Quantifying the Unseen: Measuring Game Intensity in Valorant

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ABSTRACT

Esports has rapidly evolved into a competitive arena that rivals traditional sports in both popularity and complexity. As games like Valorant, a popular first-person shooter (FPS), gains popularity, there is a growing need to understand the influences that affect competitive performance. One less researched aspect is "game intensity," which reflects a player's engagement, stress levels, and overall performance during high-stakes matches. Understanding and quantifying game intensity is crucial because it can influence decision-making, reaction times, and communication within teams, directly impacting match outcomes. Insights into game intensity can inform training programs, optimize strategies, and improve coaching tools, benefiting players, coaches, and the broader esports community.

This thesis was conducted in the context of Patterns GG Limited [GG 2024], a company that focused on developing innovative data-driven solutions. With them this thesis develops a model for measuring and analyzing player performance to evaluate intensity in Valorant. It integrates a mix of quantitative metrics, such as in-game statistics (e.g., kill-death ratios and round durations), and vocal metrics (e.g., voice volume and frequency of speaker turns). Data is collected through video recordings of gameplay, audio recordings, and game logs for performance metrics.

Correlation analysis is used to examine the relationships between these diverse parameters and intensity. Through this model and comprehensive analysis, the thesis offers both theoretical and practical contributions to understanding player intensity in Valorant, enriching competitive gaming strategies and fostering player development.

1 INTRODUCTION

In the rapidly evolving realm of esports, the competitive landscape is continuously reshaped by the release of new games, the development of innovative strategies, and the introduction of new players. Valorant, a popular first-person shooter (FPS) game developed by Riot Games [2020], has quickly risen to the top within this environment. Its unique blend of tactical gameplay and character-based strategy has not only attracted a vast player base but also sparked considerable interest in the analytical aspects of player performance and game intensity.

Understanding "intensity" in the context of esports is crucial for multiple reasons. Intensity, which encompasses a range of behaviors and auditory responses, reflects a player's engagement, stress levels, and overall performance during competitive matches. High-intensity moments can significantly influence decision-making, reaction times, and communication within teams, all of which directly impact match outcomes. Moreover, quantifying intensity can provide valuable insights for various stakeholders, including players who wish to optimize their performance, coaches looking to tailor training programs, and analysts interested in developing strategic insights. For the broader esports community, understanding intensity also has implications for game design, allowing developers to create more engaging and balanced gameplay experiences.

Traditional analyses of player performance have mainly focused on quantitative metrics such as kill-death ratios, points scored, and the time taken to complete objectives [Mora-Cantallops and Sicilia 2018][Schubert et al. 2016]. However, these metrics, while informative, offer an incomplete picture of player intensity and performance. Recognizing this gap, this thesis proposes an approach that integrates both quantitative in-game statistics and vocal metrics into the analysis.

By developing a comprehensive model for measuring and analyzing player performance, this thesis aims to evaluate the intensity of players in Valorant. Data for this thesis was collected through video recordings of gameplay, audio recordings of player communications, and detailed game logs that capture in-game performance metrics.

This thesis tries to fill a void in esports research, offering both theoretical and practical contributions to the understanding of player intensity in Valorant. By showcasing the relationship between various performance metrics and game intensity, it aims to enrich competitive gaming strategies and contribute to player development.

1.1 Objectives

The primary goal of this research is to identify low and high intensity in Valorant. To achieve this objective, the thesis will:

(1) Define "Intensity" in the context of Valorant.
(2) Create a model to identify low and high intensity moments automatically within a round of Valorant.

1.2 Research Questions

In pursuit of the stated objectives, this research seeks to answer the following key questions:

(1) What is causing intensity in Valorant?
(2) What features in Valorant can measure intensity?

1.3 Structure of the Thesis

This thesis is organized into six main chapters. The first chapter, **Introduction**, provides an overview of the research problem, objectives, and key research questions. It introduces the concept of intensity in Valorant, sets the scope of the thesis, and discusses its potential implications for the esports community.

The second chapter, **Related Work**, reviews existing literature on the definition and identification of intensity across various fields, with a particular focus on competitive gaming and sports. It explores how intensity has been previously measured, focusing on psychological and physiological factors, as well as the role of team communication in competitive gaming environments.

The third chapter, **Data Collection**, details the data collection, including the recruitment process for participants, data collection methods, and techniques for data preprocessing. It also covers the approach to transcription, data cleaning, and the creation of feature vectors for analysis.

The fourth chapter, **Model Construction and Justification**, outlines the process of constructing and selecting machine learning models to classify intensity in Valorant. This chapter includes the details of data preprocessing, model selection, the decision to use XGBoost, and the subsequent hyperparameter tuning and evaluation.

In the fifth chapter, **Results**, the performance of the machine learning models is presented, with a comparison of different classifiers. This chapter also provides a detailed analysis of gameplay metrics and their relationship to intensity, supported by visualizations of the data.

The sixth chapter, **Discussion**, interprets the findings from the results, offering insights into player behavior, game dynamics, and the effectiveness of the models used.

Finally, the **Conclusion** summarizes the key findings of the thesis, addresses the research questions, and discusses the broader implications of the results for esports performance analysis. This chapter also discusses the limitations of the thesis and suggests potential improvements for future research.

2 RELATED WORK

The study of intensity in competitive gaming environments like Valorant draws on a variety of fields, including psychology, sports science, and game analytics. Prior research has explored the concept of intensity through diverse views, ranging from physiological measurements to behavioral and cognitive analyses. This section synthesizes existing literature on the identification and quantification of intensity across these disciplines, focusing on its relevance in gaming environments. By examining how intensity has been defined and measured in related contexts, this study builds a foundation for understanding player intensity in esports and informs the development of a new framework tailored to the dynamics of Valorant.

2.1 Definition and Identification of Intensity

2.1.1 General Definition and Context. Before analyzing intensity in specific contexts like sports or gaming, I first need to define what intensity is. In its simplest form, intensity refers to the quality or state of being intense Merriam-Webster [2024]. However, this basic definition does not fully capture the complexity of the concept across different disciplines.

In psychology, Yang and Wang [2022] describe intensity as a measure of meaning or value, often referred to as "feeling tone." It encompasses the degree or strength of emotions, thoughts, or behaviors, including emotional experiences, cognitive focus, actions, and sensory experiences. This broad psychological definition emphasizes intensity as a multidimensional concept affecting various facets of human experience.

In sports, intensity is often defined through physiological parameters. Taylor [2009] refers to intensity as the amount of physiological activity, including heart rate, respiration, and adrenaline levels. Similarly, Selmi et al. [2023] measure intensity through physiological and psychological indicators during small-sided soccer games, noting the role of communication, particularly verbal encouragement, in influencing intensity levels. This view reinforces the connection between physiological responses and intensity.

When bridging sports into gaming, the definition of intensity remains closely tied to physiological responses. Damasceno et al. [2023] measure intensity based on heart rate responses during gameplay, with a focus on how accurately games like 'EA Sports: Active 2' differentiate between various intensity levels. Other views, such as Aprillia et al. [2023], simplify the measurement of intensity to time spent in a game. However, most related work agrees that heart rate is a key indicator of intensity in both sports and gaming. For instance, Porter and Goolkasian [2019] explored how stress and game content directly influence heart rate fluctuations during gameplay.

To measure intensity in a video game like Valorant, I must focus on stressful situations, which can be assessed either through the game's content or, as Selmi et al. [2023] suggest, through communication patterns.

2.1.2 Intensity Identification in Sports. In the realm of sports, quantifying intensity is critical for performance analysis, training optimization, and injury prevention. Various methods have been employed to capture intensity, each offering unique insights.

Heart rate monitoring is one such method extensively used to predict exercise intensity. Zhang [2022] demonstrated the efficacy of heart rate monitoring using Electroencephalogram (ECG) signals and pulse wave data to create regression models, highlighting its reliability and accuracy. Additionally, perceived exertion scales, such as the Borg Rating of Perceived Exertion (RPE), provide a robust subjective tool for measuring exercise intensity and correlating it with physiological markers Borg and Noble [1974].

Technological advancements have also contributed to intensity measurement in sports. GPS devices and accelerometers track movement intensity in team sports, offering detailed insights into player performance. Chen et al. [2022] emphasized the importance of combining multiple intensity metrics to create a comprehensive picture of physical demands. Furthermore, lactate threshold testing provides a precise measure of sustainable exercise intensity for endurance athletes, helping optimize training Scherr et al. [2012]. In elite soccer, high-intensity running activity has been shown to significantly impact team success, with positional differences influencing intensity levels Salvo et al. [2009].

2.1.3 Intensity Identification in Gaming Environments.

In gaming, especially esports, intensity encompasses both physical and emotional dimensions. Roohi et al. [2019] developed an automatic emotion annotation system for game streams, using neural network analysis of facial expressions, voice emotions, and audio features like pitch and loudness. Their system detected high-intensity emotional events with up to 80.4% accuracy, showcasing the potential of psychophysiological measurements in gaming.

Physical intensity also plays a role in gaming environments, particularly in virtual reality (VR) games. Evans et al. [2021] explored the physical activity intensity in VR, showing that certain games could reach moderate intensity levels using measures such as heart rate reserve, ratings of perceived exertion, and accelerometry.

Psychophysiological measurements also contribute to understanding intensity in VR exergames. Barathi et al. [2020] identified gaze fixations, pupil diameter, and skin conductivity as indicators of affective valence and arousal during high-intensity gaming, offering valuable insights for personalizing gaming experiences.

Additionally, Chang-shan [2011] examined vocal intensity differences in speakers, a concept that can be adapted to analyze vocal intensity in gaming environments, further broadening our understanding of player engagement.

In summary, intensity is a multifaceted concept that is context-dependent, spanning physiological, psychological, and emotional dimensions across sports and gaming environments. Heart rate monitoring, perceived exertion scales, and psychophysiological measurements are some of the most reliable methods for capturing intensity, whether through physical activity or emotional engagement. To measure the intensity in video games like Valorant, the focus should be places on stressful situations, which can be evaluated using game content, physiological responses, and communication patterns.

2.2 Team Communication in Competitive Gaming

Effective communication is vital for the success of teams in competitive gaming. It extends far beyond simple interaction and involves strategic planning, real-time decision-making, and emotional support during high-stakes scenarios. Both verbal and nonverbal communication play crucial roles in ensuring coordination, strategy implementation, and overall team performance. This section reviews the literature on team communication in competitive gaming, focusing on both verbal and non-verbal aspects.

2.2.1 Verbal Communication.

Verbal communication in competitive gaming involves direct spoken interaction between team members, often facilitated through voice chat or in-game text chat. These communication tools serve as the backbone for conveying strategic plans, coordinating movements, and disseminating critical information during matches. Numerous studies have demonstrated the benefits of verbal communication for groups or online communities Freeman and Wohn [2019]; Hilvert-Bruce et al. [2018]; Tang et al. [2018].

One such study, conducted by Hew et al. [2003], focused on the usability and sociability of the Xbox

Live voice channel. Their work sheds light on how verbal communication through voice channels can influence social interactions and usability in online gaming. They found that although users expect voice to improve coordination and engagement, practical issues like voice channel control and distinguishing speakers often detract from the experience.

Lober et al. [2007] also emphasized the significance of communication modalities in gaming. They conducted studies comparing audio and chat communication in online multiplayer games, highlighting the impact of group size on media choice. Their research suggests that the efficiency and productivity of a team can vary significantly depending on the communication medium utilized.

Further supporting the importance of verbal communication, Lausic et al. [2015] and Lausic et al. [2014] analyzed verbal communication patterns in team sports such as tennis doubles. They found that winning teams exhibited higher levels of verbal communication, using more action, emotional, encouragement, and planning statements compared to losing teams. These findings underscore the importance of verbal communication in achieving coordination and success, a principle applicable to esports. Similarly, Zargham et al. [2020] explored verbal communication in a VR game setting, finding that interactions with multiple interlocutors fostered a stronger sense of team spirit and camaraderie.

2.2.2 Non-Verbal Communication. Non-verbal communication in gaming environments includes text chat, 'pings', pre-defined messages, and visual signals that do not involve spoken words Tan et al. [2022]. These forms of communication can be crucial for conveying information quickly and efficiently, especially in high-pressure situations.

Leavitt et al. [2016] examined the use of "pings" in the game *League of Legends*, a non-verbal communication tool that provides auditory and visual cues to teammates. Their study revealed a positive relationship between the use of pings and team performance, demonstrating that non-verbal communication tools enhance coordination and effectiveness. They noted, however, a non-monotonic and concave relationship, where excessive use of pings could lead to decreased performance, indicating the importance of balancing non-verbal cues.

Although Valorant offers a more extensive ping wheel, there are currently no APIs available to extract detailed data on ping usage, limiting the applicability of this information in our study. Nonetheless, previous research emphasizes the critical role of non-verbal communication in gaming performance.

Lausic et al. [2015] also investigated the role of non-verbal sensitivity in team sports. Their findings suggest that winning teams exhibit higher levels of non-verbal sensitivity, improving their ability to communicate effectively and coordinate actions. This insight into non-verbal communication in sports supports the idea that non-verbal cues are vital for successful team dynamics in gaming as well.

Based on the literature, it is clear that communication, both verbal and non-verbal, is a key factor in solving tasks successfully in competitive gaming. Verbal communication tends to be most impactful in coordinating actions and maintaining team morale. However, non-verbal communication, through tools like pings, also plays an essential role in enhancing team coordination and performance. Finding how this communication relates to intensity is a research gap that this thesis aims to explore.

2.3 Valorant as a Competitive Gaming Environment

Valorant is a free fps video game developed by Riot Games specifically for the Windows platform. Drawing inspiration from Counter-Strike: Global Offensive (CS:GO), Valorant features competitive play between two squads, each composed of five players. A unique twist in Valorant is that every agent possesses distinctive abilities. An agent is a playable character that is chosen before the match starts. Matches are played in a series of up to 24 rounds with the first to 13 with a difference of two to win. The teams are assigned to either attackers or defender. The attacking team is responsible for planting a bomb, whereas the defending team aims to prevent these efforts. Teams switch roles after the first 12 rounds Fernanda et al. [2022].

The game provides a diverse roster of agents, each categorized by specific roles and abilities, including duelists, initiators, controllers, and sentinels a full list is provided in Table 1. These roles each come with their own play-styles: duelists excel in direct confrontations, initiators can initiate team fights, controllers master terrain manipulation, and sentinels provide support for their teammates.

Additionally, Valorant offers a selection of ten distinct maps, each presenting its own set of strategic intricacies and environmental challenges. The maps include Fracture, Breeze, Icebox, Bind, Haven, Split, Ascend, Pearl, Lotus, and Sunset all designed with unique layouts and themes.

The objective for players is to either successfully plant/defuse the bomb or to eliminate the enemy team. A round concludes upon the defeat of a team or the completion of set objective. Players that were eliminated in a round must wait until the round is over, or until they get revived. Some agents have the ability to bring a player back from the dead and give them a second chance. The game features an economy system allowing players to buy weapons and equipment at the beginning of each round, funded by the currency given buy the game. Players receive money after every round, and carry over everything they did not spend, up to a maximum of $9k.

2.4 Summary of Literature, Research Gaps, and Goals

Existing research on game intensity in competitive environments like esports draws from various fields, including psychology, sports science, and game analytics. Studies have explored intensity through different lenses, such as physiological measurements, behavioral analyses, and communication patterns. For example, intensity in traditional sports is often measured using physiological indicators like heart rate, perceived exertion scales, or performance metrics. In gaming environments, researchers have employed psychophysiological methods (e.g., facial recognition and heart rate monitoring) and game-specific metrics to quantify intensity levels.

However, there are several gaps in the literature concerning the measurement and understanding of game intensity in esports:

- **Limited Focus on FPS Games:** While some studies have examined game intensity in esports, there is a lack of research focusing specifically on first-person shooter (FPS) games like Valorant, which involve distinct mechanics and dynamics compared to other game genres.
- **Integration of Diverse Metrics:** Previous research predominantly relies on singular metrics such as physiological responses or in-game statistics. There is a need for an integrated approach that combines multiple types of data, including vocal metrics, in-game statistics, and player communication patterns, to provide a more comprehensive understanding of game intensity.
- **Player Experience and Team Dynamics:** Few studies have explored how subjective experiences of intensity, such as perceived stress and focus, correlate with objective performance metrics. Moreover, the role of team dynamics, including verbal and non-verbal communication, remains underexplored in relation to game intensity.
- **Machine Learning for Intensity Classification:** While some research has applied machine learning models to predict performance in esports, there is limited application of these techniques to classify intensity levels based on a combination of quantitative and qualitative data.

Table 1: List of Valorant Agents by Role at the time of data collection [Valorant Wiki Contributors 2024]

Controllers	Duelists	Initiators	Sentinels
Astra	Iso	Breach	Chamber
Brimstone	Jett	Fade	Cypher
Clove	Neon	Gekko	Deadlock
Harbor	Phoenix	KAY/O	Killjoy
Omen	Raze	Skye	Sage
Viper	Reyna	Sova	
	Yoru		

Given these gaps, the primary goal of this thesis is to develop a comprehensive framework for measuring and analyzing game intensity in Valorant by integrating quantitative in-game statistics and vocal metrics. This study aims to:

- **Identify and Define Intensity:** Clearly define "intensity" within the context of Valorant, drawing from existing literature and new empirical findings.
- **Develop a Multi-Metric Model:** Create a model that combines multiple data sources, including in-game statistics, vocal metrics, and player self-reports, to automatically identify low and high-intensity moments.
- **Analyze Intensity's Impact on Performance:** Examine how different levels of intensity influence individual and team performance outcomes in competitive matches.
- **Contribute to Esports Research:** Offer both theoretical and practical contributions to the field of esports performance analysis by expanding the understanding of intensity and its role in player and team dynamics.

3 DATA COLLECTION

For data collection, I gathered data from all five players from one of two team across multiple gaming sessions, ensuring a thorough representation of game performance and audio communication.

3.1 Participant Recruitment

To gather a diverse and high-level dataset, participants were recruited from the Valorant community, focusing on teams actively competing in the game's ranked modes. Recruitment was facilitated through various online platforms where competitive Valorant players are active, such as community Discord servers and esports forums.

The study targeted experienced players with a minimum rank of `Diamond 1` which represents the top 11.4% of all Valorant players globally [Tales 2023], ensuring that the dataset reflected gameplay from highly skilled participants. I recruited 15 participants, organized into two teams, with each team consisting of five primary players and additional substitutes to provide flexibility in scheduling. One team even had experience in organized competitive environments, providing a high level of strategic play and communication that was crucial for the study.

Each team was asked to participate in a minimum of 10 matches. For Team 1 the players' matches played ranged from 7 to 14 games, with substitutes playing between 7 to 9 matches. For Team 2 the players' matches played ranged from 2 to 10 games, with substitutes playing between 2 to 5 matches.

All participants were informed about the study's objectives, the nature of the data collection (including game metrics and voice communication), and their rights as participants. Informed consent was obtained from all players before they engaged in the study, ensuring they were fully aware of their ability to withdraw from the study at any point. This recruitment process was designed to create a dataset that not only reflected high-level gameplay but also adhered to the ethical standards of participant consent and confidentiality.

3.2 Gameplay and Communication Data

Data collection was performed using a combination of advanced tools to gather detailed in-game performance metrics and communication data. Leveraging the Patterns GG Limited [GG 2024] dashboard and the Riot Games API [Riot Games 2023]. The Patterns GG Limited dashboard is a tool that uses the Overwolf API [Overwolf Ltd. 2024], screen recording and access to its users microphones to collect data for Valorant or CS:GO2 [Valve Corporation 2024].

With these tools I obtained a dataset that included key in-game actions, performance statistics, and economic metrics, all of which are essential in evaluating game intensity. This model allowed me to capture the nuanced elements of gameplay that contribute to intensity, such as, kills, damage dealt, and strategic events; like bomb detonations and clutch plays.

Additionally, I recorded audio communications among team members to explore the qualitative aspects of their interactions. Using the Patterns GG dashboard and Discord's bot [Craig], I was able to document verbal exchanges that provided critical insights into the team dynamics, communication strategies, and real-time decision-making processes. This combination of game metrics and communication data created a comprehensive understanding of how both gameplay and player interactions drive the intensity of each match.

3.3 Transcription and Data Cleaning

Following the collection of voice data, I employed OpenAI's Whisper model [Radford et al. 2022] for transcription. A local instance of the model was deployed to ensure the privacy and confidentiality of the voice recordings, adhering to strict ethical standards. Although the Whisper model facilitated the transcription process, challenges such as accuracy issues and technical difficulties resulted in a partial dataset.

After reviewing the dataset, a very poor performance was noticed. The data had timestamps that were off by multiple seconds, entire transcriptions were missing, and Whisper had a poor performance correctly transcribing game specific words, such as character names or places. Therefore, the data had to be manually transcribed for every player resulting in only five fully cleaned matches per team due to time restraints.

3.4 Self-Reported Intensity Measures

In addition to the objective game and communication data, subjective intensity data was collected directly from the players using an online survey administered after each game. The survey aimed to measure players' perceived intensity during gameplay with questions such as, 'On a scale of 1 to 5, how intense did you find the last match?' where 1 indicated 'Not Intense at All' and 5 indicated 'Extremely Intense.'

These self-reported intensity levels allowed me to correlate players' subjective experiences with the objective in-game data, offering a dual perspective on game intensity that includes both internal player perceptions and external performance metrics.

3.5 Data Processing and Feature Vector Construction

Once the data collection phase was completed, a rigorous data cleaning process was conducted to ensure the validity and quality of the dataset. This included removing incomplete or inconsistent data points, leading to a final dataset of 115 datapoints, derived from 23 games with five players per game.

Due to the limited number of successfully transcribed games with reliable voice recordings, amounting to only 10 matches, a choice was required as to whether the voice data should be included in the analysis. Given the importance of maintaining a larger dataset for a more comprehensive analysis, I decided to exclude the voice data from the final analysis. This choice allowed me to retain a greater number of games and maintain the robustness of the dataset while focusing on the more abundant gameplay metrics and survey data.

The feature vector constructed for this study includes various gameplay and interaction metrics (see Table 5 in the Appendix for a full list of features). Key features included player performance indicators such as kills, damage dealt, and accuracy metrics (e.g., headshots and body shots). Economic factors like loadout value and resources spent were also included to provide insight into the strategic decisions made during each match. Furthermore, the feature vector incorporated critical in-game events such as bomb detonations, clutches, and ceremonial moments like flawless victories and team aces, all of which contribute to the overall intensity of the game.

Among these features is the "Match Intensity," which represents the subjective intensity level of each match as rated by the players on a 5-point Likert scale, where 1 indicates 'Not Intense at All' and 5 indicates 'Extremely Intense.' The intensity metric was used to correlate players' subjective experiences with the objective in-game data, providing a dual perspective on game intensity.

The distribution of match intensity levels across the dataset is illustrated in Figure 1. This figure shows that most matches cluster around intensity levels 2 and 3, with fewer matches at the extreme ends of the intensity scale (1 and 5). This distribution likely reflects the game's matchmaking system, which aims to pair players of similar skill levels. It also raises questions about how players perceive match difficulty and whether certain intensity levels correlate with specific gameplay behaviors or strategies.

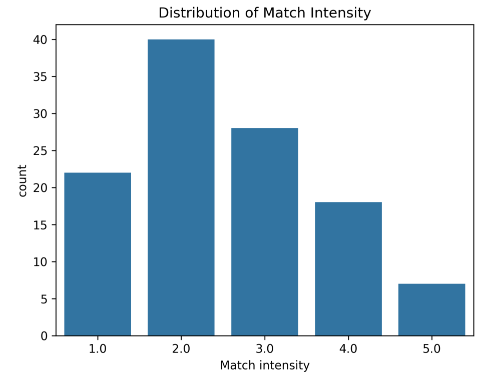

Figure 1: Histogram of Match Intensity Distribution: Depicting the frequency of matches across different intensity levels, illustrating the balance and competitiveness within the game's matchmaking system.

4 MODEL CONSTRUCTION AND JUSTIFICATION

4.1 Introduction to the Model

The objective of this study is to predict 'Match Intensity' levels in Valorant games using a machine learning approach. Given the nature of the problem, a supervised learning methodology was adopted. The dataset consists of feature vectors that represent various in-game metrics (such as the number of kills, damage dealt, economic expenditures) along with their corresponding intensity labels, which range from 1 to 5. Each instance in the dataset is paired with a known intensity label, making this problem suitable for supervised learning.

Supervised learning enables the model to learn from labeled data, where the goal is to find a mapping from the input features (game metrics) to the output labels (intensity levels). For this purpose, the XGBoost (Extreme Gradient Boosting) model was selected due to it outperforming other models and its ability to model complex, non-linear relationships through gradient boosting techniques.

To further enhance the model's performance, feature selection was performed using XGBoost's feature importance scores. This process identified the 15 most relevant features for the prediction task, including 'enemy_average_kill_times', 'win_status', 'enemy_armor', 'CeremonyThrifty', and 'enemy_economy_loadoutValue' a full list and the explenation of their meaning is provided in the appendix in Table 6. These features capture various aspects of gameplay that are significant for predicting match intensity.

After selecting these features, hyperparameter tuning was conducted using a grid search to optimize the model's performance. The best-performing hyperparameters are listed in Table 3.

4.2 Model Selection and Comparison

Several machine learning models were evaluated for their performance, including:

- **Random Forest:** A robust tree-based ensemble model that handles non-linearity and feature interactions well.
- **Support Vector Machine (SVM):** Effective in high-dimensional spaces and can adapt to classification tasks with non-linear boundaries.
- **K-Nearest Neighbors (KNN):** A simple, instance-based learning algorithm that makes predictions based on the nearest training samples in the feature space.
- **Multi-Layer Perceptron (MLP):** A feedforward neural network that can model complex relationships within the data.
- **Logistic Regression:** A linear model used as a baseline to compare the performance of more complex models.
- **Gradient Boosting:** Another tree-based model that builds sequential models to reduce prediction errors.

Each model was tested and compared using cross-validation, and their performance metrics: accuracy; F1-score; precision; recall, were evaluated. The results can be seen in Table 2.

4.3 Choice of XGBoost

XGBoost is an ensemble model that builds multiple decision trees sequentially, where each tree attempts to correct the mistakes of the previous ones. It is particularly suited for structured tabular data like the one used in this study and offers several advantages:

- **Handling Complex Data:** XGBoost is capable of handling complex feature interactions, which is beneficial for this problem where gameplay intensity depends on multiple interrelated factors.
- **Regularization:** XGBoost includes built-in regularization parameters (e.g., `reg_alpha` and `reg_lambda`) that help reduce overfitting, making it a robust choice for this dataset.
- **Imbalance Handling:** XGBoost can also be tuned to account for class imbalance through custom weighting, complementing the oversampling done by SMOTE.

4.4 Data Processing

To ensure optimal performance of the machine learning models, several data preprocessing steps were applied to the dataset, which consisted of feature vectors representing various metrics from Valorant games. Each group of five rows represented different player perspectives of a team within the same game. The preprocessing steps included:

- **Normalization:** The features were scaled using the `StandardScaler` to ensure that all features were on the same scale, which is crucial for the performance of many machine learning algorithms. This step mitigates the influence of features with larger magnitudes and ensures that each feature contributes equally to the model.

- **Balancing the Dataset:** To address the class imbalance in the 'Match Intensity' labels, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. SMOTE generates synthetic samples for the minority classes by interpolating between existing instances, effectively balancing the class distribution. After applying SMOTE, the dataset contained a total of 200 samples, with each intensity class having an equal representation of 40 samples. This balanced dataset improved the robustness of model training and evaluation.

- **Data Splitting and Cross-Validation:** The dataset was divided into training, validation, and test sets to facilitate model development and evaluation. An initial split allocated 60% of the data for training, while the remaining 40% was reserved for validation (20%) and testing (20%). Stratified sampling was used during these splits to maintain the original class distribution across all subsets.

  To further evaluate and select the best-performing models, a Stratified K-Fold cross-validation technique was employed on the training set. Specifically, a 5-fold cross-validation was conducted to ensure that each fold maintained the original class distribution. This method involved splitting the training set into five folds, with each fold being used as a validation set once while the remaining folds were used for training. This process allowed for a comprehensive evaluation strategy, reducing the risk of overfitting and ensuring model selection was based on generalizable results.

- **Feature Selection:** To enhance the model's performance and interpretability, feature selection was conducted using XGBoost's feature importance scores. An initial XGBoost model was trained on the balanced dataset to determine the importance of each feature in predicting 'Match Intensity' levels. The model's inherent ability to rank features based on their contribution to the prediction task allowed for the selection of the top 15 most relevant features. These selected features are listed in Table 6.

4.5 Hyperparameter Tuning

Once XGBoost was selected, hyperparameter tuning was conducted using `RandomizedSearchCV`. The key hyperparameters tuned include:

- **Learning Rate:** Lower values (0.01 to 0.1) were explored to ensure gradual convergence and to avoid overshooting the global minimum.
- **Max Depth:** The depth of the trees was limited (e.g., `max_depth=2`) to prevent overfitting while capturing sufficient complexity.
- **Number of Estimators:** The number of trees was adjusted to 100 to ensure that the model performed well without excessive computational costs.
- **Subsample and Colsample:** Parameters such as `subsample=0.8` and `colsample_bytree=0.8` were used to introduce randomness, which helps prevent overfitting and improves generalization.

5 RESULTS

5.1 Model Comparison

To identify the most effective machine learning model for predicting 'Match Intensity', several untuned base models were evaluated using a 5-fold Stratified K-Fold cross-validation approach. These models included Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), Logistic Regression, Gradient Boosting, and XGBoost.

The performance metrics used to compare the models included accuracy, F1-score, precision, and recall, as these metrics provide a comprehensive view of each model's effectiveness, especially in handling class imbalance. The results presented in Table 2 are the average metrics obtained from the stratified K-Fold cross-validation process. XGBoost, a gradient-boosted decision tree model, emerged as the best-performing model. This model achieved the highest accuracy of 32.6%, outperforming the other models.

Table 2: Comparison of Model Performance Based on Key Metrics for Intensity Classification in Valorant. The table compares accuracy, precision, recall, and F1-scores across various machine learning models. The models predicted the 'Match Intensity' on a 5 point scale

Model	Accuracy	F1-score	Precision	Recall
XGBoost	0.326	0.298	0.299	0.326
Random Forest	0.304	0.265	0.268	0.304
MLP	0.293	0.266	0.267	0.293
KNN	0.292	0.249	0.250	0.292
SVM	0.283	0.241	0.223	0.283
Gradient Boosting	0.281	0.261	0.287	0.281
Logistic Regression	0.260	0.222	0.215	0.260

As evident from Table 2, XGBoost was selected for further tuning and testing due to its better performance across all metrics.

5.2 Hyperparameter Tuning

Following the selection of XGBoost, a grid search was conducted to fine-tune the hyperparameters. Various configurations were tested for hyperparameters such as `learning_rate`, `max_depth`, `n_estimators`, `subsample`, `reg_alpha`, and `reg_lambda`. The best-performing hyperparameter configuration is presented in Table 3.

With these optimal hyperparameters, the XGBoost model was retrained and evaluated on the test set. The resulting performance metrics, including precision, recall, and F1-score for each intensity class, are summarized in Table 4.

As seen in Table 4, the model performed reasonably well, with a weighted accuracy of 57.5%. Precision, recall, and F1-scores were generally high for higher intensity classes (Intensity 3, 4, and 5), while performance was lower for the lower intensity classes (Intensity 1 and 2).

Table 3: Best Performing Hyperparameter Configuration for XGBoost Based on Grid Search Optimization.

Hyperparameter	Best Value
colsample_bytree	0.8
learning_rate	0.1
max_depth	2
n_estimators	100
reg_alpha	0.1
reg_lambda	1.5
subsample	0.8

Table 4: Detailed Performance Metrics (Precision, Recall, F1-Score, and Support) for each Intensity Class in the Retrained and Tuned XGBoost Model.

Class	Precision	Recall	F1-score	Support
Intensity 1	0.50	0.38	0.43	8
Intensity 2	0.22	0.25	0.24	8
Intensity 3	1.00	0.38	0.55	8
Intensity 4	0.78	0.88	0.82	8
Intensity 5	0.62	1.00	0.76	8
Average/Total	0.62	0.58	0.56	40

5.3 Confusion Matrix Analysis

To provide further insight into the performance of the tuned XGBoost model, a confusion matrix was generated to visualize the model's predictions compared to the actual intensity classes (Figure 2). The confusion matrix helps to identify specific patterns of misclassification, particularly where the model has difficulty distinguishing between classes.

The confusion matrix shows that the model performs well in predicting the highest intensity level (Intensity 5), with 8 correct predictions and no misclassifications. However, there is notable misclassification among the lower intensity levels. For example:

- Intensity 1 has 5 instances incorrectly classified as Intensity 2.
- Intensity 2 has 3 instances incorrectly classified as Intensity 1 and 2 instances as Intensity 5.

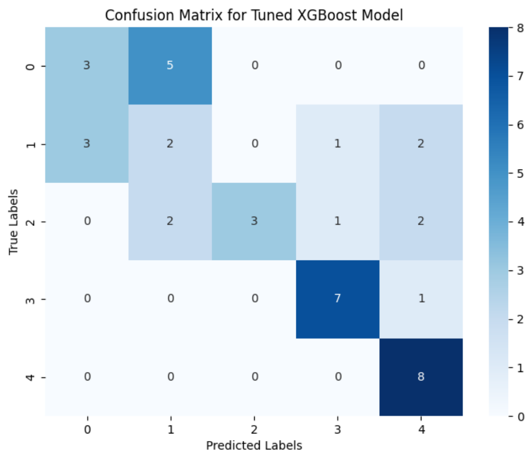

Figure 2: Confusion Matrix for Tuned XGBoost Model. Intensity labels here are ('Match Intensity'-1)

- Intensity 3 is often confused with Intensities 2 and 5.

These results suggest that while the model is effective at identifying the highest intensity level, it struggles to differentiate between the lower intensity levels, potentially due to overlapping feature values or similarities in the gameplay metrics across these intensity levels.

5.4 Descriptive Analysis

In this section, I analyzed several key features of match data from a multiplayer game to understand how different factors correlate with match intensity, player economy, and overall gameplay performance. The data consists of metrics such as *economy_spent*, *kills*, *score*, and various ceremony events, among others. This analysis aims to provide insights into how gameplay variables interact, the distribution of player behavior across different intensity levels, and the presence of outliers, which might represent extreme strategies or unusual gameplay conditions.

To conduct this analysis, I used a variety of visualization techniques, including box plots, heatmaps, histograms, and correlation matrices. First, I calculated the Z-scores for the dataset to identify any significant outliers. Outliers were defined as data points with Z-scores greater than 3 or less than -3, which were saved and analyzed separately.

I also performed exploratory data analysis (EDA) on the dataset, focusing on the distribution of key gameplay metrics. This involved visualizing the distribution of numeric features such as *kills*, *damage*, *economy_spent*, and ceremony-related events. Furthermore, I generated a correlation heatmap in Table 4 to explore the relationships between different variables and how they contribute to overall match outcomes. A detailed analysis of match intensity was also conducted, with special attention paid to the distribution and behavior of the economy spent by players.

5.4.1 Box Plot of Economy Spent by Match Intensity. The box plot (Figure 3) visualizes the distribution of *economy_spent* across different levels of match intensity, ranging from 1 to 5. As shown in the plot, there is a slight upward trend in median economy spent as match intensity increases. This suggests that as matches become more intense, players tend to invest more in better equipment, possibly in an effort to secure a competitive advantage. However, the middle range remains relatively stable, implying that the overall spending habits of players do not fluctuate wildly, despite the intensity of the match.

Interestingly, the presence of outliers at all intensity levels indicates that some players tend to deviate significantly from the norm. These deviations could be the result of either aggressive or conservative economic strategies. For example, some players may be hoarding their resources for critical rounds, while others might be overspending in an attempt to overwhelm opponents early on.

5.4.2 Feature Correlation Heatmap. To better understand the relationships between different gameplay metrics and their impact on predicting 'Match Intensity' levels, a correlation analysis was conducted. A correlation heatmap, shown in Figure 4, was generated to visualize the strength and direction of the correlations between all the features

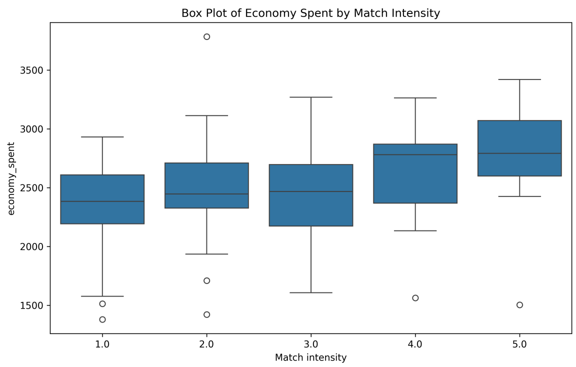

Figure 3: Box Plot of Player Economy Spent Across Match Intensity Levels: Visualizing the distribution of resources spent by players as match intensity increases, highlighting economic strategies in varying gameplay scenarios.

in the dataset, including their correlation with the target variable, 'Match intensity'. The heatmap uses color intensity to represent correlation coefficients, with darker red colors indicating strong positive correlations and darker blue colors indicating strong negative correlations.

From the heatmap, several features exhibited notable correlations with 'Match intensity':

- *enemy_economy_loadoutValue*, a feature that represents the monetary value the enemies equipment, showed a moderate positive correlation with 'Match intensity' (approximately 0.45), suggesting that games where the enemy team has a higher loadout value are often associated with higher intensity matches.
- *damage*, a feature that recorded the damage dealt by the player, demonstrated a moderate positive correlation with 'Match intensity' (approximately 0.42), indicating that games with higher total damage dealt tend to have a higher intensity level.
- *roundNum*, the total number of rounds in a game, showed a weak positive correlation with 'Match intensity' (approximately 0.35), implying that longer matches might be associated with higher intensity.
- *enemy_score*, a feature recording the performance of the enemies, had a moderate positive correlation with 'Match intensity' (approximately 0.40), suggesting that higher enemy team scores are often found in higher intensity matches.
- *economy_loadoutValue*, a feature that represents the monetary value the player's equipment also exhibited a weak positive correlation with 'Match intensity' (approximately 0.28), indicating that better-equipped teams are often involved in more intense matches.
- *Bomb detonated*, the amount of rounds in which the bomb detonated, had a weak positive correlation with 'Match intensity' (approximately 0.25), suggesting that successful bomb detonations slightly relate to higher match intensity.
- *CeremonyThrifty*, the amount of rounds that the player' team won with a combined lower loadout value than the enemies, showed a weak negative correlation with 'Match intensity' (approximately -0.22), indicating that rounds where a thrifty ceremony occurs (winning with a low budget) tend to have slightly lower match intensity.

These correlations highlight which features are more strongly related to 'Match intensity' and provide valuable insights into gameplay dynamics. The features with moderate positive correlations, such as *enemy_economy_loadoutValue*, *damage*, and *enemy_score*, suggest that aspects related to both team and enemy performance, as well as the game's economic conditions, play significant roles in defining match intensity.

5.4.3 Distribution of Match Intensity. The distribution of match intensity (Figure 1) reveals that most matches cluster around intensity levels 2 and 3, with fewer matches at the extreme ends of the intensity scale (1 and 5). The skewness of the distribution suggests that the majority of games are relatively balanced, with only a minority of matches being either very low or very high in intensity.

This distribution likely reflects the game's matchmaking system, which aims to pair players of similar skill levels. It also raises questions about how players perceive match difficulty and whether certain intensity levels correlate with specific gameplay behaviors or strategies. For example, further analysis could investigate whether high-intensity matches are more likely to result in higher economy spending or whether players adopt different strategies in lower-intensity games.

5.4.4 Numeric Features Distribution. The distribution of various numeric gameplay features (Figure 5) provides insights into player behavior and game dynamics. For example, features such as *armor* and *economy_spent* show right-skewed distributions, indicating that a majority of players tend to spend moderately, with a few spending significantly more. This could be due to strategic choices, where certain players aim to conserve resources while others prioritize immediate advantages.

Other features, such as *kills*, *damage*, and *score*, display more normal distributions, suggesting a consistent level of player performance across matches. The distribution of ceremony events like *CeremonyTeamAce* and *CeremonyFlawless* is more sporadic, which makes sense as these events represent specific achievements and are less common in typical matches.

5.4.5 Outliers Analysis. Outliers were identified using Z-scores and saved in a separate file for further examination. These outliers represent extreme values in the dataset, which could indicate either extraordinary gameplay situations or potential data anomalies. For example, a player with an exceptionally high economy spent could be using an unconventional strategy, or it could reflect an unusual match scenario such as multiple overtimes.

Understanding these outliers is crucial for gaining a full understanding of the gameplay environment. While outliers can sometimes be disregarded as anomalies, they can also represent important edge cases that merit closer examination. In some cases, these outliers might represent opportunities for innovation in gameplay strategies or offer insights into unique match dynamics that are not captured by the majority of the dataset.

6 DISCUSSION

This thesis aimed to define "intensity" in the context of Valorant and develop a machine learning model capable of automatically identifying low and high-intensity moments within a round. The results provide critical insights into the factors that contribute to intensity in Valorant and help to answer the core research questions of this thesis: (1) What causes intensity in Valorant? (2) Which features can effectively measure intensity?

The findings indicate that match intensity in Valorant is primarily driven by several key gameplay dynamics. Features such as *enemy_economy_loadoutValue*, *damage*, and *enemy_score* demonstrated moderate positive correlations with 'Match Intensity' (e.g., $r \approx 0.45$, $r \approx 0.42$, and $r \approx 0.40$, respectively). This suggests that matches where the enemy team is better equipped, involves higher damage output, and where the enemy performs better are perceived as more intense. These features reflect heightened engagement, strategic decision-making, and critical moments that define the concept of intensity in a competitive setting like Valorant.

Other features, such as *roundNum* and *economy_loadoutValue*, also contributed to intensity but with weaker correlations (e.g., $r \approx 0.35$ and $r \approx 0.28$, respectively). The weak correlation between *roundNum* and intensity implies that longer games might be perceived as more intense due to higher stakes or critical decision points, while the correlation with *economy_loadoutValue* suggests that a teams' resources influence perceived intensity to a lesser degree. On the other hand, features like *CeremonyThrifty*, which had a weak negative correlation with intensity ($r \approx -0.22$), suggest that rounds won through economic disadvantages tend to be less intense, likely due to the less contested nature of these rounds.

The XGBoost model used for this thesis could identify intensity within a game with an accuracy of over 57%, with its main strength lying in identifying high intensity.

However, this thesis also has limitations. The dataset may not capture all factors influencing intensity, such as individual player skills, team communication dynamics, or external conditions affecting performance. Additionally, the moderate correlations for some features suggest that other unexamined variables could further explain intensity variations in Valorant matches.

A notable limitation of this thesis is the exclusion of voice data from the final analysis. While the original methodology included plans to analyze vocal metrics—such as communication patterns, communication context, and frequency of speaker turns—to capture emotional aspects of intensity, technical challenges in transcription accuracy and time constraints led to the decision to exclude this data. As a result, this thesis does not account for the potential impact of communication patterns and vocal intensity on perceived game intensity.

7 CONCLUSION

This thesis set out to explore and define "intensity" within the context of Valorant, a tactical first-person shooter game, and to develop a machine learning model that could automatically identify low and high intensity games. By analyzing various gameplay metrics and their relationship to perceived intensity, the thesis offers a nuanced understanding of the factors contributing to intensity and proposes a practical model for automatic intensity detection.

The thesis identified that features such as *enemy_economy_loadoutValue*, *damage*, and *enemy_score* are significant indicators of match intensity. These features, reflecting dynamic gameplay conditions like engagement frequency and enemy threat levels, were crucial for defining what constitutes intensity in a competitive gaming environment. The machine learning model developed using these insights demonstrated its utility in accurately detecting intensity levels, providing a foundation for enhancing player experience, coaching strategies, and tactical planning in esports contexts.

Future research should incorporating a more comprehensive dataset, including player-specific attributes, voice data, or additional performance metrics. Exploring alternative analytical methods, such as deep learning models or ensemble approaches, could also enhance the accuracy of automatic intensity detection. These approaches could provide deeper insights into the complexities of competitive gaming and contribute to a broader understanding of how intensity is perceived and managed in esports.

Overall, this thesis contributes to the field of game analytics by providing a model for understanding intensity in Valorant and offering a practical solution for its detection. The findings emphasize the importance of indicators of intensity, such as player performance, enemy threat levels, and economic strategies, and highlight potential directions for future research to build on these insights.

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Appendix

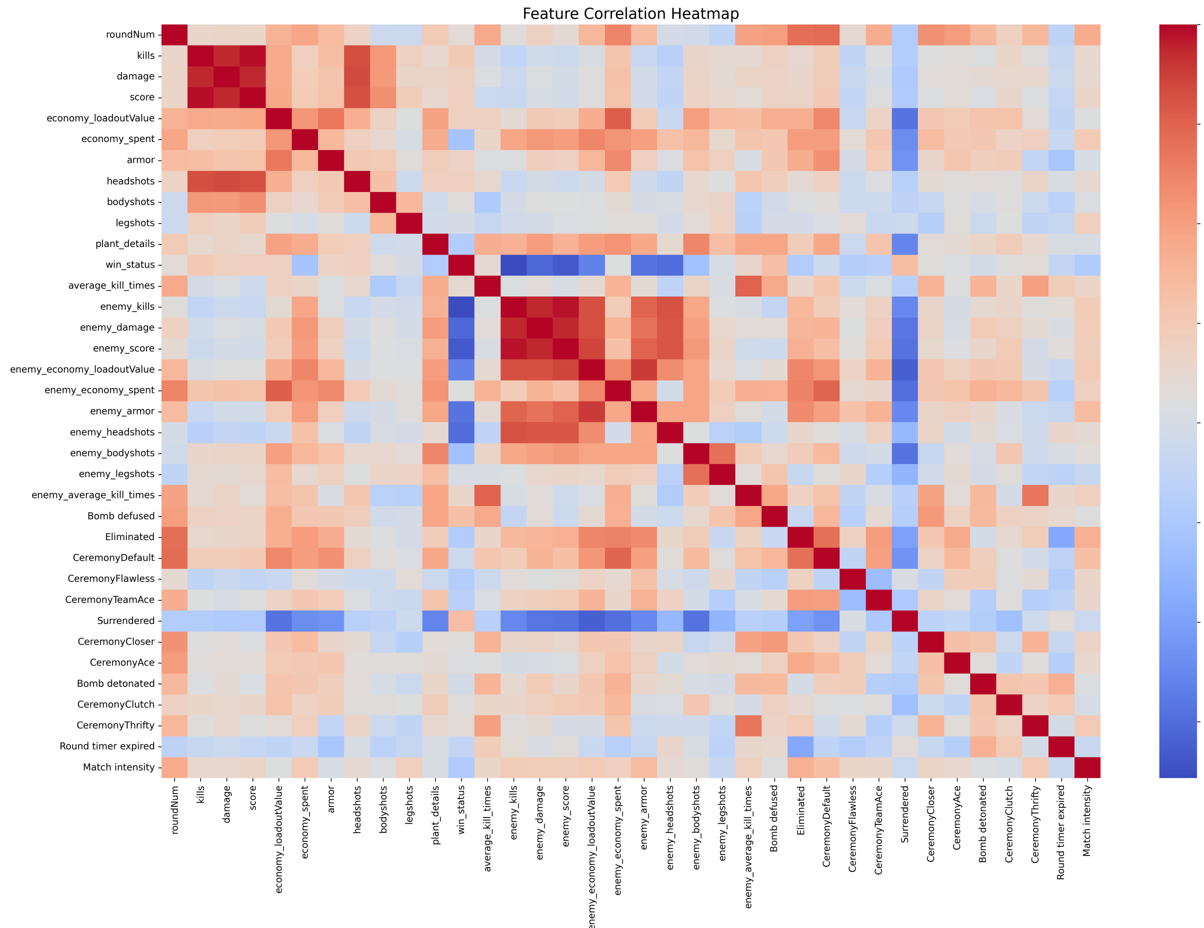

Figure 4: Correlation Heatmap of Gameplay Features: Showcasing the relationships between various in-game performance metrics, revealing key associations that influence overall match outcomes.

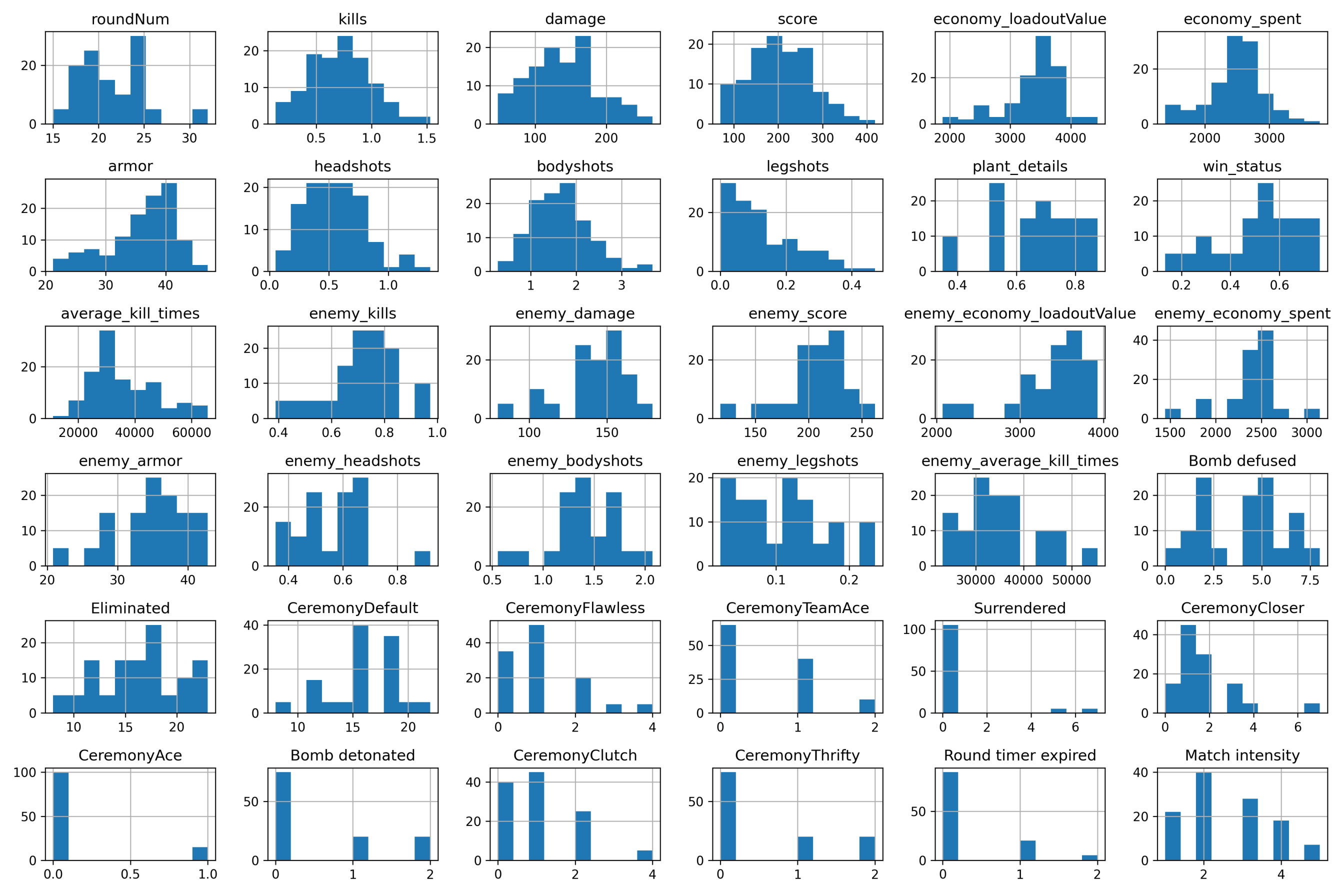

Figure 5: Distribution of Key Numeric Gameplay Features: Analyzing player behavior through distributions of metrics such as kills, damage, and economy spent, offering insights into strategic decision-making across matches.

Table 5: Explanation of Features in Relation to Valorant Gameplay

Feature	Description
`roundNum`	The total number of rounds in the match. Valorant matches are composed of multiple rounds where teams switch sides after 12 rounds.
`kills`	The total number of kills by the player in the match. A critical factor in determining performance.
`damage`	The average amount of damage dealt by the player during a round.
`score`	The average score based on performance in a match, including kills, assists, plants, defusals, etc. calculated by the Riot API.
`economy_loadoutValue`	The average value of the weapons and abilities purchased by a player/team at the beginning of the round (economy rating).
`economy_spent`	The average credits spent by a player on weapons, shields, and abilities in the beginning of a round.
`armor`	The average amount of armor purchased by the player. Player can either buy 25 or 50 armor.
`headshots`	The average number of headshots delivered by a player per round, resulting in higher damage output.
`bodyshots`	The average number of body shots delivered by a player during a round.
`legshots`	The average number of leg shots delivered by a player during a round.
`plant_details`	Information regarding the amount of spike (bomb) placements. (1 every round, 0 no rounds)
`win_status`	The average outcome of a round for a team (win/loss).
`average_kill_times`	The average time it takes for a player to secure kills within a round.
`enemy_kills`	The average number of kills achieved by the opposing team.
`enemy_damage`	The average amount of damage dealt to players by the opposing team.
`enemy_score`	The average score obtained by the opposing team in the match, based on performance metrics of Riot API.
`enemy_economy_loadoutValue`	The average value of the opposing team's weapons and abilities, indicating their financial state.
`enemy_economy_spent`	The average credits spent by the opposing team on weapons, shields, and abilities.
`enemy_armor`	The average amount of armor purchased by the enemy team.
`enemy_headshots`	The average number of headshots delivered by the opposing team.
`enemy_bodyshots`	The average number of body shots delivered by the opposing team during engagements.
`enemy_legshots`	The average number of leg shots delivered by the opposing team during engagements.
`enemy_average_kill_times`	The average time it takes for the opposing team to secure kills within a round.
`Bomb defused`	Indicator of how many times the spike (bomb) was successfully defused by the defending team in a round.
`Eliminated`	Indicator of how many times the player were eliminated in the round.
`CeremonyDefault`	Indicator for a default ceremonial event (e.g., round end animation).
`CeremonyFlawless`	Indicator for a flawless victory ceremony (no team members died during the round).
`CeremonyTeamAce`	Indicator for a team ace ceremony (one player eliminated the entire opposing team).
`Surrendered`	Indicator for whether the team surrendered in the match.
`CeremonyCloser`	Indicator for a closer ceremony, which occurs at critical closing moments of the match.
`CeremonyAce`	Indicator for an ace ceremony (one player eliminated the entire opposing team).
`Bomb detonated`	Indicator of whether the spike (bomb) was successfully detonated by the attacking team in a round.
`CeremonyClutch`	Indicator for a clutch ceremony (a player won the round despite overwhelming odds).
`CeremonyThrifty`	Indicator for a thrifty round ceremony (team won despite spending significantly less than the enemy).
`Round timer expired`	Indicator of whether the round ended due to the round timer expiring.
`Match intensity`	The subjective intensity level of the match, as stated by the player in a survey.

Table 6: Selected Features for XGBoost Model Based on Feature Importance

Feature Name	Description
enemy_average_kill_times	The average time it takes for the opposing team to secure kills within a round.
win_status	The average outcome of a round for a team (win/loss).
enemy_armor	The average amount of armor purchased by the enemy team.
CeremonyThrifty	Indicator for a thrifty round ceremony (team won despite spending significantly less than the enemy).
enemy_economy_loadoutValue	The average value of the opposing team's weapons and abilities, indicating their financial state.
Bomb defused	Indicator of how many times the spike (bomb) was successfully defused by the defending team in a round.
enemy_score	The average score obtained by the opposing team in the match, based on performance metrics of Riot API.
plant_details	Information regarding the amount of spike (bomb) placements. (1 every round, 0 no rounds)
roundNum	The total number of rounds in the match. Valorant matches are composed of multiple rounds where teams switch sides after 12 rounds.
damage	Total damage dealt by the player.
CeremonyFlawless	Indicator for a flawless victory ceremony (no team members died during the round).
enemy_legshots	The average number of leg shots delivered by the opposing team during engagements.
Bomb detonated	Indicator of whether the spike (bomb) was successfully detonated by the attacking team in a round.
economy_loadoutValue	The average value of the weapons and abilities purchased by a player/team at the beginning of the round (economy rating).
enemy_headshots	The average number of headshots delivered by the opposing team.