the "meta". These changes fall outside the scope of this study, as the selected timeframe does not encompass these updates. Additionally, players are likely to still be adapting their gameplay styles during this period of implementation, and it remains uncertain whether these changes will be maintained in the long term.

The match identification list is ultimately used to request match data. During

[3]https://www.op.gg

this extraction process, the application can access data not only from the specified player but also from players on both the ally and enemy teams. In summary, for each match, data from 10 players can be obtained. This enables the analysis of both positive and negative match outcomes for the same role. Additionally, it allows for the identification of whether a player's result was influenced by team performance or if it was primarily due to their individual contribution.

We published all algorithms developed for the data extraction from the LoL API[4] on *GitHub*[5], a platform designed for hosting code and facilitating version control for project collaborators.

5.3 Preprocessing

After completing extraction, we cleaned the dataset to meet our research objectives. From 1,695,348 initial instances, we removed the following:

- **Empty Columns**: Columns containing only 0 values were removed, as they indicated that none of the analyzed players performed the associated task.
- **Matches Not of Type Summoner's Rift PvP**: Matches that did not meet the criteria of being Summoner's Rift PvP were excluded. This avoids matches with insufficient data, such as Summoner's Rift PvE matches, which only include data from 5 players, or matches that do not align with the analyzed criteria of a MOBA format, such as ARAM, Arena, and TFT. In the dataset, only ARAM matches were identified among the excluded types.
- **Matches with Duration Less Than 600 Seconds**: Matches lasting less than 600 seconds were removed, as they likely represent early surrender scenarios. If a player is Away from Keyboard (AFK) or disconnects within the first 10 minutes (600 seconds), the remaining players can vote to end the match without penalties.
- **Duplicated Matches**: Duplicate matches were removed, as data was extracted from players who participated in the same matches together.
- **Missing Values in the Player-Role Label Column**: Instances with missing values in the player-role label column were excluded, as the role information is essential for the research. The number of missing values in the dataset was not significant enough to warrant a more complex imputation approach.

[4] https://github.com/Pinkstrenhi/LoL-Data-Extraction-From-API.git
[5] https://github.com

If any player in a match met exclusion criteria, we removed all data entries sharing that "matchId". This ensured consistency when comparing roles across tasks.

To protect user identities and streamline processing, we anonymized player data. We replaced summoner names with standardized labels (e.g., Player_1, Player_2). The "matchId" field remains available to enable future match-specific research..

5.4 Data Characteristics

After preprocessing, the dataset retained 981,380 instances, each representing a player from a specific match. Consequently, the dataset comprises 98,138 unique matches, with 10 players per match.

The dataset also contains 165,260 missing values in the "kills" feature. This occurred because the "kills" feature was extracted after the initial data collection, and the corresponding match data had already been removed from the LoL API, resulting in a "Data not found - match file not found" error.

We conducted an analysis on the four features related to player-roles, focusing on the scores achieved in tasks and the conceptual framework of each player-role. Based on this analysis, we chose the feature "individualPosition" as the label, for the following reasons:

- **Feature "lane"**: Indicates only the area of the map where the player was located during the match. However, players may choose to play a role in an unconventional lane, such as an ADC role in the jungle, making this feature less reliable for role identification.
- **Feature "role"**: Reflects the gameplay style rather than the specific player-role. It includes attributions that are shared across multiple roles, rather than being unique to each role.
- **Feature "teamPosition"**: Contains attributions for the five player-roles but is less precise compared to "individualPosition". Additionally, it has more instances of missing values, which are assigned to the Jungle role in the "individualPosition" feature.

The constructed dataset is balanced, as most matches include two players with the same role, one on each team. However, there are instances where a single team has more than one player assigned to the same role. Although these cases are in the minority, they contribute to the unequal distribution of data across player-roles. Consequently, the number of instances per role, listed in ascending order, is as follows: Support (194,911), ADC (195,438), Middle (195,657), Top (195,842), and Jungle (199,532).

We made the dataset publicly available on the Game Analytics Research Group website[6], to ensure accessibility for scholarly use and promoting research transparency.

5.5 Data Segregation

As we previously mentioned, the Commitment metric incorporates a temporal component to evaluate the evolution of a player's engagement. Consequently, it is essential to define this metric and partition the dataset accordingly to determine from which timestamp d_i will be derived.

For casual player data, we tested a daily, weekly, and monthly basis segregation. The date used for this determination was derived from the attribute "gameEndTimestampToDate", which represents a conversion of the epoch/Unix format timestamp stored in the attribute "gameEndTimestamp" into a date format. We performed this conversion using the *DateTime library* in *Python*.

The original attribute, "gameEndTimestamp", represents the precise date and time at which the match concluded. We selected this attribute over the match start date because it provides more reliable information, particularly given that the analysis focuses on match outcomes.

Data was visualized using histograms, as shown in Figure 5.1, to evaluate the chosen timestamp segregation for the metric. Segregating data by month obscured certain fluctuations in player engagement, which could be useful for broader analyses, such as seasonal investigations. Conversely, segregating data by day revealed excessive detail, which is beneficial for highly specific analyses, such as determining whether target matches occur only on certain days of the year rather than throughout the entire year. For this study, a daily segregation was unnecessarily granular, while a monthly segregation lacked sufficient detail. Thus, the weekly segregation was chosen as the most appropriate for the analysis.

[6]https://www.ppgia.pucpr.br/~paraiso/Projects/GameAnalytics/

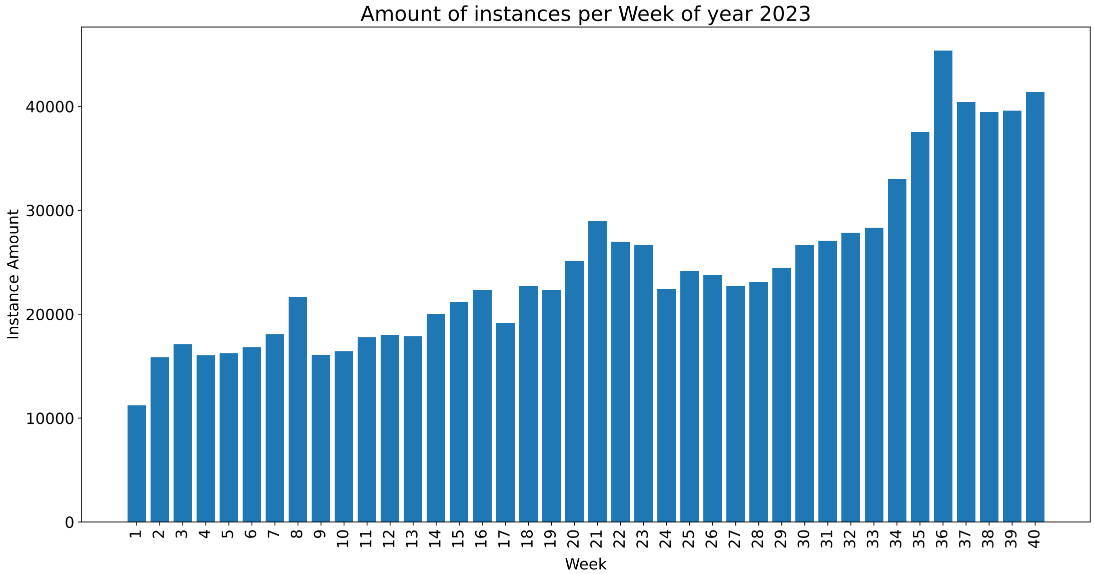

Figure 5.1: Amount of data, which is the player's information in a match, divided per week.

Once the segregation was defined, the dataset was divided into new files corresponding to each week. These weekly files were further splitted according to player-roles, as detailed in Chapter 6. This step is crucial for applying the Commitment metric, as these files will subsequently be segmented by task, and each task must be associated with a specific player-role.

In summary, the data extracted from the LoL API was organized into smaller files. Initially, the data was segmented based on the week of the year in which the match occurred, followed by further division according to player-roles. Given this, it is possible to determine the d_i element of the Commitment vector, by counting the amount of played matches per week.

5.5.1 eSports Dataset

Between April and June 2024, we established a partnership with Liberty, an eSports team competing in the Brazilian Championship of League of Legends (CBLOL). Through this collaboration, the team provided a dataset containing match data from both splits of 2024, including information from all 10 CBLOL teams.

A split is divided into three phases: phase-of-points, playoffs, and finals. However, only during the phase-of-points is it possible to collect data from all teams. In the playoffs, only six teams remain, and the finals are contested by just two teams. Due to the limited data availability in the playoffs and finals, as well as the changes in outcome conditions, we considered only data from the phase-of-points for this study.

Each CBLOL split consisted of 18 matches during the phase-of-points, typically played on weekends. Since the Commitment vector accounts for fluctuations in players' scores, analyzing matches individually would not provide varying scores for comparison. To address this, we paired matches, resulting in two matches per round — totaling nine rounds per split.

The match outcome considered was from the match with the highest score obtained ($S_i - max$), as this score is used to determine the player's Commitment level. For example, considering the two matches that compose a round, if a team won one match in which the analyzed player achieved a score of 90 in a given task, but lost the other match in which the same player achieved a score of 150 in the same task, the Commitment vector will be constructed by setting S_{i-min} = 90 and S_{i-max} = 150. In this case, the match outcome associated with the highest score (150) is considered, which corresponds to a negative outcome.

Due to the structure of the eSports scenario, players are evenly distributed across roles. Some players participate in both splits while remaining on the same team, whereas others switch teams, alternate between matches, or either leave the professional scene or begin their careers. These variations result in an unbalanced distribution of data per player.

The dataset consists of 1,800 instances — 900 per split — representing the features and respective scores obtained by each player in each match. Overall, the dataset includes instances from 67 unique players. With unique identifiers, tasks, champions, roles, and other features, the dataset contains a total of 280 attributes. Of these, 88 were considered relevant tasks for the proposed method. Attributes that were discarded pertained to highly specific tasks (e.g., completeSupportQuestInTime, multikillsAfterAggressiveFlash) that had very few instances or none at all. We conducted a Pearson correlation test to identify tasks with a high correlation (above 80%). Tasks that conveyed similar information were excluded to prevent bias. However, certain tasks that represented critical player actions were retained in the dataset despite their high correlation (e.g., "goldEarned" and "champExperience").

The role of each player was determined using information from an eSports statistics repository[7], which documents details about the game and most professional players, as well as through live broadcasts. Since eSports players typically do not change roles throughout their careers, the identified role was assigned to all data associated with the same player unique identifier. The attribute used to distinguish players was "riotIdGameName", which may change if a player joins a different team. In contrast, "summonerName" represents the name assigned when the account was created and remains unchanged (e.g., summonerName "FLA Kuri" have a "riotIdGameName" "PNG Kuri", the current team of Kuri is PNG).

After computing Commitment using casual players' data, we conducted subsequent experiments exclusively with eSports data. This decision was based on the greater stability and control over the data, as well as the need to validate the obtained results. Matches from eSports championships can be verified through live broadcasts, allowing confirmation of key events such as which team achieved a positive or negative outcome, when a player destroyed a tower, or who contributed to eliminating the Baron. Such verification is not possible for casual players' matches, as they typically lack supplementary evidence beyond the data provided by the API.

Due to confidentiality agreements associated with the partnership with Liberty, the dataset cannot be made available on the Game Analytics Research Group website or any other public platform. Access to the dataset is restricted to authorized researchers, following the ethical and legal requirements.

[7]https://lol.fandom.com/wiki/

6 Method

This chapter presents the proposed method, including its requirements and characteristics.

6.1 Method's Assumptions

The proposed method, see method architecture in Figure 6.1, aims to measure player Commitment to the role-specific tasks performed during matches. Consequently, it is referred to as Commitment per Task. This metric is designed for application in a MOBA game context, where each player-role is primarily determined by their chosen champion and the area of the map in which they engage.

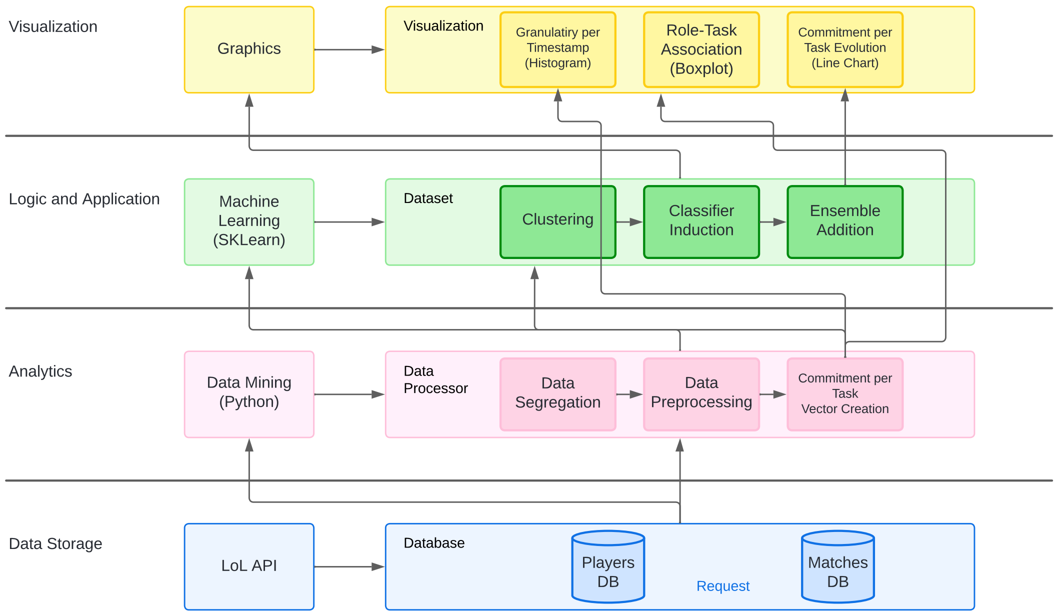

Figure 6.1: Architecture of the proposed method, the Commitment per Task.

In this study, the Commitment per Task metric is applied to a specific MOBA game. However, it can be adapted for use in other MOBA games or even different game genres, provided there is a clear division of player-roles and associated tasks. This metric can be used for an evaluation of player actions and their contribution to the match outcome, by applying supervised ML approaches, focusing on individual performance rather than team actions or more comprehensive metrics. In order to predict Commitment, the ML approaches consider the numerical values of the vector v_i, which consist of two components: the number of matches played in that role and the corresponding scores achieved — d_i, S_{i-min}, S_{i-max}, ΔS_i elements of v_i.

For casual players, the d_i element of the Commitment metric corresponds to the number of matches played per week. On the other hand, for eSports analysis, the d_i element is defined by the amount of matches played per round.

Afterwards, the Commitment levels are utilized to measure players' performance according with their teams' strategy. The proposed metric is called Compliance, which provide insights to eSports players, coaches, staff, and others. The Compliance metric can be used to investigate where a player is making flaws and must improve. Nevertheless, Compliance also validate the proposed strategy towards the match outcome.

6.2 Data Requirements

The implementation of the Commitment per Task and Compliance metrics requires the following elements:

- An unique player identifier.
- An unique match identifier.
- In-game actions that can be associated with a specific player-role.
- A clear identification of player-roles.
- The outcome of the match (e.g., win or loss).
- A temporal element to differentiate data, unless specific peculiarities are considered.
- Data from the opposing team to enable comparison of performance scores with enemy players.

6.3 Data Features

This section outlines the characteristics of the datasets for both casual and eSports players.

6.3.1 Casual Players Dataset

To construct the Commitment vector, it is essential to identify which in-game actions will be classified as tasks and associate them with specific player-roles. Of the 107 features present in the casual players dataset, 75 were retained as tasks. The remaining 32 were excluded for the following reasons:

- Non-numerical features, such as those with boolean or string attributes, as well as date format attributes derived using the *Python DateTime library*.
- Features related to player, match, and champion identification.
- Features related to player and champion levels within the match.
- Features related to champion experience gained during the match.
- Timestamps associated with the start and end dates of the match, as well as calculations of its duration.

Building on the work of Gaina, and Nordmoen (GAINA; NORDMOEN, 2018) and Jang, Woo, and Kim (JANG; WOO; KIM, 2022), which provide descriptions of player-roles and associations with specific tasks, along with a statistical analysis of the extracted data, all 75 tasks were associated with player-roles, as detailed in Table 6.1. Consequently, each task is linked to at least one player-role. Among the roles, Jungle has the highest number of associated tasks (62), followed by Top (52), Middle (49), ADC (49), and Support (41).

Table 6.1: Association of player-roles and tasks, according to the literature descriptions, graphical and statistical analysis.

Associated Player-Role	Tasks
TOP	tookLargeDamageSurvived
JGL	baronKills, objectivesStolen, elderDragonKillsWithOpposingSoul, elderDragonMultikills, dragonKills, enemyJungleMonsterKills, epicMonsterSteals, killsWithHelpFromEpicMonster, neutralMinionsKilled, soloBaronKills, totalTimeCCDealt, trueDamageDealt
MID	magicDamageDealtToChampions
ADC	largestCriticalStrike
SUP	wardsKilled, wardsPlaced, completeSupportQuestInTime, totalUnitsHealed, visionScore, visionWardsBoughtInGame
TOP, JGL	damageSelfMitigated
TOP, ADC	turretTakedowns
JGL, ADC	damageDealtToObjectives
JGL, SUP	controlWardsPlaced, detectorWardsPlaced, totalHeal, wardTakedowns, wardsGuarded
TOP, JGL, MID	magicDamageDealt
TOP, MID, ADC	damageDealtToBuildings, damageDealtToTurrets, totalMinionsKilled, turretKills, turretPlatesTaken

Table 6.1: Association of player-roles and tasks, according to the literature descriptions, graphical and statistical analysis.

Associated Player-Role	Tasks
TOP, JGL, MID, ADC	multikillsAfterAggressiveFlash, bountyGold, goldEarned, kills, largestKillingSpree, largestMultiKill, multikills, physicalDamageDealt, physicalDamageDealtToChampions, soloKills, totalDamageDealt, totalDamageDealtToChampions
TOP, JGL, MID, SUP	enemyChampionImmobilizations
TOP, JGL, MID, ADC, SUP	abilityUses, legendaryCount, multiKillOneSpell, assists, baronTakedowns, deaths, deathsByEnemyChamps, inhibitorKills, inhibitorsLost, longestTimeSpentLiving, magicDamageTaken, physicalDamageTaken, pickKillWithAlly, skillshotsDodged, skillshotsHit, takedowns, teamBaronKills, teamRiftHeraldKills, totalDamageTaken, trueDamageDealtToChampions, trueDamageTaken, turretsLost, teamElderDragonKills, objectivesStolenAssists, spell1Casts, spell2Casts, spell3Casts, spell4Casts, turretsTakenWithRiftHerald

6.3.2 eSports Players Dataset

In the eSports context, three role-task associations were analyzed: one based on descriptions and attributions found in the literature, and two provided by Liberty — one from the head analyst and another from the scout analyst.

In the literature attribution, all 88 features considered as tasks were assigned to player-roles. Discarded features exhibited one or more of the following characteristics:

- The feature represented a highly specific action with few occurrences in the dataset, if any.
- The feature represented an identification of the player, champion, match, or other entities.
- The feature was not a continuous value related to the score obtained by the player.

The Liberty attribution focused on the features that constituted the team's strategy, excluding those that were not expected to be fulfilled by players, in addition to those already excluded based on the literature attribution. The remaining tasks for each player-role, in ascending order, were as follows: Jungle (36), Top (35), ADC (31), Support (26), and Mid (25).

6.3.3 Datasets Characteristics

The two datasets analyzed in this study differ significantly in terms of size, balance, and players' skills. Nevertheless, both datasets are essential for understanding the broader MOBA scenario and its unique characteristics.

The casual players dataset contains a larger number of instances and a greater variety of unique players. However, most players in this dataset are represented by only a single match, which limits the availability of gameplay history required for the Commitment metric. The matches spans several weeks in 2023 and do not include the most recent game updates.

On the other hand, the eSports players dataset, while highly balanced and providing the necessary match history, contains a limited number of instances. This lack of instances corresponds with the matches being played only when schedule, according to the championship phases. The dataset contains matches from the 2024 season of CBLOL, the last season before the change in the Americas championship.

6.4 Work Steps

This section outlines the key steps taken in this study to achieve the proposed objectives. The process is illustrated in Figure 6.2, which summarizes the methodological workflow, providing a structured overview of the study's progression — from data acquisition to actionable insights grounded in performance metrics. The diagram is divided into four main steps: (i) obtaining and processing data, (ii) calculating commitment per task for casual players, (iii) calculating commitment per task for eSports players, and (iv) measuring compliance, predicting outcomes, and generating gameplay suggestions. Each step builds upon the previous one, ensuring consistency and coherence throughout the analysis.

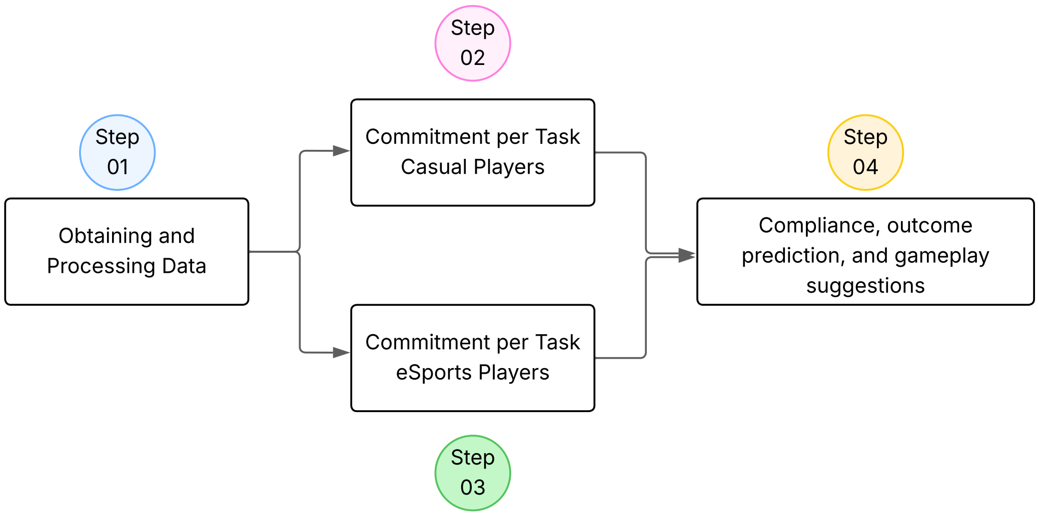

Figure 6.2: Proposed method main steps.

6.4.1 Step 01 - Obtaining and preparing data

The first step, illustrated in Figure 6.3, involves the creation of datasets for both casual and eSports players. For casual players, data is extracted from the LoL API, while for eSports players, the data was provided by a former Brazilian LoL team.

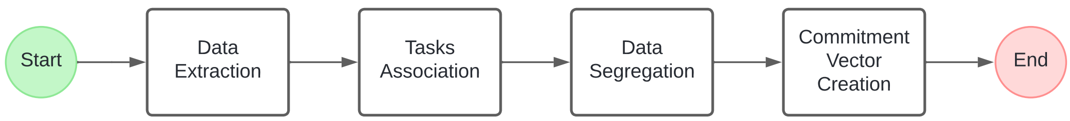

Figure 6.3: Diagram representing the Step 01 of the proposed method.

The datasets are preprocessed by removing features that cannot be considered tasks, are overly specific, or are never executed in each context. After preprocessing, the datasets are segregated by timestamp: a 40-week period for casual players, and by round for eSports.

Once the files are organized, the Commitment vectors are generated. Each vector is composed of the obtained scores and the number of matches played, as described further in this chapter.

6.4.2 Step 02 - Commitment per Task

The second step, illustrated in Figure 6.4, uses the dataset structured for casual players, establishing the foundation for subsequent steps and incorporating the (d_i) element of the Commitment vector, which represents the number of matches played per week.

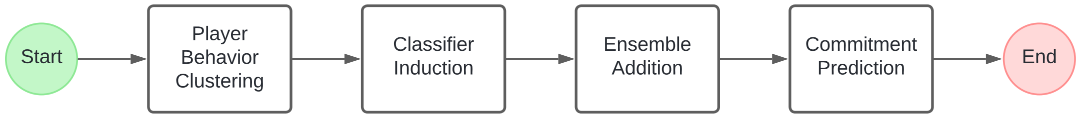

Figure 6.4: Diagram representing the Steps 02 and 03 of the proposed method.

The K-means algorithm was chosen to partition the data into groups due to its lower susceptibility to outliers, a common characteristic of the dataset, which reflects the inherent variability in a game scenario. The groups represent levels of Commitment, defined as low, average, and high. Therefore, the value of K for the clustering method was set to three (K = 3). The groups were labeled according to the following logic presented in Equation 6.1:

$$S_{max-low} < S_{max-average} < S_{max-high} \tag{6.1}$$

This means that the group with the lowest mean score in the S_{i-max} attribute is labeled as low, the group with an intermediate score is labeled as average, and the group with the highest score is labeled as high.

The data obtained from the clustering results, following the labeling process, is input into a classifier. The Random Forest algorithm was chosen for this purpose due to its ability to handle multiple features and its robustness against outliers. Finally, the data is processed through an ensemble method, specifically the Voting Classifier, to determine the levels of Commitment (i.e., the categorical values: low, average, and high) assigned to each group over time. Each classifier included in the ensemble represents player behavior at a specific timestamp. This approach enables the model to adapt to newly identified behaviors — attributable to game updates or shifts in the champions' meta — and compare them with previously defined patterns. The ensemble method facilitates the analysis of player behavior volatility and other player-related factors, which may arise from variations in player performance or changes in the game environment.

6.4.3 Step 03 - Commitment for eSports

In this step, illustrated in Figure 6.4, the same methods from Step 02 are applied. However, the dataset changes from the one extracted from the LoL API to the dataset provided by the former Brazilian LoL team, which contains data from eSports players.

Since eSports teams play according to the championship phases, the number of matches played is fixed for each period. eSports teams do not play every day or every week. Additionally, some teams are eliminated as the championship progresses and will only compete again in the following season, creating gaps of several months between matches. Therefore, one of the objectives of Step 03 is to demonstrate the applicability of the Commitment metric to eSports data.

6.4.4 Step 04 - Compliance in predictions and for gameplay suggestions

Once the Commitment levels are defined, the performance of each player can be evaluated based on their role-specific tasks and the team's strategy. A new metric, called Compliance, is introduced, which assigns numerical values to the Commitment levels, reflecting the player's assertiveness in meeting the team's expectations. This step is illustrated in Figure 6.5. The Compliance scores are then converted into percentage values and used as features for match outcome prediction, as following the coaches' orders is also considered a task that players must fulfill.

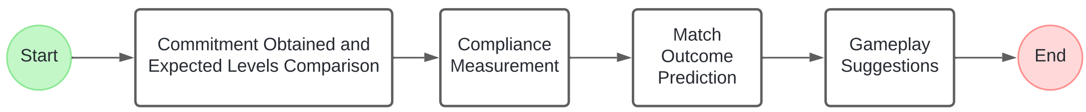

Figure 6.5: Diagram representing the Step 04 of the proposed method.

For match outcome prediction, the LightGBM (LGBM) classifier was chosen. LGBM demonstrated the highest accuracy — an evaluation metric used for binary classifications (e.g., win or lose) — among the tested models and balanced the contributions of weighted tasks more effectively[1]. This approach also takes into account the specificities of each player-role.

[1] *One Drive* - Outcome Prediction

To analyze whether players were underperforming or if a negative match outcome was due to the team's strategy, a Point-Biserial correlation between Compliance and match outcome was computed. The Point-Biserial correlation is particularly appropriate in this context because it measures the strength and direction of the association between a continuous variable (Compliance score) and a categorical variable (match outcome: win or loss).

Finally, to provide gameplay suggestions aimed at increasing the likelihood of a positive match outcome, a Pearson correlation was applied to the normalized Compliance scores and task contribution weights. The Pearson correlation is suitable in this case because both variables — Compliance and task contribution weights — are continuous and approximately interval-scaled. This method enables the identification of linear associations between the degree of compliance with specific tasks and their relative importance in determining match success. By quantifying the strength and direction of these relationships, it becomes possible to prioritize improvements in tasks whose compliance is most strongly associated with favorable outcomes. The normalization process followed Equation 6.2:

$$Normalized = \frac{n - n\_min}{n\_max - n\_min} \tag{6.2}$$

Moreover, the difference between Compliance scores and task contribution weights was calculated to assess how closely the two values align. This analysis helps determine whether player performance aligns with the expected outcomes based on the contribution of each task. The Compliance of tasks with high contribution weights on outcome prediction was analyzed, with a focus on providing gameplay suggestions when the Compliance score fell below 1 — the maximum achievable score within the Compliance metric.

6.5 Proposed Metrics

In this section, an overview of the newly proposed metrics — Commitment per Task and Compliance — will be presented, following a discussion of the metric that inspired this study: the Commitment metric.

6.5.1 Commitment

The Commitment metric, developed by Kummer, Nievola, and Paraiso (KUMMER; NIEVOLA; PARAISO, 2017), was initially designed to measure a player's attachment to a game in the context of MMORPGs. In MMORPGs, gameplay is not divided into discrete matches but involves continuous interaction with the game world, where player progress is saved and accessible in future sessions. This metric evaluates two key elements: the total time a player spends in the game and the scores they achieve. For each analyzed timestamp, a vector v_i, see Equation 6.3, is created to represent all components utilized by the metric to represent a player i:

$$v_i = \{id_i, d_i, S_{i-min}, S_{i-max}, \Delta S_i\} \tag{6.3}$$

id_i represents the player's unique identifier; d_i denotes the number of days played; S_{i-min} and S_{i-max} correspond to the minimum and maximum scores achieved during d_i; and ΔS_i is defined as S_{i-max} - S_{i-min}, representing the difference between the maximum and minimum scores.

The ΔS_i element is crucial for analyzing score fluctuations over time. A small difference between scores suggests stable engagement, while a large difference indicates unstable engagement. S_{i-min} and S_{i-max} indicate the range from which ΔS_i is derived. These three pieces of information are essential for the metric, as the vector can yield the same ΔS_i value from different S_{i-min} and S_{i-max} values. For example, a ΔS_i of 20 can be derived from S_{i-min} of 60 and S_{i-max} of 80, or from S_{i-min} of 5 and S_{i-max} of 25.

Afterward, Kummer, Nievola, and Paraiso (KUMMER; NIEVOLA; PARAISO, 2018) applied the Commitment metric to predict when a player would abandon a game, a scenario referred to as Churn. This was achieved without modifying the metric, allowing their Churn prediction to account for both player engagement and disengagement. The Commitment metric can be influenced by various factors, including updates to game features, characters, and environments, as well as external factors such as holidays and vacations (KUMMER; NIEVOLA; PARAISO, 2017).

Instances are categorized into three levels of Commitment: low, average, or high, according to the mean of S_{max-i} and following the logic of Equation 6.4:

$$S_{max-low} < S_{max-average} < S_{max-high} \tag{6.4}$$

This classification is achieved through a combination of unsupervised and supervised ML methods, as outlined in Steps 02 and 03 of this study (refer to Chapters 4 and 6 for further details). Initially, an unsupervised clustering approach using the K-means algorithm groups instances into three clusters based on similarity, as detailed in Chapter 6. Subsequently, the clustering results are used as input for supervised methods, including classifiers and an Ensemble model, to determine the appropriate Commitment level for each group obeying a temporal aspect.

Once the Commitment level is determined, the instances are prepared for use in performance measurement and match outcome prediction. This enables the analysis of various player-related aspects, such as the volatility of in-game behaviors over time, and their correlation with performance fluctuations or game updates. Additionally, analyzing Commitment levels in relation to specific in-game tasks helps players identify when they are achieving their expected performance thresholds, whether self-defined or established by a coach in an eSports context.

6.5.2 Commitment per Task

The Commitment per Task is a new metric derived from the Commitment metric, specifically designed to assess player engagement in task-specific contexts within MOBA games. It is calculated using the same formula described in Equation 6.3.

Unlike the original Commitment metric, the Commitment per Task incorporates S_{min-i} and S_{max-i} as the scores obtained in specific tasks, rather than the players' levels. These tasks are assigned based on each player's role and may include objectives such as dealing damage, providing vision, eliminating NPCs, and others.

The d_i element of the metric has also been modified, shifting from played days to played matches, to better align with the dynamics of a MOBA scenario. This adjustment aims to account for the unique characteristics of each match, as champion attributes are reset at the start of every game.

A vector v_i is generated for each task rather than for each player. This approach results in multiple vectors that can be compared to provide a comprehensive analysis of players' overall performance. Furthermore, these vectors can be analyzed in relation to a player's match history as well as in comparison with vectors of players from different teams who occupy the same role.

6.5.3 Compliance

The Compliance metric was developed to assess how well a player aligns with the team's strategy. By comparing previously obtained Commitment levels with expected levels, this metric provides a percentage that reflects the accuracy of a player's performance in adhering to strategic objectives.

The first step in calculating the Compliance metric involves converting the Commitment and expected levels into scores c_i, see Equation 6.5:

$$c_i = \begin{cases} 1, & \text{if } cl_i == s_i, \\ 0.5, & \text{else if } cl_i == "Average" \text{ and } (s_i == "High" \text{ or } s_i == "Low"), \\ 0, & \text{else if } cl_i \neq s_i \end{cases} \tag{6.5}$$

Where cl_i represents the Commitment level a player i obtained, and s_i denotes the expected level according to the team's strategy. The scoring process follows these conditions: If a player achieves the expected level, they receive a score of 1. If the expected level was "high" or "low" and the player obtained "average," they receive a score of 0.5 to acknowledge the partial alignment with the expected level. If the player does not achieve the expected level, the score is 0. Thus, for each player, a vector containing Compliance scores for all completed tasks is obtained.

Compliance is calculated as the sum of all scores, divided by the amount of n scores. The result is then multiplied by 100 to express the value as a percentage, see Equation 6.6:

$$Compliance = \frac{\sum_{i=1}^{n} c_i}{n} \times 100 \tag{6.6}$$

7

Results

This chapter presents the final results obtained, covering the data extraction process up to the completion of all proposed steps.

7.1 Attribution of Tasks to Player-Roles

In addition to the descriptions derived from the literature, an analysis of the extracted data was performed using boxplots. These visual graphics depict the distribution of data labeled according to player-roles for each task, demonstrating that the literature-based descriptions align with the role-task associations observed in actual gameplay. It is important to note that in the casual players dataset, the ADC role is represented as Bottom, and the Support role is labeled as Utility. Statistical values were also incorporated to complement the analysis, as illustrated in Table 7.1.

Table 7.1: Statistical analysis of the casual players dataset, considering the ADC role, being illustrated by three tasks: assists, totalDamageDealtToChampions, and visionScore.

	assists	**totalDamageDealtToChampions**	**visionScore**
mean	6.88	20880.67	19.65
standard deviation	4.36	12658.86	10.64
min	0.0	55.0	0.0

max	38.0	151057.0	164.0

As roles primarily responsible for managing the main lanes, Top, Middle, and ADC exhibit the highest number of NPC minion kills (see Figure 7.1). In contrast, Jungle players spend minimal time in the main lanes, while Support players focus on providing vision and utility rather than dealing damage or eliminating enemies.

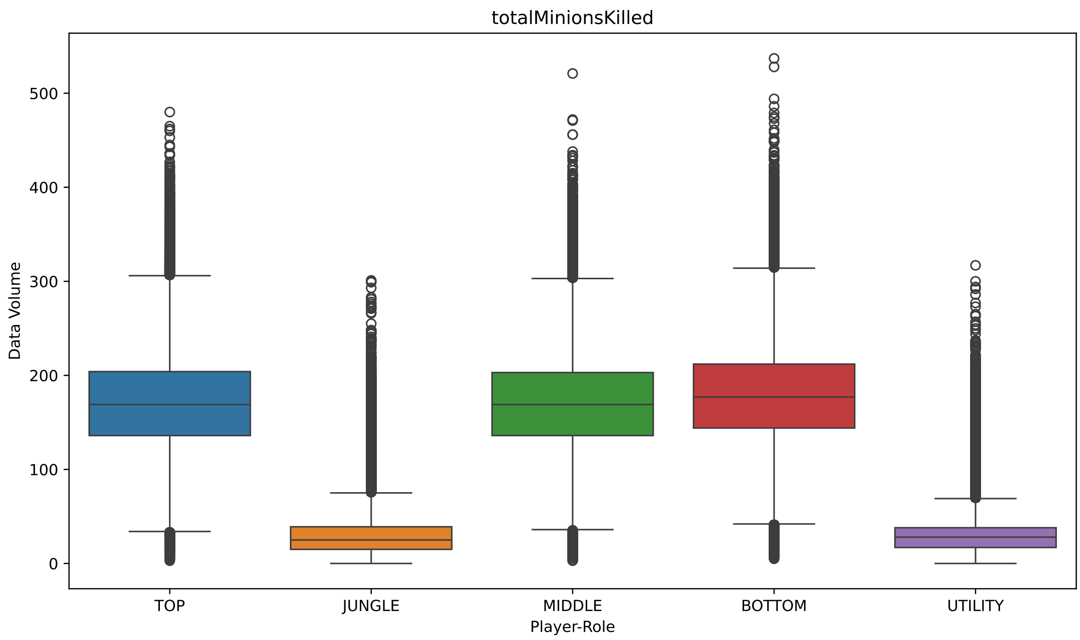

Figure 7.1: Boxplot analysis of the amount of data considering the task "Total Minions Killed", and the player-roles associations. This presents a task common to more than one player-role following literature descriptions.

The vision score was analyzed as an example of a task attributed by the literature to a specific role, as illustrated in Figure 7.2. For instance, providing map vision by placing wards or removing enemy wards to limit their visibility is a task primarily associated with the Support role.

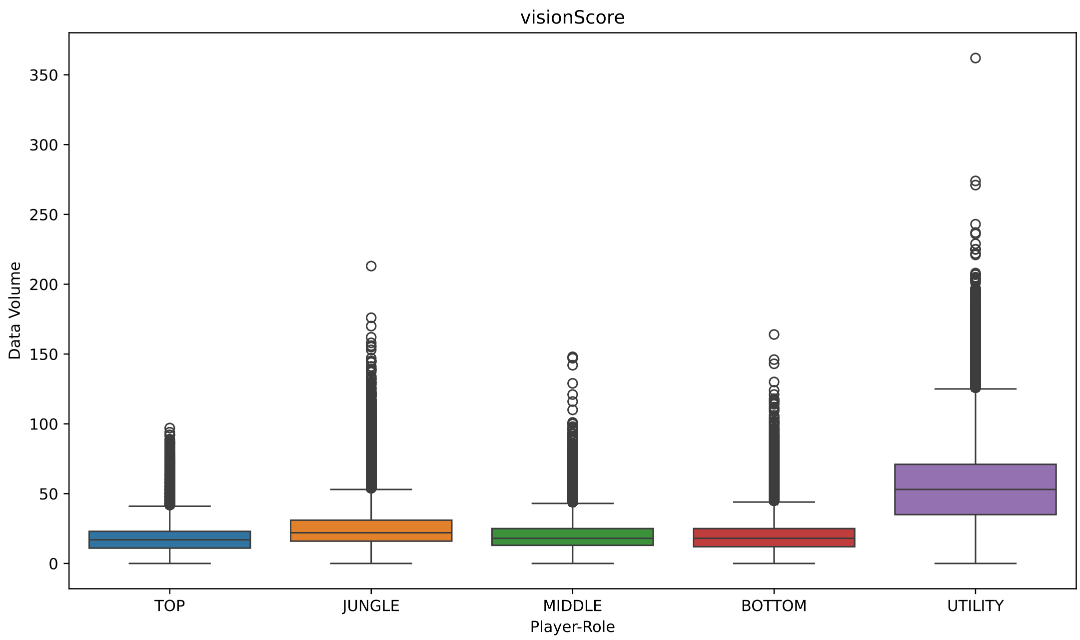

Figure 7.2: Boxplot analysis of the amount of data considering the task "Vision Score", and the player-role association. This presents a task corresponding to a single player-role following literature descriptions.

This type of analysis was conducted for all in-game actions present in the dataset, as detailed in Table 6.1. These actions were combined with player-role descriptions to establish a set of tasks that serve as scores for the Commitment vector.

7.2 Clustering Data with K-means

The selected clustering algorithm, K-means, includes a parameter K value that determines the number of groups to which data will be assigned. Mazeto, Kummer, and Paraiso. (MAZETO; KUMMER; PARAISO, 2018) evaluated potential values for the clustering process. The authors observed that dividing the data into four groups resulted in less distinct instances compared to using three groups. As a result, the three-group structure proposed by these authors, as well as by Kummer, Nievola, and Paraiso (KUMMER; NIEVOLA; PARAISO, 2017) and Humenhuk, Kummer, and Paraiso (HUMENHUK; KUMMER; PARAISO, 2021), was applied as the K value (K = 3), to represent the levels of Commitment.

The clustering method assigns a numerical label to each data instance, dividing them into groups. Based on the mean of S_{max-i} for each group, the numerical labels were translated into categorical values — low, average, and high. The labeling process adhered to the following the criteria of Equation 6.4. An example of this labeling is presented in Table 7.2.

Table 7.2: Result of the cluster method with the translation of the labels from numerical to categorical, utilizing the mean of S_{max-i}. It utilized the Commitment vector of the task "visionScore" to illustrate it.

Player	Week	Task	AmountPerWeek	sMin	sMax	Delta	Cluster	Label
Player_1267	1	visionScore	2	69	83	14	0	Avarage
Player_1272	1	visionScore	1	80	80	0	0	Avarage
Player_1278	1	visionScore	1	106	106	0	0	Avarage
Player_1283	1	visionScore	1	34	34	0	2	Low
Player_1287	1	visionScore	1	35	35	0	2	Low
Player_1292	1	visionScore	2	47	82	35	1	High
Player_1296	1	visionScore	4	46	62	16	2	Low
Player_1299	1	visionScore	1	19	19	0	2	Low
Player_1312	1	visionScore	2	116	163	47	0	Avarage
Player_1317	1	visionScore	1	121	121	0	0	Avarage

These features were input into classifiers and an ensemble method to define the Commitment levels. The objective was to identify the most suitable algorithm and parameter configuration for subsequent experiments.

7.3 Commitment Levels

To construct the Commitment vector, the datasets were segmented based on time periods: a 40-week timestamp for casual players and the rounds of CBLOL for eSports. Each timestamp presents a unique set of characteristics, yielded by the application of the clustering approach. For example, the same score a player obtained in a task might be classified as low in one timestamp and high in another. This occurs because the clustering groups consider only the scores from a single timestamp, thus capturing the behavioral patterns of players during that interval. As a result, player performance can vary due to factors like game updates or external elements such as vacations and holidays. To address these variations in player-related aspects, supervised ML methods were applied.

The Random Forest algorithm considers the analyzed tasks' scores, the label — low, average, or high — assigned through the clustering approach, and the d_i element of the Commitment vector. For each timestamp, a unique classifier is trained, and these classifiers are then integrated into an ensemble method. The ensemble uses all classifiers as references to determine the Commitment levels. To define the Commitment for the first timestamp, only the first classifier is considered (e.g., RandomForest_Timestamp_1); for the second timestamp, the first and second classifiers are considered (e.g., RandomForest_Timestamp_1 and RandomForest_Timestamp_2), and so on. The classifiers must remain consistent through iterations, preserving the characteristics of their respective timestamps. For example, if the classifier is used in the first timestamp, it must produce the same result in subsequent timestamps. In this study, the ensemble method employed was the Voting Classifier with a hard voting parameter, which assigns "votes" to each class and determines the output based on the majority vote.

7.4 Commitment per Task Evolution

The evolution of Commitment per Task, based on weekly segregation — casual players dataset — was visualized using the *Matplotlib and Seaborn libraries*, as shown in Figures 7.3, 7.4, 7.5, 7.6, and 7.7. The line plots depict the evolution of Player_9594, selected for having the most extensive dataset distributed across multiple weeks. Only the evolution of a single player is presented to avoid redundancy.

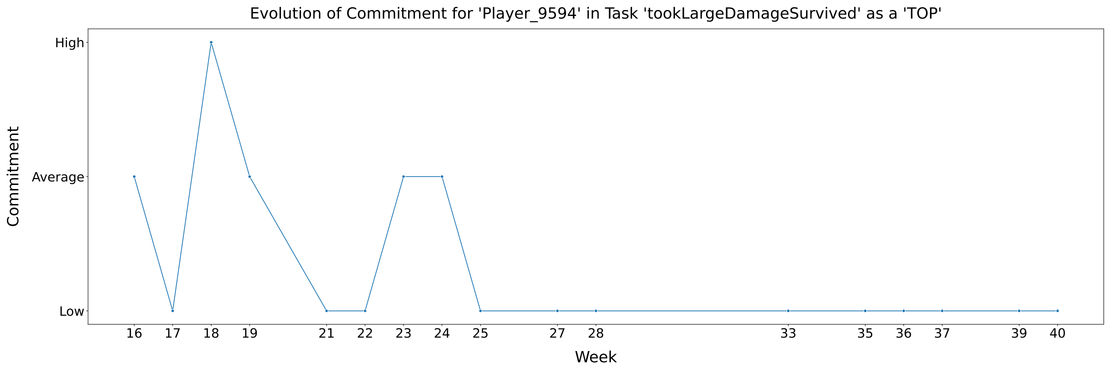

Figure 7.3: Evolution of the Commitment per week of Player_9594, as a Top, and considering the associated task "tookLargeDamageSurvived".

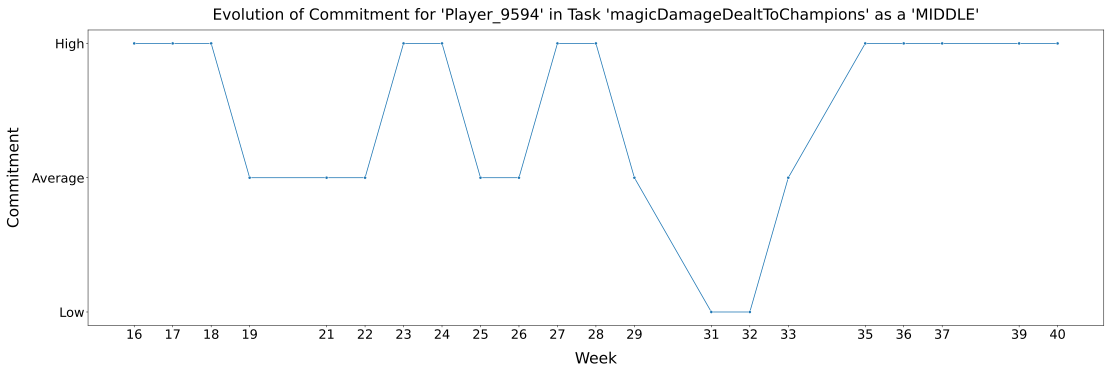

Figure 7.4: Evolution of the Commitment per week of Player_9594, as a Middle, and considering the associated task "magicDamageDealtToChampions".

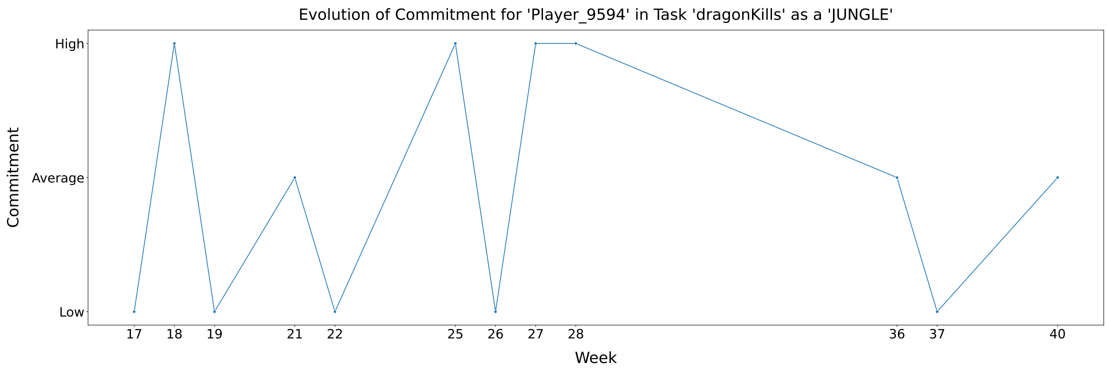

Figure 7.5: Evolution of the Commitment per week of Player_9594, as Jungle, and considering the associated task "dragonKills".

Figure 7.6: Evolution of the Commitment per week of Player_9594, as a Support (Utility), and considering the associated task "visionScore".

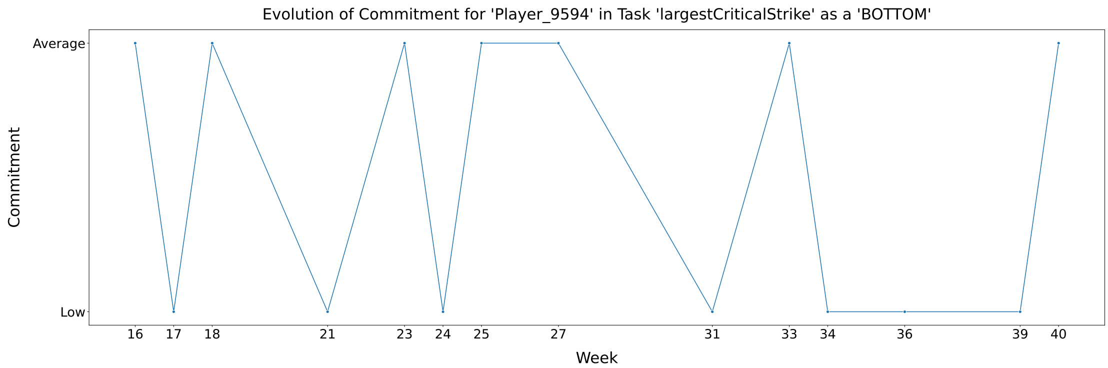

Figure 7.7: Evolution of the Commitment per week of Player_9594, as an ADC (Bottom), and considering the associated task "largestCriticalStrike".

To demonstrate the association between tasks and player-roles, the selected tasks for the plots were those exclusively linked to a specific role and those that best characterize it:

- **Top role**: The task considered was surviving after taking significant damage (*tookLargeDamageSurvived*), reflecting the resilience of tank champions typically chosen for this role.
- **Middle role**: As this role often involves mage champions who rely on the Mana attribute to cast spells, the task selected was the amount of magical damage dealt to enemies (*magicDamageDealtToChampions*).
- **Jungle role**: Responsible for jungle monsters, this role focuses on solo eliminations or dealing the most damage to them. Thus, the number of dragons eliminated (*dragonKills*) was chosen as the representative task.
- **Support role**: Given the role's responsibility for ward placement and removal, vision score (*visionScore*) was selected as the representative task, which measures the amount of map vision provided or blocked (in the enemy team perspective).

- **ADC role**: This role focuses on dealing the highest physical damage to enemies and eliminating as many as possible. Therefore, the largest critical strike damage dealt to an enemy (*largestCriticalStrike*) was selected as the representative task.

Through these line plots, it is evident that Player_9594 exhibits a more consistent and higher levels of Commitment when playing as a Support. Conversely, the player demonstrates lower Commitment when playing as a Top. For the other roles, Commitment fluctuates significantly across weeks, showing notable variations.

For the eSports dataset, the same analysis was conducted, as illustrated in Figures 7.8, 7.9, 7.10, 7.11 and 7.12. It is important to note that, in this context, the data was segregated according to the CBLOL rounds, where each round consists of two matches per week.

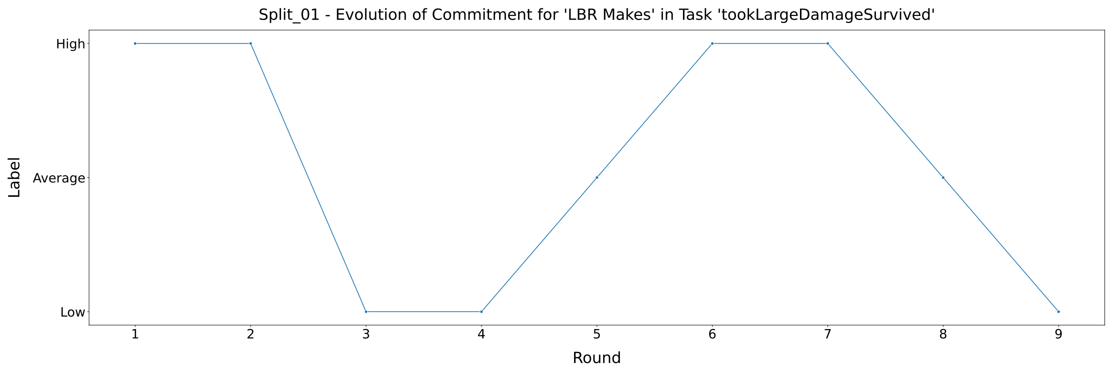

Figure 7.8: Evolution of the Commitment per round of player "LBR Makes", as a TOP, and considering the associated task "tookLargeDamageSurvived".

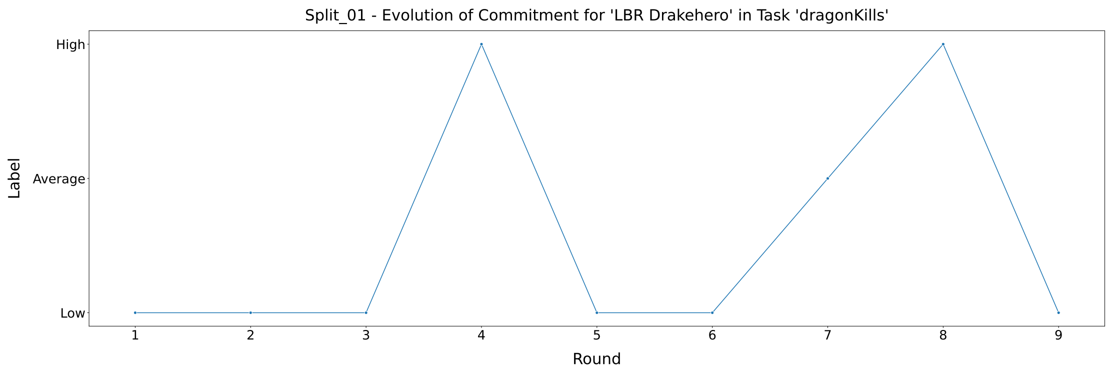

Figure 7.9: Evolution of the Commitment per round of player "LBR Drakehero", as a JGL, and considering the associated task "dragonKills".

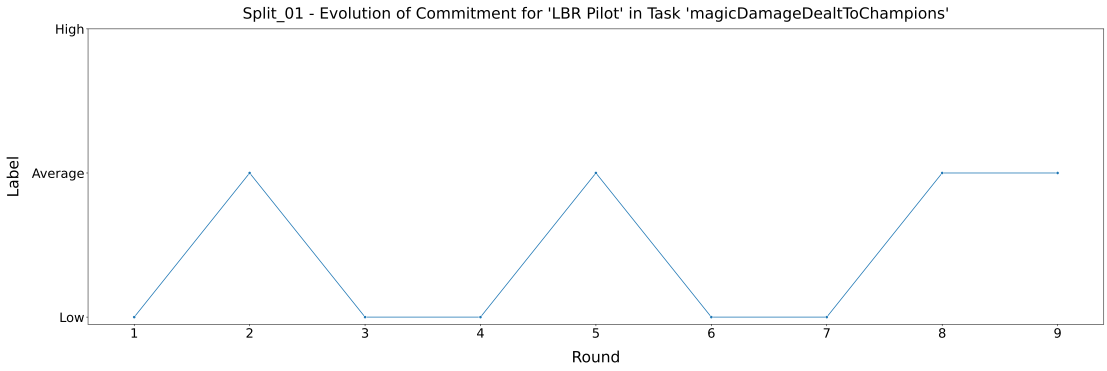

Figure 7.10: Evolution of the Commitment per round of player "LBR Pilot", as a MID, and considering the associated task "magicDamageDealtToChampions".

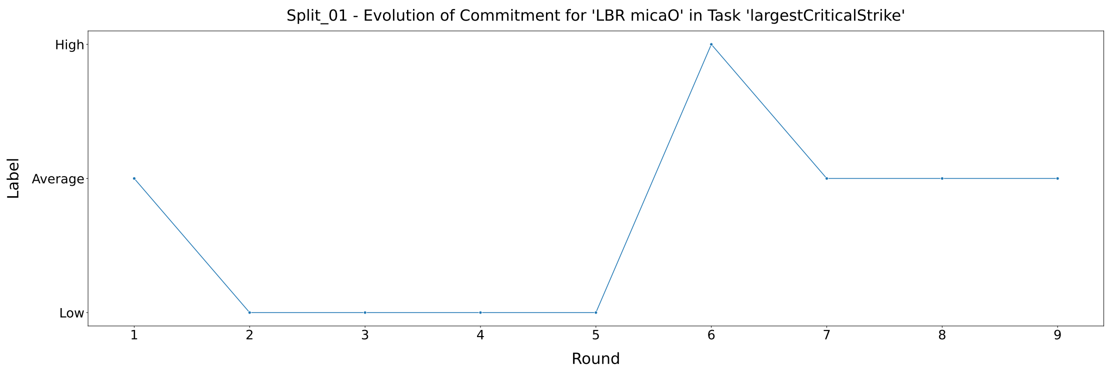

Figure 7.11: Evolution of the Commitment per round of player "LBR micaO", as an ADC, and considering the associated task "largestCriticalStrike".

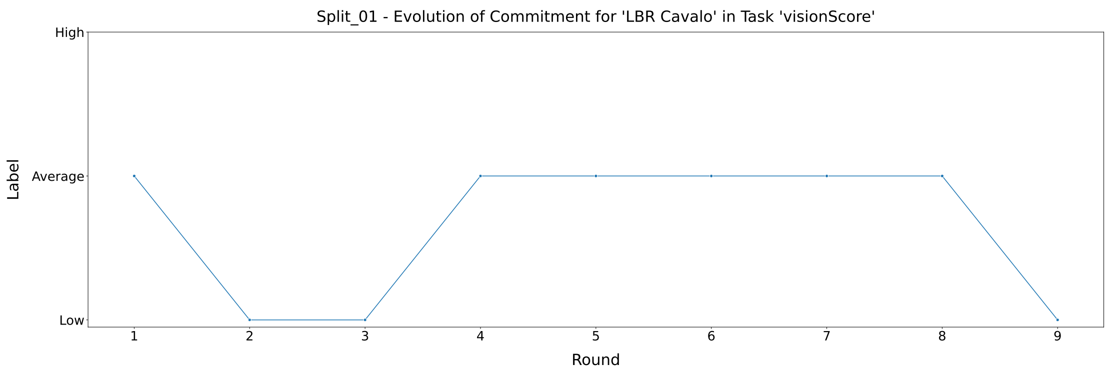

Figure 7.12: Evolution of the Commitment per round of player "LBR Cavalo", as a SUP, and considering the associated task "visionScore".

In the Top role, player "LBR Makes" exhibited an average or high Commitment in the task "tookLargeDamageSurvived" in most rounds, with about a third of rounds showing low Commitment. This suggests that the player focuses on the armor and resilience aspects of the role.

On the other hand, "LBR Pilot" (Middle) and "LBR Cavalo" (Support) did not display any high Commitment in the analyzed tasks. Therefore, both players did not achieve the same performance as their peers, once the Commitment is defined based on global behavior. Pilot fluctuated between low and average Commitment, while Cavalo exhibited a more stable pattern, maintaining average Commitment in six rounds, five of which were consecutive.

The jungler, "LBR Drakehero", showed a low Commitment level in two-thirds of the rounds. He had only one round with average Commitment, and two rounds with high Commitment. This suggests limited control of the jungle between the middle and bottom lanes.

The ADC, "LBR micaO", only reached high Commitment in round 06. However, he displayed stable behavior from rounds 02 to 05 and 07 to 09, which reflects an evolution from low to average Commitment levels.

Nevertheless, the Commitment levels alone do not serve as performance indicators. As shown in Figures 7.13 and 7.14, Makes and Drakehero exhibit two distinct behaviors regarding the task "deaths".

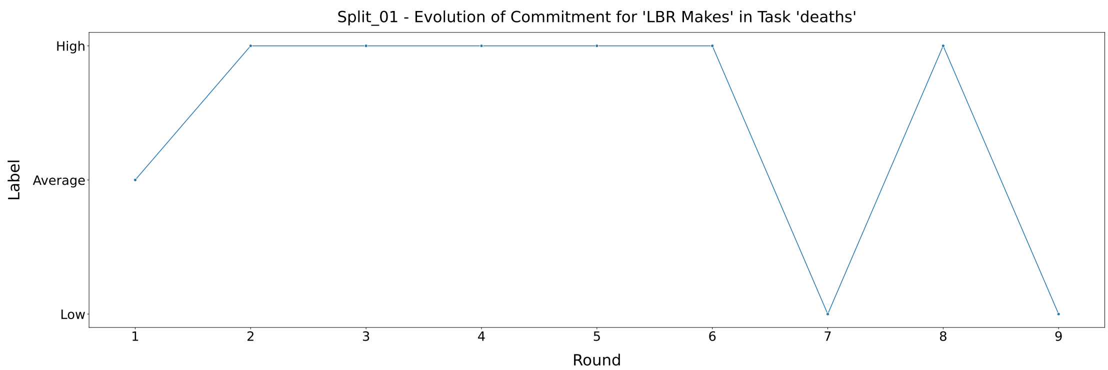

Figure 7.13: Evolution of the Commitment per round of player "LBR Makes" on task "deaths".

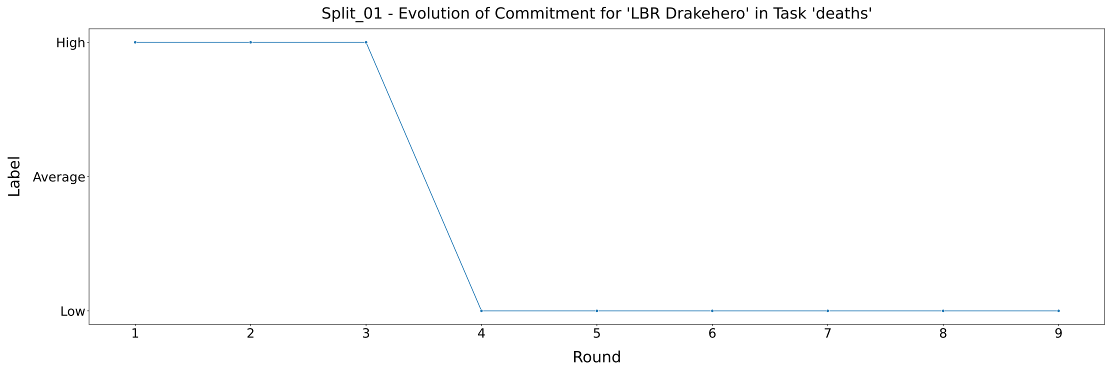

Figure 7.14: Evolution of the Commitment per round of player "LBR Drakehero" on task "deaths".

While in some tasks the Commitment level aligns with performance levels, in the task "deaths", there is an inverse relationship: low performance is indicated by high Commitment, while high performance is shown by low Commitment.

This brief analysis, based on the results of the Commitment per Task metric, does not cover all aspects of gameplay but serves as an illustrative example of how the proposed method can be applied. These visual analyses support **H1**: The Commitment metric can be used to measure players' engagement in the tasks associated with their roles. The graphs illustrate how consistently a player executes role-specific tasks over a given period, thus validating the metric's usefulness for assessing engagement.

7.5 eSports Evaluations

H2 concerns the application of the Commitment metric without the element d_i. This was intended to model an eSports context, where matches are organized by championship phases and team standings. However, after analyzing the eSports dataset, the number of matches played per championship round was found to effectively represent d_i. Therefore, H2 was not supported.

Through our partnership with Liberty, we obtained the team's expectations regarding player performance. These expectations were defined by the head and scout analysts, considering two factors: the player-role and the chosen champion. As a result, four tables were generated — two for each scenario.

A Kappa Coefficient test was conducted to verify the agreement rate between expectations. The Kappa statistic is particularly suitable in this context, as it evaluates inter-rater agreement for categorical data while accounting for agreement that may occur by chance. This provides a more reliable interpretation of how consistently both professionals aligned in their assessments of expected player behavior. However, most of the obtained coefficients were below 60%, indicating a general lack of agreement between analysts regarding what actions a player should take in a match to achieve higher performance.

For the top role, as shown in Table 7.3, the highest agreement found was 73.33% for the task "damagePerMinute" in Split 02. On the other hand, the same task in Split 01 had only 20.00% agreement.

Table 7.3: Agreement rate, referring to Top players' performances, between eSports analysts.

TOP - Task	Split 01	Split 02
damagePerMinute	20.00%	73.33%
physicalDamageDealtToChampions	27.27%	40.00%
magicDamageDealtToChampions	61.90%	38.46%
turretPlatesTaken	-20.00%	33.33%
trueDamageDealtToChampions	-	27.27%
killsNearEnemyTurret	-11.11%	-21.74%
maxCsAdvantageOnLaneOpponent	-	18.37%
goldPerMinute	40.00%	15.79%
assists	-	13.04%
firstBloodKill	16.67%	-11.11%
goldEarned	40.00%	9.09%
kills	-9.09%	9.09%
laningPhaseGoldExpAdvantage	-	-9.09%
maxLevelLeadLaneOpponent	-7.69%	-7.69%
killParticipation	-	-5.66%
killsUnderOwnTurret	-20.00%	3.03%
soloKills	-20.00%	2.04%

In the jungle role, as shown in Table 7.4, both "longestTimeSpentLiving" and "KDA" had 100% agreement. It was the role with the most tasks exhibiting at least 10% agreement, with most of these related to Split 01.

Table 7.4: Agreement rate, referring to Jgl players' performances, between eSports analysts.

JGL - Task	Split 01	Split 02
longestTimeSpentLiving	100.00%	-
kda	100.00%	-
physicalDamageDealtToChampions	59.26%	14.29%
kills	58.23%	58.14%
damagePerMinute	55.41%	34.15%
laningPhaseGoldExpAdvantage	48.24%	-
maxCsAdvantageOnLaneOpponent	48.24%	11.76%
goldPerMinute	47.62%	19.64%
totalDamageDealtToChampions	46.99%	-2.27%
earlyLaningPhaseGoldExpAdvantage	46.34%	25.00%
champExperience	45.00%	23.40%
champLevel	45.00%	-
magicDamageDealtToChampions	45.00%	-
totalEnemyJungleMinionsKilled	36.05%	15.63%
teamDamagePercentage	36.05%	-2.27%
firstTowerAssist	34.00%	-
firstTowerKill	34.00%	-
firstTurretKilled	34.00%	-
takedownOnFirstTurret	34.00%	-
goldEarned	31.25%	18.18%
turretKills	26.67%	-
turretTakedowns	26.67%	-
firstBloodKill	21.43%	-
enemyJungleMonsterKills	17.50%	-

Table 7.4: Agreement rate, referring to Jgl players' performances, between eSports analysts.

JGL - Task	Split 01	Split 02
assists	14.44%	-
neutralMinionsKilled	14.44%	-
totalAllyJungleMinionsKilled	14.44%	-
alliedJungleMonsterKills	14.44%	-
jungleCsBefore10Minutes	14.44%	-
killsNearEnemyTurret	12.00%	-
killAfterHiddenWithAlly	10.00%	-
killParticipation	10.00%	-
pickKillWithAlly	10.00%	-

For the Middle role, only two tasks exhibited any agreement, as shown in Table 7.5, both with 70.00%. These tasks — "magicDamageDealtToChampions" and "physicalDamageDealtToChampions" — represent the damage caused to enemy champions.

Table 7.5: Agreement rate, referring to Mid players' performances, between eSports analysts.

MID - Task	Split 01	Split 02
magicDamageDealtToChampions	-	70.00%
physicalDamageDealtToChampions	-	70.00%

For the ADC role, in Split 01, only the task "laneMinionsFirst10Minutes" had an agreement rate of 100%, as shown in Table 7.6. In contrast, for Split 02, the highest agreement rate was 63.64%.

Table 7.6: Agreement rate, referring to ADC players' performances, between eSports analysts.

ADC - Task	Split 01	Split 02
laneMinionsFirst10Minutes	100%	-

Table 7.6: Agreement rate, referring to ADC players' performances, between eSports analysts.

ADC - Task	Split 01	Split 02
totalMinionsKilled	47.37%	-
goldPerMinute	47.37%	47.83%
physicalDamageDealtToChampions	41.18%	-
maxCsAdvantageOnLaneOpponent	29.58%	63.64%
damagePerMinute	-11.11%	-9.09%
earlyLaningPhaseGoldExpAdvantage	6.25%	29.41%
laningPhaseGoldExpAdvantage	6.25%	29.41%
totalDamageDealtToChampions	-5.26%	-4.35%
teamDamagePercentage	1.10%	0.75%
dragonKills	-	7.69%
turretPlatesTaken	-	1.64%

All remaining tasks not listed in Tables 7.3,7.4,7.5, and 7.6 had no agreement rate. Additionally, the support role exhibited the highest level of disagreement among analysts, with no agreement rate found.

Therefore, the expected levels of Commitment were derived from the "most experienced" analyst, in this case, the scout analyst. According to the team, the scout analyst was responsible for investigating each player's actions and their consequences on the match. This approach is similar to the proposed method; however, this approach relies more heavily on human input, potentially introducing bias.

7.6 Compliance

With the Commitment levels established, it was possible to begin evaluating the players' and teams' performances. The Compliance metric is applied to each task, scoring a value that represents players' adherence to strategy, as explained in Chapter 2, following this logic:

$$c_i = \begin{cases} 1, & \text{if } cl_i == s_i, \\ 0.5, & \text{else if } cl_i == "Average" \text{ and } (s_i == "High" \text{ or } s_i == "Low"), \\ 0, & \text{else if } cl_i \neq s_i \end{cases} \tag{7.1}$$

The metric returns a vector of all tasks and their corresponding Compliance scores, as illustrated in Figure 7.7. These Compliance scores are then summed to provide the total Compliance score, which is subsequently divided by the number of analyzed tasks. This process results in the mean Compliance, which is finally expressed as a percentage.

Table 7.7: Compliance vector with the obtained scores of each player on tasks.

Player	**Match**	**assists**	**champExperience**	**dragonKills**	**goldEarned**	**kills**	**longestTimeSpentLiving**	**magicDamageDealtToChampions**	**neutralMinionsKilled**
RED Aegis	Split_02_Round_09	0.5	0.0	1.0	0.5	1.0	0.0	0.0	0.0
FX Shini	Split_02_Round_09	0.0	0.5	0.0	0.0	0.0	1.0	1.0	1.0
VKS Disamis	Split_02_Round_09	0.5	0.0	0.0	0.5	1.0	1.0	0.0	0.0
LLL Croc	Split_02_Round_09	1.0	0.0	0.0	0.0	0.5	1.0	1.0	0.0
PNG CarioK	Split_02_Round_09	0.0	0.5	1.0	1.0	1.0	0.0	0.5	1.0
LOS Seize	Split_02_Round_09	0.5	1.0	0.0	1.0	1.0	1.0	1.0	1.0
FUR Wiz	Split_02_Round_09	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.5
KBM scary	Split_02_Round_09	1.0	0.0	0.0	0.5	1.0	0.0	0.5	0.0
LBR Levizin	Split_02_Round_09	0.5	1.0	0.0	1.0	1.0	0.0	1.0	1.0
ITZ Yampi	Split_02_Round_09	1.0	1.0	0.0	1.0	1.0	1.0	0.5	1.0

A test was conducted to define the values used by the Compliance metric for the scoring process. Initially, a binary approach was adopted, scoring 1 when players met the expected Commitment level and 0 when they did not. However, this approach proved to be overly punitive, as it failed to account for players' efforts to reach the expected Commitment level. This approach would have led to the exclusion of a wide range of scores that contribute to the evaluation of Compliance, reducing the precision of the method. In this manner, the approach applied scores 0.5 when the expected level is either high or low, but the player achieves an average Commitment. An example of the metric's output can be seen in Table 7.8. By considering the player's effort, the metric is able to provide valuable insights for both players and coaches regarding their performances.

Table 7.8: Compliance vector of player "LBR Levizin" in Round 06 of Split 02 of CBLOL, considering the scout analyst expectations.

Task	Score
assists	1.0
champExperience	1.0
dragonKills	0
goldEarned	1.0
kills	1.0
longestTimeSpentLiving	1.0
magicDamageDealtToChampions	0.5
neutralMinionsKilled	1.0
physicalDamageDealtToChampions	1.0
totalAllyJungleMinionsKilled	0.5
totalDamageDealtToChampions	1.0
totalEnemyJungleMinionsKilled	1.0
totalTimeSpentDead	1.0
trueDamageDealtToChampions	0.5
turretKills	0
turretTakedowns	1.0
alliedJungleMonsterKills	1.0

Table 7.8: Compliance vector of player "LBR Levizin" in Round 06 of Split 02 of CBLOL, considering the scout analyst expectations.

Task	Score
damagePerMinute	1.0
dragonTakedowns	0
earlyLaningPhaseGoldExpAdvantage	1.0
enemyJungleMonsterKills	1.0
goldPerMinute	1.0
jungleCsBefore10Minutes	0.0
kda	0
killAfterHiddenWithAlly	1.0
killParticipation	1.0
killsNearEnemyTurret	0
laningPhaseGoldExpAdvantage	1.0
maxCsAdvantageOnLaneOpponent	0
pickKillWithAlly	1.0
takedownOnFirstTurret	1.0
teamDamagePercentage	1.0
Compliance	64.1

7.7 Match Outcome Prediction

Four classifier algorithms were tested to predict match outcomes: Decision Tree, Random Forest, LightGBM, and a neural network, specifically the Multilayer Perceptron (MLP). An experiment was conducted to determine which classifier achieved the highest accuracy and to identify the optimal parameters for each model. The parameters considered in the experiment can be seen in Table 7.9.

Table 7.9: Tested classifiers and their respective parameters for match outcome prediciton.

Associated Player-Role	Parameters
Decision Tree	"criterion": ["gini", "entropy", "log_loss"], "splitter": ["best", "random"], "max_depth": [None, 5, 10, 15],
Random Forest	"criterion" : ["gini", "entropy", "log_loss"], "max_depth": [None, 5, 10, 15, 20, 30], "min_samples_split": [2, 5, 10, 15]
LightGBM	"num_leaves": [31, 50], "learning_rate": [0.01, 0.1], "n_estimators": [50, 100, 200]
MLP	"hidden_layer_sizes": [(50,), (100,), (50, 50)], "activation": ["identity", "logistic", "tanh", "relu"], "solver": ["lbfgs", "sgd", "adam"], "learning_rate": ["constant", "invscaling", "adaptive"]

Through the GridSearchCV method, all classifiers and parameters were tested, with cross-validation determined by StratifiedKFold, considering 5 folds. This process yielded the best parameters to achieve higher accuracy for the provided classifiers. The experiment was conducted in two modes: per role and per champion. These modes correspond to the evaluations provided by Liberty. The per champion mode was only analyzed with the analyst evaluation, as no literature descriptions or associations of champions to roles were found. The results of the experiment can be observed in Table 7.10.

Table 7.10: Obtained accuracy in each analyzed classifier for the prediction of match outcome.

Evaluation	Classifier	Split	Accuracy	Parameters
Per Role				
Decision Trees (DT)				

Evaluation	Classifier	Split	Accuracy	Parameters
Literature	DT	01	76.53%	"criterion": "gini" "max_depth": 5 "splitter": "best"
Analyst	DT	01	76.13%	"criterion": "gini" "max_depth": 10 "splitter": "random"
Literature	DT	02	87.78%	"criterion": "entropy" "max_depth": 5 "splitter": "random"
Analyst	DT	02	86.89%	"criterion": "entropy" "max_depth": 5 "splitter": "random"
Random Forest (RF)				
Literature	RF	01	82.31%	"criterion": "entropy" "max_depth": None "min_samples_split": 2
Analyst	RF	01	80.09%	"criterion": "entropy" "max_depth": 10 "min_samples_split": 2
Literature	RF	02	85.11%	"criterion": "gini" "max_depth": 10 "min_samples_split": 2
Analyst	RF	02	84.22%	"criterion": "gini" "max_depth": 20 "min_samples_split": 5
Multilayer Perceptron (MLP)				
Literature	MLP	01	80.07%	"activation": "relu" "hidden_layer_sizes": (100,) "learning_rate": "constant" "solver": "adam"
Analyst	MLP	01	78.98%	"activation": "tanh" "hidden_layer_sizes": (100,) "learning_rate": "adaptive" "solver": "sgd"

Evaluation	Classifier	Split	Accuracy	Parameters
Literature	MLP	02	83.11%	"activation": "tanh" "hidden_layer_sizes": (100,) "learning_rate": "constant" "solver": "adam"
Analyst	MLP	02	82.89%	"activation": "logistic" "hidden_layer_sizes": (50,) "learning_rate": "invscaling" "solver": "adam"
LightGBM (LGBM)				
Literature	LGBM	01	80.54%	"learning_rate": 0.1 "n_estimators": 200 "num_leaves": 31
Analyst	LGBM	01	81.64%	"learning_rate": 0.1 "n_estimators": 100 "num_leaves": 31
Literature	LGBM	02	88.67%	"learning_rate": 0.1 "n_estimators": 200 "num_leaves": 31
Analyst	LGBM	02	87.33%	"learning_rate": 0.1 "n_estimators": 200 "num_leaves": 31
Per Champion				
Decision Trees (DT)				
Analyst	DT	01	77.42%	"criterion": "entropy", "max_depth": None, "splitter": "random"
Analyst	DT	02	80.22%	"criterion": "gini", "max_depth": 5, "splitter": "random"
Random Forest (RF)				
Analyst	RF	01	81.20%	"criterion": "gini", "max_depth": 20, "min_samples_split": 2

Evaluation	Classifier	Split	Accuracy	Parameters
Analyst	RF	02	85.33%	"criterion": "entropy", "max_depth": 15, "min_samples_split": 5
Multilayer Perceptron (MLP)				
Analyst	MLP	01	78.97%	"activation": "tanh", "hidden_layer_sizes": (100,), "learning_rate": "constant", "solver": "lbfgs"
Analyst	MLP	02	80.89%	"activation": "relu", "hidden_layer_sizes": (100,), "learning_rate": "adaptive", "solver": "adam"
LightGBM (LGBM)				
Analyst	LGBM	01	83.40%	"learning_rate": 0.1, "n_estimators": 200, "num_leaves": 31,
Analyst	LGBM	02	87.33%	"learning_rate": 0.1, "n_estimators": 100, "num_leaves": 31,

The LGBM classifier provided the highest accuracies as a result of the applied experiment, except for the literature in Split 01, where the Random Forest classifier achieved an accuracy rate of 82.31%, while LGBM reached 80.54%. In the per role mode for the literature evaluation, the best parameters found were: learning rate: 0.1, n_estimators: 200, num_leaves: 31. For the analyst evaluation, the best parameters were: learning rate: 0.1, n_estimators: 100, num_leaves: 31. These configurations were selected as optimal for the problem, taking into account the model's precision, generalizability, and the time required for the training phase. In cases where these parameters did not yield the highest accuracy, the differences between the chosen and tested parameters were not statistically significant.

On the other hand, in the per champion mode, the analyst evaluation for both splits only varied in the "n_estimators" parameter, with a value of 200 for Split 01 and 100 for Split 02. The "learning_rate" and "num_leaves" parameters achieved higher accuracy with the same values, set to 0.1 and 31, respectively.

These analyses supports H3, which states that the tasks associated with player roles, combined with the Commitment and Compliance metrics, can serve as predictive features in a classification model to determine match outcomes. Feature importance was assessed, highlighting the tasks with the greatest influence on match results.

7.8 Gameplay Suggestions

As a natural extension of H3, H4 was explored by analyzing how player-role tasks could guide strategic suggestions based on their impact on match outcomes. Both Commitment and Compliance metrics were integrated in these final experiments.

During the match outcome prediction, an attribute from the GridSearchCV method was extracted to weigh the contribution of each task towards the outcome, namely the "feature_importances_". To analyze player performance and suggest potential gameplay adjustments aimed at achieving a positive result, each Compliance score vector and task contribution weight were normalized and compared.

This experiment considered the following hypotheses:

- ***Ho (Null hypothesis)***: There is no statistically significant difference between Compliance scores and task contribution weights.
- ***Ha (Alternative hypothesis)***: There is a statistically significant difference between Compliance scores and task contribution weights.

These hypotheses aim to assess whether a significant difference exists between Compliance scores and task contribution weights, thereby indicating how adherence to the proposed strategy impacts match outcomes.

The comparison was conducted using two continuous variables, and consequently, a Pearson correlation was applied, with an *alpha* of 5% to validate the hypotheses. However, the p-values obtained through the correlation varied across rounds and players, resulting in cases where *Ho* could not be rejected and others where it could. For example, see the p-values obtained for player "LBR Makes" in Split 01, as shown in Table 7.11.

Table 7.11: Obtained p-values through the Pearson correlation applied to Compliance scores and tasks' contribution weights of player "LBR Makes", on split 01.

Round	P-Value (Pearson)
01	0.7507
02	0.2073
03	0.0023
04	0.3603
05	0.7852
06	0.6589
07	0.7641
08	0.2512
09	0.0428

To provide gameplay improvement suggestions based on match outcomes, the mean of the task contributions was calculated. Tasks with weights equal to or above this mean were identified as the most relevant for the outcome. If the Compliance score of these relevant tasks was below the maximum value (1), a suggestion was made detailing the amount by which the Compliance score should be increased in each round. An example of this can be seen in Table 7.12.

The Compliance score reflects the alignment between the team's strategy and the player's Commitment. For tasks such as "deaths", "inhibitorsLost", and "totalDamageTaken", which indicate a negative context in gameplay, no suggestions to decrease the Compliance score are made. If a player achieves a Compliance score of 1 for these tasks, it means they met the expected Commitment level.

In addition to providing suggestions, the difference between the normalized values of the contribution weights and Compliance scores was calculated. This difference indicates the percentage of Compliance that is lacking to fully align with the contribution towards the match outcome, offering more detailed insights than simply suggesting a target Compliance score.

In Table 7.12, as with all other tasks and players, the score is subtracted from the contribution. A discrepancy can be observed between the suggestion and the difference, where a player may exhibit a high normalized score for a task, yet their performance remains suboptimal from a Compliance perspective.

A negative difference indicates that the player exceeds the task's contribution weight but has room for improvement in Compliance to reach optimal performance. Conversely, a positive difference suggests underperformance relative to the task's contribution.. An example of overall team Compliance is illustrated in Figure 7.15, where Liberty's Compliance levels were analyzed during Split 01 of CBLOL, specifically Round 07, and compared with the strategy proposed by the scout analyst.

Figure 7.15: Obtained Compliance values by Liberty in Split 01 - Round 07, considering the strategy and expectations of the team's scout analyst.

The ADC "LBR micaO" exhibited the highest Compliance level at 62.1%, followed by the Support "LBR Cavalo" with 54.0%, indicating a closer adherence to the expected strategic behavior. In contrast, the Top "LBR Makes", Jungle "LBR Drakehero", and Mid "LBR Pilot" presented substantially lower Compliance values — 38.7%, 34.4%, and 34.0%, respectively — suggesting possible deviations from the planned execution or greater contextual variability during this match. This disparity highlights the importance of role-specific assessments in understanding how strategic guidelines are operationalized in competitive settings. Such analyses can assist coaching staff in refining role-based instructions and identifying areas where strategic alignment may be improved.

Table 7.12: Gameplay suggestions and analysis of difference in relation to the obtained Compliance scores and tasks contributions weights of player "LBR Leandrinn".

Task	Score	Suggestion	Difference
goldEarned	0.0	Player LBR Leandrinn should increase the Compliance score (0.0) on task goldEarned in 1.0	The difference between normalized score (0.00%) and contribution (1.36%) is 1.36%
killParticipation	0.5	Player LBR Leandrinn should increase the Compliance score (0.5) on task killParticipation in 0.5	The difference between normalized score (16.67%) and contribution (1.93%) is -14.73%

7.9 Running Example

To demonstrate the application of the method, *Player_00* — a hypothetical player used solely for illustrative purposes — will be analyzed.

After obtaining and preparing the dataset, the Commitment vectors are generated based on matches from the defined period — weekly for casual players and per round for eSports players. The formula for the Commitment vector is as follows:

$$v_i = \{id_i, d_i, S_{i-min}, S_{i-max}, \Delta S_i\}$$

For this example, assume that the tasks associated with *Player_00* are limited to kills, goldEarned, and visionScore. During a specified period, the vectors are defined as follows:

$$kills = \left\{Player\_00, 5, 3, 15, 12\right\}$$

$$goldEarned = \left\{Player\_00, 5, 9450, 17850, 8400\right\}$$

$$visionScore = \left\{Player\_00, 5, 100, 220, 120\right\}$$

Here, *Player_00* represents the id_i element; 5 denotes the number of matches played during the period (d_i); 3, 9450, and 100 correspond to the minimum scores achieved ($S_i - max$); 15, 17850, and 220 represent the maximum scores achieved

($S_i - max$); and 12, 8400, and 120 indicate the difference between $S_i - max$ and $S_i - min$ (ΔS_i).

Once the Commitment vectors are generated, a clustering approach will group them into three categories. The vectors considered by the cluster represent those from the same task performed by multiple players during the same period. Consequently, this approach will illustrate the evolution of Commitment for each task. For example:

$$kills = \{Player\_00, 5, 3, 15, 12\} -> ClusterGroup = 2$$

$$kills = \{Player\_000, 3, 1, 7, 6\} -> ClusterGroup = 0$$

$$kills = \{Player\_0000, 7, 5, 17, 12\} -> ClusterGroup = 2$$

To determine the groups, the mean of the $S_i - max$ values for each group is analyzed based on the following criteria:

$$S_{max-low} < S_{max-average} < S_{max-high}$$

The mean of group 2 is 16, pretend the mean from group 1 is 10, and of group 0 is 7. Consequently, group 2 is assigned the label "high," group 1 is labeled "average," and group 0 is labeled "low." This assignment is based on the following rationale:

$$7(Low) < 10(Average) < 16(High)$$

The scores — $S_i - min$, $S_i - max$, and ΔS_i — along with the number of matches played (d_i) and the labels assigned to each group, are input into a classifier. Each classifier represents player behavior for a specific period, resulting in multiple classifiers. To account for all observed behaviors and determine the Commitment levels, an ensemble method is applied.

$$kills = High$$

$$goldEarned = Average$$

$$visionScore = Low$$

With the Commitment levels established for each task, player, and period, it becomes possible to calculate Compliance. Expectations for Commitment levels must be predetermined, either through literature review or based on the insights of a specialist. In this case, the expectations are defined as follows:

$$kills = High$$

$$goldEarned = High$$

$$visionScore = High$$

The Compliance metric initially generates scores — 0, 0.5, and 1 — based on the alignment of players' Commitment levels with the predefined expectations. The scores are assigned according to the following logic:

$$c_i = \begin{cases} 1, & \text{if } cl_i == s_i, \\ 0.5, & \text{else if } cl_i == "Average" \text{ and } (s_i == "High" \text{ or } s_i == "Low"), \\ 0, & \text{else if } cl_i \neq s_i \end{cases}$$

To avoid being overly punitive and to acknowledge players' efforts in striving to achieve the expected Commitment levels, a score of 0.5 is assigned when a player achieves an average level in a task where low or high was expected. Therefore:

$$kills = 1$$

$$goldEarned = 0.5$$

$$visionScore = 0$$

Compliance is a metric that quantifies players' overall alignment with their team's strategy. All assigned scores are summed and divided by the number of analyzed tasks, resulting in a mean Compliance value. This mean is then converted into a percentage, representing the final result of the Compliance metric:

$$Compliance = \frac{\sum_{i=1}^{n} c_i}{n} \times 100$$

Where:

$$Compliance\_Player\_00 = \frac{(1 + 0.5 + 0)}{3} \times 100$$

$$Compliance\_Player\_00 = 0.5 \times 100$$

$$Compliance\_Player\_00 = 50\%$$

Once the Compliance of each player is determined, the value is incorporated into the dataset alongside the Commitment levels. An example of the dataset instance is as follows:

$$Player\_00 = Low, Average, Low, High, High, Low, Average, High, 50\%$$

For match outcome prediction, the Commitment levels are converted into numerical values, with 0 representing low, 1 representing average, and 2 representing high. Compliance is retained in its decimal form to ensure the algorithm incorporates this value as well. The resulting outcome is then added to the dataset and further translated into binary values of 0 or 1:

$$Player\_00 = 0, 1, 0, 2, 2, 0, 1, 2, 0.5, true$$

The contribution of each task to the prediction of match outcomes was recorded and normalized to serve as the basis for gameplay suggestions. The mean contribution was calculated, and only tasks exceeding this mean were considered relevant for the suggestion phase.

$$kills = 1.12\%$$

$$goldEarned = 1.54\%$$

$$visionScore = 1.71\%$$

These tasks were analyzed, and if any of them did not achieve a Compliance score of 1 — indicating that the player fully adhered to the team's strategy — a suggestion is generated for players to improve their Compliance, specifying the required increase.

Since, for the task "kills," the player achieved a Compliance score of 1, no suggestion is provided. However, for the "goldEarned" and "visionScore" tasks, the method generates the following recommendations:

- *"Player_00 should increase the Compliance score (0.5) on task goldEarned in 0.5"*
- *"Player_00 should increase the Compliance score (0.0) on task visionScore in 1.0"*

The difference is calculated using the normalized contribution and normalized scores. For the scores, the normalized value is derived as the mean between $S_i - min$ and $S_i - max$ from the Commitment vector.

$$kills = 1.12\% - 1.16\%$$

$$goldEarned = 1.54\% - 1.00\%$$

$$visionScore = 1.71\% - 1.04\%$$

The results are as follows:

- "kills: *The difference between normalized (1.16%) score and contribution (1.12%) is -0.04%*"
- "goldEarned: *The difference between normalized (1.00%) score and contribution (1.54%) is 0.54%*"
- "visionScore: *The difference between normalized (1.04%) score and contribution (1.71%) is 0.67%*"

These differences provide a complementary analysis of player performance, indicating whether a player is underperforming or outperforming. Consequently, players and coaches can identify areas for improvement in a more comprehensive and targeted manner.

8

Conclusions

This research aimed to assess player performance in MOBA games by analyzing in-game tasks specific to each role, allowing for a more precise evaluation of player actions and decisions through Commitment and Compliance analysis. One of the proposed approaches, Commitment per Task, refines the original Commitment metric to better align with role-specific tasks. The other approach, Compliance, compares the Commitment levels obtained through the metric with the team's strategic expectations.

This method was proposed to address a gap identified in the literature regarding the evaluation of player performance, which often overlooks individual aspects of gameplay. Existing works predominantly rely on generic metrics and/or analyze in-game actions with uniform weighting, failing to account for role-specific contributions.

The Commitment per Task metric evaluates player engagement in assigned roles by analyzing task performance scores and the number of matches played within a specific period. The dataset is clustered into three groups — low, average, and high — based on the mean of maximum scores obtained, aligning with the original metric's categorical levels. These clusters are then used to train a classifier, which considers both the obtained scores, the d_i element (i.e., the amount of played matches during a determined timestamp), and their respective labels. Additionally, an ensemble method leverages these classifiers, incorporating historical data so that the number of considered classifiers increases over time.

All obtained Commitment levels were compared with the team's strategy.

At this stage, both literature-based expectations and those from an eSports team were considered, resulting in two separate analyses of player performance. This comparison produced Compliance scores, representing how accurately players' Commitment levels aligned with expectations. These Compliance scores are generated for each task, producing a vector of scores that is used by the metric to determine the final Compliance value. The Compliance for each player-role is calculated by summing the scores across all associated tasks, dividing by the number of tasks, and converting the result into a percentage.

Subsequently, match outcomes were predicted using the Compliance and Commitment levels of players at each timestamp. A set of classifiers was tested to identify the most accurate model. After determining the best classifier for the problem, match outcome predictions achieved an accuracy exceeding 80%.

The contribution of each task to outcome prediction was analyzed to generate gameplay suggestions. A correlation test was conducted to evaluate the null and alternative hypotheses, with results varying across players and timestamps, reflecting different scenarios within the dataset. However, Compliance scores for the most impactful tasks helped identify areas for improvement. Additionally, the difference between normalized Compliance and contribution values provided a more detailed assessment of player performance.

The primary challenge arose during the development of algorithms for extracting data from the LoL API. This process involved adapting to frequent API updates, understanding the required protocols for data requests, and leveraging personal expertise in *Python* programming. Despite the significant time investment required for research and development, this phase ultimately yielded a comprehensive dataset of casual players. This dataset not only supports the current study but also holds potential for future research on MOBA player behavior.

Initially, a continuous-value Commitment level was proposed. However, a review of the process and objectives revealed that implementing it would demand substantial rework of Steps 02 and 03. Given the time constraints for completing this study, efforts were instead focused on refining the Compliance metric and generating gameplay suggestions.

The proposed method effectively measured player engagement in role-specific tasks through the Commitment per Task metric. It utilized the obtained Commitment levels to assess player performance, predict match outcomes, and ultimately provide suggestions for performance improvement, aiming to increase the chances of a positive match outcome.

Although the results were evaluated by the head analyst through the partnership with Liberty, the gameplay improvement suggestions could not be tested in a real scenario with direct player feedback. This was due to the restructuring of the LoL championship for the Americas region in 2025, which led to Liberty ceasing its activities.

8.1 Limitations and Future Studies

As team strategies are usually defined individually based on experience and subjective judgment, consensus on each player's match objectives may vary, representing a limitation. Expectations among coaches, analysts, broadcasters, and the audience can vary significantly. Consequently, the analysis may be influenced by the evaluator's judgment, potentially introducing bias.

Future studies should focus on analyzing in-game events that cannot be fully captured by tabular data, such as the strategic use of objectives as shields or to inflict damage based on the proximity of enemies to the structure. Another example includes a player "stepping forward" to pressure opponents, thereby gaining map control, securing objectives, avoiding or initiating teamfights, and other tactical maneuvers.

Additionally, suggestions can be generated by combining tabular and visual data, along with insights derived specifically from visual information. This approach could enhance player training, as providing real-time suggestions during matches would be impractical and fall outside the scope of the game's design.

Future research could explore applying the Commitment and Compliance metrics, which consider players' historical performance, within matchmaking systems. This approach could benefit the game by recommending suitable champions to players and suggesting compatible players for team formations. Such a system could reduce the frequency of player turnover in the eSports scene, as teams would be formed based on metric-driven compatibility rather than human decisions.

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