Universidade do Minho
Escola de Engenharia
Departamento de Informática

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Performance Optimization and Reporting Platform for Esports

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Master dissertation
Master Degree in Informatics Engineering

Dissertation supervised by
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ABSTRACT

The gaming industry has undergone some changes with the investments and professionalization of the sector, changing the way of playing video games from traditional leisure to be like a sportsman job. There are currently organized multiplayer video games competitions with professional players, know as *Electronic Sports (Esports)*.

These professional video games players can be compared to athletes once they're part of a team and with training, their performance can be improved as well as, given certain factors, conditioned. The emergence of team coaches was naturally introduced, and he's responsible for optimizing team performance.

Due to this fact, arises the need to develop tools with the aim of improving the performance of these professional players as well as increasing the duration of their careers by taking care of their physical and mental health.

It was proposed for this study the development of a **Performance Optimization and Reporting Platform for Esports** to help the coaches and players, continuously and automatically collecting their behavioral states and reporting the obtained results in order to guide the training to improve individual and team performance.

This platform was tested in a real environment, with professional teams as a case study, where it was possible to analyze the impact of mental fatigue and behavioral biometric performance on devices interaction in players' game results.

Keywords: Esports, Player, Team, Competition, Biometrics, Coach, Monitoring, Data Analysis, Recommendations System, Prediction, *Machine Learning (ML)*

RESUMO

A indústria de jogos de video eletrónicos sofreu algumas alterações com investimentos e profissionalização do setor, mudando o modo de tradicional lazer a jogar para um trabalho similar a um atleta. Atualmente, há competições organizadas, de jogos eletrónicos multi-jogador, com jogadores profissionais, conhecidas como Esports.

Esses jogadores profissionais podem ser comparados com atletas, uma vez que fazem parte de uma equipa e o seu desempenho pode ser melhorado com treino e condicionado através de determinados fatores. O surgimento de treinadores de equipa foi naturalmente introduzido sendo ele responsável por otimizar o desempenho da equipa.

Devido a estes factos, surge a necessidade de desenvolver ferramentas com o objetivo de melhorar o desempenho desses profissionais, bem como aumentar a duração de suas carreiras, cuidando de sua saúde física e mental.

Foi proposto para este estudo o desenvolvimento de uma **Plataforma de otimização de desempenhos e relatórios para Esports** para auxiliar os treinadores e jogadores, recolhendo de forma contínua e automática os seus estados comportamentais e reportando os resultados obtidos, com a finalidade de orientar o treino para melhorar o desempenho individual e de equipa.

A plataforma foi testada em ambiente real, com equipas profissionais como caso de estudo, onde foi possível analisar o impacto da fadiga mental e do desempenho biométrico comportamental na interação em dispositivos nos resultados dos jogos dos jogadores.

Keywords: Esports, Jogador, Equipa, Treinador, Competição, Biométricas, Monitorização, Análise de Dados, Sistema de recomendação, Previsão, ML

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ACRONYMS

A

Artificial Intelligence.

Application Programming Interface.

D

Department of Informatics.

E

Electronic Sports.

G

GG Esports Academy.

L

League of Legends.

League Points.

M

Integrated Master in Informatics Engineering.

Machine Learning.

R

Root-Mean-Square Error.

U

User Interface.

University of Minho.

1

INTRODUCTION

1.1 BACKGROUND

Far from slowing down and even further to show any signs indicative of ”game over”. On the contrary, the electronic games sector continues to expand. And electronic sports games (Esports) in particular. *Berenberg Bank*, one of the world’s oldest investment banks based in Hamburg, has analyzed the sector, made estimates and forecasts that by 2025 the global Esports market will be worth close to 17,500 million euros.

The evolution of Esports in recent years has been exponential in terms of players, competitions, prizes and sponsorships. What started with small home-made ’LAN parties’ is nowadays an industry that involves millions, professional players and hundreds of millions of viewers scattering around the world.

This dissertation report describing the Master’s work developed in the context of *Integrated Master in Informatics Engineering (MIEI)* held at *Department of Informatics (DI)*, *University of Minho (UM)* is based on the processing and representation of information associated with an intelligent system with *Artificial Intelligence (AI)* using ML techniques to create a performance optimization and reporting platform.

The research will address this Esports community and market, more precisely, teams of participating players in organized competitions of multiplayer games.

This dissertation also is held in the company *AnyBrain, SA*, developer of the *Performetric* product, used in the development and implementation of the study, with is a real-time non-invasive and non-intrusive mental fatigue monitoring system that measures and effectively manages mental fatigue through analysis of user computer interactions that operates in the background.

1.2 Motivation and Objectives

The proposed research can be important to bring a new, useful and qualified solution to Esports market in order to help professional teams and players, in top-level competitions, optimizing their training to obtain better results and managing their mental fatigue to extend their career duration.

At a personal level, the motivation will be the conclusion of the master's degree study cycle already inserted in an enterprise environment and that this development contributes to an extension of their provided services.

Since this is a final work of completing a cycle course of study it will be also a motivation and an objective to use some subjects learned along this educational pathway, especially the knowledge gained in the MIEI specialization profiles

The research aims to analyze the combination between in-game player performance manifested into game metrics and behavioral biometric states, measured by *Performetric* with the objective of creating a real-time recommendation system based on the detailed analysis of these relations in the expectation of improving individual player and team performance.

1.3 Challenges and Hypotheses

The research presents some possible challenges like gaining the confidence of professional players in order to install a new and unknown software on the machines where they play and that this does not interfere in their game-play.

Any error, deconcentration or loss of performance in the fluidity of the game-play caused by the installed software can lead the player to give up the study or the service in case of deployment.

Due to the type of task, the interaction patterns, with devices, of a player and a programmer, are completely different. The associated challenges with this study will include, among others, the analysis of mental fatigue predicted by *Performetric* and if professional players are affected in the same way as the users for which the software was designed (office companies and *Call-Centers*), the ability to identify if there is a noticeable difference between the behavioral biometric interaction performance between amateur and professional players, ability to design AI in professional players to be able to perform some kind of prediction, knowing that there are countless factors that can influence the player's performance in the game.

Another challenge is to have access to a complete and automatic real-time data collection service for players game metrics. The new privacy policies of data and the interest for the game producer in making available resources so that research projects can be carried out may be a hindrance to the replication of this study in other games.

The hypotheses of this study are:

- Can the mental fatigue state before a game influence the performance of a player in the course of it?
- Can the mental fatigue state during a game influence the performance of a player in the course of it?
- Can human performance through behavioral biometrics measures indicate a considerable impact on the player's performance?
- Can AI be used to find player game patterns and with that make predictions in future games?

1.4 CONTRIBUTIONS

At the moment there are already several tools that provide statistical analysis of a given game about the outcome and metrics obtained on it. None of these solutions analyzes the behavioral biometric performance itself of the player during the game nor does it correlate them with the outcome of the game, making this research an advantage compared to other platforms.

The *Performetric* software was developed with a different target audience than the analyzed one. This research can contribute to extend and improve its services of managing mental fatigue and performance for Esports market.

A service created through this research may provide a recommendation service in which the player can rely on decision-making in different scenarios and configurations

This study may also serve as a lever for new studies related to the comparison of traditional sports athletes with these Esports players, such as the comparison of resistance to physical and mental fatigue in the performance of their role, the impact of physical exercise on the performance of Esports players, the comparison of performance in situations of stress and nervousness as well as many other examples.

1.5 RESEARCH METHODOLOGY

Regarding the research methodology it was adopted the action-research methodology. Initially a crucial search of relevant concepts information was performed for the solution design process construction. A compilation and organization of information relevant to the problem was carried out and a solution proposal for the problem was conceived. In the final stage, the respective conclusions were formulated to evaluate the results obtained. This research methodology has five iterated identifiable phases:

- **Diagnosing** - Definition of the problem and its characteristics;
- **Action planning** - Requirements analysis for a valid and useful solution;
- **Action taking** - Development of a prototype in order to achieve the defined objectives;
- **Evaluation** - Analysis and prototype correction based on the results obtained;
- **Specifying learning** - The diffusion of knowledge and results obtained in the scientific community.

1.6 DISSERTATION STRUCTURE

This document is divided into six main chapters: Introduction (Chapter 1), State of Art (Chapter 2), The problem and is challenges (Chapter 3), Development (Chapter 4), Case Studies (Chapter 5) and Conclusions (Chapter 6). The Bibliography used is presented at the end of the document.

- **Introduction** - In the first chapter there is a brief description of the current Esports situation, an introduction to key concepts, motivation, objectives, research methodology, development environment and a description of the document structure;
- **State of the art** - In the chapter two is exposure an overview of the background research, important related concepts, some studies on performance, mental fatigue as well as an approach to the Esports market and the current solutions and tool
- **The problem and its challenges** - The third chapter outlines the project, a description of the proposed solution to identify problems and challenges and the explanation of the system architecture developed;
- **Development** - In chapter four are present the decisions, implementations and the scientific evidence of results;
- **Case Studies** - Chapter five describes a case study based on the application of the development phase in a real scenario. It's including all the data analysis and results obtained.
- **Conclusion** - In the last chapter, some conclusions, that includes a critical overview of the performed work, are presented with an analysis of the work developed, contributions made and recommendations for future work.

2

STATE OF THE ART

2.1 PERFORMANCE

What is Performance?

On many occasions it is used in the context of public displays, or when someone plays some part in the artistic area, as an actor, for example. Performance can also be the set of results obtained in a given test by a person.

In the world of motorized mechanisms, such as a automobile, performance corresponds to the ability to achieve the desired result efficiently.

In the sporting context the performance of an athlete or team is related to their yield and contribution or to a sporting prowess. For example, no one expected much from the team, but after a fantastic performance, they managed to win the game.

According to Lawler (2005) team performance is highly influenced by the process variable. This represents a competitive advantage for organizations, enabling them to face the current challenges and threats since this variable has a significant impact on three performance criteria: productivity, quality and member satisfaction. Also he said that nowadays, it is no longer enough to work only as a team, the present and the future require us teams that achieve high performance so that they can survive and excel as well as satisfying its followers.

The current interest in the performance of organizations emerged from the imperative economic-technological said de Faria Enes and da Costa, dating back the origins of enterprises, where they are constantly looking for scaling up productivity and economies movements, and people-centered management model

Under Katzenbach and Smith (2015) ideology one of the most powerful stimuli in team efficiency is the quality of individual and team performance goals definition and the work approach that is intended.

Organizations are concerned with improving individuals' performance only by considering their difficulties and limitations, not considering other variables belonging to different levels of analysis, as pointed out by Yang and Holzer (2006), such as the work context and its influence the performance of a position, for example.

2.2 Esports

Right now there's a reason why more than eight million people watch live streams from other people playing video games reports Hamari et al. (2017). Esports, which is a generic term for competitive multiplayer video games.

The most common video game genres associated with Esports are a multiplayer online battle arena, fighting, real-time strategy, and first-person shooter. Although organized online and offline competitions were a part of the culture of video games, these were largely amateur players until the end of the year 2000. With the participation of professional players and spectatorship in these events saw a great increase of popularity and consequent growth in the market estimating that, revenues will reach $696 million this year and grow to $1.5 billion by 2020 as brand investment doubles.

Professional gamers are often associated with gaming teams and/or broader gaming associations. In addition to prize money from tournament wins, players may also be paid a separate team salary. Team sponsorship may cover tournament travel expenses or gaming hardware. Wikipedia (2018)

2.3 Performance in Esports

According to Froböse (2011) study, reported by Schütz (2016), we can compare Esports players to professional athletes since they spend many hours of their day practicing their personal or team skills to improve their aspirations at a high level. Having said that, it is not inappropriate to associate the existing body care and existing studies in other areas of the daily life of the athlete trying to help improve the mind for a better performance avoiding the fatigue of decisions being this the greatest benefit of the professionals inserted to assist these athletes.

An article from Schütz (2016) says that professional gaming teams believe that supervising the body at nutritional level, through meal planning, on a physical level, following an exercises plan, as well as psychological monitoring of Esports athletes can reveal immediate benefits in their performance, as well as in the of his career, taking advantage of the experience gained throughout years of playing trying to counteract the fact that the life of the players is quite short.

In Esports, just like conventional sports, there are training days, rules and tactics to achieve the goals of beating your opponents. For this, we have the coaches that before each match analyzes and studies the opposing team to realize their weaknesses in the play moves and techniques most used, in order to train their team and to guarantee satisfactory results. The coach follows step by step every match and in the intervals makes the necessary changes and strategies according to the performance of the team and the opponents. The coach is also often the one who gives all the psychological support and is the closest person of the players, always trying to leave all team players calm and confident so that nothing can disrupt the game.

The most competitive teams in the world are already pushing the boundaries of improving player wellness (Smith, 2017).

2.4 PERFORMETRIC

Launched in August 2015, Performetric is a real-time monitoring system that allows the management of mental fatigue in a non-invasive way.

Performetric aims to develop leisure and work context-aware environments that may improve quality of life, wellness, mental health and individual performance.

Moreover, it also aims to support a better management of the employees and their work time. This translates into a positive impact in the organization's productivity and an increased quality of life and better health of the employees as described by Pimenta et al..

To assess the level of fatigue, the system looks at the interaction patterns of the user with the keyboard and the mouse. This process is implemented using a background application that captures the events fired by the keyboard and mouse in an entirely transparent way. This way, individuals are able to carry out their tasks as usual, without being influenced by the monitoring. The features considered are used by or inspired in behavioral biometrics. In what concerns the keyboard, the features considered are:

- **Key Down time**: The time during which a key is pressed down while typing. Units: Milliseconds (ms);
- **Time between keys**: The time between the release of a key and the pressing of the following one. Units: Milliseconds (ms);
- **Error per key**: The number of times that the backspace or delete keys are used in comparison with the remaining keys;
- **Keys Pressed**. The total number of keys pressed in the block interval (5 minutes).
- **Writing Velocity**: Mean Keys Pressed per minute during block interval (5 minutes). ;

Concerning the mouse, the features considered in this work were:

- **Mouse Velocity**: the velocity at which the cursor of the mouse travels in the screen; Units: Pixel/Milliseconds (px/ms)
- **Mouse Acceleration**: the acceleration of the cursor of the mouse at a given time; Units: $Pixel/Milliseconds^2$ (px/ms^2)
- **Time Between Clicks**: Time spent between clicks. Units: Milliseconds (ms);
- **Distance Between Clicks**: the distance at which the cursor of the mouse travels between clicks in the screen; Units: Pixels (px)
- **Mouse Precision**: the percentage of excess deviation of a straight line in a distance at which the cursor of the mouse travels in the screen from point A to B between clicks;
- **Mouse Distance**: the distance at which the cursor of the mouse travels in the screen; Units: Pixels (px)

- **Mouse Excess Distance**: the percentage of excess deviation of a straight line in a distance at which the cursor of the mouse travels in the screen from point A to B;

Performetric uses the seven-point USAFSAM Mental Fatigue Scale, created in 1979 by Dr. William F. Storm and Captain (Dr.) Layne P. Perelli of the Crew Performance Branch of the USAF School of Aerospace Medicine, Brooks AFB, San Antonio, Texas, and then used in many field and laboratory tests. The scale items are shown in figure 1.

Figure 1: *Performetric* Fatigue Scale

Levels 1-3 mean that the individual is not tired, while levels 4-5 indicate the the individual is experiencing some fatigue and levels 6-7 that the individual is really tired which could lead to an unsafe or health-damaging scenario. An example of *Performetric* UI can be seen in the figure 2.

Figure 2: *Performetric* UI

2.5 MENTAL FATIGUE IN SPORTS

In 2016 Hutchinson, spent several months doing "brain endurance training" before running a marathon, exploring the idea that the ability to resist mental fatigue is a key skill required in endurance competition.

He said that Marcora et al., of the *University of Kent*, had demonstrated the negative effects of mental fatigue on endurance performance. *Samuele Marcora* had also shown that brain endurance training, doing simple but cognitively challenging tasks on a computer, for example, can build your resistance to mental fatigue.

What the results would be in truly elite athletes?

Are the best athletes just physically superior to the rest of us, or are they also mentally superior?

A study in *PLoS ONE*, from researchers at the *University of Canberra* along with collaborators at various other institutions (including *Marcora*), takes a stab at these questions, with very interesting results.

The study compared two groups of cyclists: 11 elite professionals, and 9 recreational riders. They each did two 20-minute time trials, one preceded by a 30-minute cognitive task requiring inhibitory control (*Stroop* task) which would induce mental fatigue, and the other preceded by a control task (simply gazing at black cross on a white screen for 10 minutes).

From study they find that the professional cyclists were significantly better than the amateurs at the *Stroop* task. On average, they managed to get 705 correct responses during the 30-minute period, compared to 576 for the amateurs. (The number of correct response combines how accurate you are with how fast you do it; the pros got significantly faster at reacting as the session went on.)

This suggests that the pros had significantly greater "inhibitory control," a trait that seems closely linked to endurance performance. In some ways, the essence of pushing to your limits in endurance sports is learning to suppress the instinct of give up.

They also naturally find that, in the 20-minute cycling time trial, the pros were faster than the amateurs. But the pros produced two virtually identical trials after the mentally fatiguing task and the control task; the amateurs, on the other hand, were significantly slower (average power lower by 4.4 percent) after the mentally fatiguing task. In other words, the pros were better able to resist the effects of mental fatigue.

There are two broad possibilities. One is that they were born that way, and that's one of the reasons they've ended up as elite athletes. After all, it takes an extraordinary amount of discipline and response-inhibition to do the training and make the lifestyle changes required to become elite.

The other possibility is that it's the training itself that has helped the mind adapt to better resist fatigue, just as the body adapts to resist physical fatigue.

2.6 Performance analysis and biofeedback systems

2.6.1 *Mobalytics*

Mobalytics is a personal performance analytics for competitive LoL gamers. The system uses in-game data that's available through Riot's *Application Programming Interface (API)* to calculate player performance and provide actionable advice on how to improve.

- Highlights the strengths and weaknesses to help boost players game;
- Measures performance for different skills (like Farming, Teamplay and Consistency), giving a personal Gamer Performance Index (GPI) score;
- Based on GPI, the system defines the game skills and provides the player with a detailed breakdown of his strengths and weaknesses;
- Pre Game and Post Game analysis tools show actionable advice for every step on players path to becoming a better;

2.6.2 *Shadow.GG*

Shadow.GG is a Esports analysis platform that allows you to deeply understand game and team behavior by providing instant information and quick iterations throughout your training process.

- Have deep insights into players opponent style of play;
- Provides an array of exclusive visualizations that deliver the clarity needed to arrive at solid conclusions;
- Reduces player analysis time by providing all relevant opponents information automatically;
- Products: *LoL*, *Counter-Strike* and *Dota 2* Match Replay, Scrim Tracking, Champions pools, Statistical analysis portal

2.6.3 *OP.GG*

OP.GG is a LoL global service and are constantly working to expand our areas of operation. Currently provide data to users in Japan, North America, Europe West, Europe Nordic & East, Oceania, Brazil, Latin America South, Latin America North, Russia, Turkey, Korea

- Provide users with a ton of information coupled with a simple UI;
- Massive, well organized database;
- Manages tens of billions of user data;
- Leading global provider of League statistics;
- Supported by Riot Games.

2.6.4 *Overwolf*

Overwolf is a software platform which allows developers to create extensions for video games. Extensions created for the *Overwolf* platform are often focused on providing in-game services that would normally require a user to exit the game. The platform has gained traction in competitive video games, such as Esports and *MMORPGs*, where native extensions are often forbidden due to concerns about cheating. *Overwolf* extensions sidestep this concern, since they do not interact with the game engine; they operate exclusively on the overlay created by the main *Overwolf* program.

2.6.5 *Fatigue Science*

FatigueScience is a platform that combines wearable tech with biomathematical science from the US Army Research Lab to offer unprecedented insight into sleep and fatigue. This solution helps sports scientists, medical staff, physical therapists, nutritionists, and strength coaches make the connection between sleep and athletic performance.

- Help identify athletes with poor sleep or potential sleep disorders;
- Bi-weekly or monthly summaries for team management, to highlight goals and progress;
- Tells from a sports scientist how sleep affects performance, and gives practical advice to improve both;
- The sports experts can review an athlete's data and provide specific recommendations to help them with their sleep.
- Looks at athletes scheduling to discover how even minor tweaks could have big benefits.

2.6.6 *Fusion Sport*

FusionSport created *Smartbase* witch is a solution for coaches, scientists, athletes, and managers. One place where's stored all of data, and automated a range of reporting and alerting features like administrative profiles, medical information, fitness tests and training programs through to coaching data, performance analysis and psychological testing and training to assess athlete readiness, manage injuries and return to play, run training programs, assess performance and keep athletes at their best, week in, week out.

2.7 SUMMARY

The elaboration of this state of the art made it possible to realize and confirm the constant growth and consolidation of the Esports market worldwide. Competitive teams are currently investing in tools that can bring some advantage to their team against opposing teams, as well as caring about nutrition, physical activity and mental state of their players.

The current services and tools for professional Esports teams only consider the final scores and metrics of each game by providing statistical analysis on them.

The platform resulting from this study can bring something new to the Esports market, since it analyzes performance behavioral biometrics through the *Performetric* software during the game. Through these analyzes it is possible to justify the game results of the players with their game and interaction performance aggregation.

3

THE PROBLEM AND ITS CHALLENGES

Being a very unexplored area, with significant monetary movements involved and with the aspect of player statistics for the coach as well as the area of human performance that has been applied in other contexts (i.e. military), this presents itself as a motivation for research and development.

As mentioned, being a recent area of application, there is still not much information and studies carried out in this area, thus becoming a challenge. Although the possibility of comparison with similar applications in different areas, many of which in sports at the professional level.

There are also challenges in the use of standardized player-to-player patterns, since each will have different strategies and characteristics so it will be challenging to create a profile, from game to game, being prepared for several presets and types of game.

The fact that the target population of experience present a similar age group can be understood as a first iteration of pattern establishment through their relationship, although prediction of success with a functional solution, the average age of player/career time can increase, without loss of quality, constitute a challenge.

In short, the final challenge will be to optimize the player's game performance, either through recommendations for choices before games, as well as statistics that prove what biometric factors have to improve in their performance, ideally recommended after the coach's analysis.

3.1 PROPOSED APPROACH - SOLUTION

This project was developed according to an action-research methodology, in which, faced with the presence of a given challenge, a solution hypothesis is stipulated.

A compilation and organization of information relevant to the problem was carried out and a solution proposal for the problem was conceived.

In the final stage, the respective conclusions were formulated to evaluate the results obtained. Thus, the project was carried out according to the following steps:

- Bibliographic Investigation;
- Development or usage of the learning module of interaction patterns and game strategy;
- Performing tests and collecting data in Esports teams;
- Implementation of reporting platform for coaches;
- Implementation of recommendation system for performance optimization;
- Writing the Master Dissertation.

The objectives fulfilled for the solution of the proposed approach were:

- Analysis and development of a platform for analysis of behavioral patterns in electronic games;
- Analysis of game patterns using Data Mining and statistical processes;
- Creation of a recommendation system using ML;
- Creation of an application programming interface in order to make the recommendation system a service;

The objectives of the dissertation were:

- State-of-the-art analysis of the behavioral patterns and activities of Esports players who have direct team connections in professional competitions;

- Use or development of a module for capturing patterns of interaction with the computer during the game;
- Conducting an experiment to collect behavioral data from players using the previous module;
- Learning patterns of behavior based on experience data;
- Validation of behavior patterns and models developed in a case study;
- Specification of an alert and recommendation system.

3.2 SYSTEM ARCHITECTURE

The architecture of the proposed system includes not only the simple acquisition and classification of the data but also a perception of the environment. Users may interact with devices, that are integrated into the environment and provide information about users, their interaction patterns and their surroundings and context.

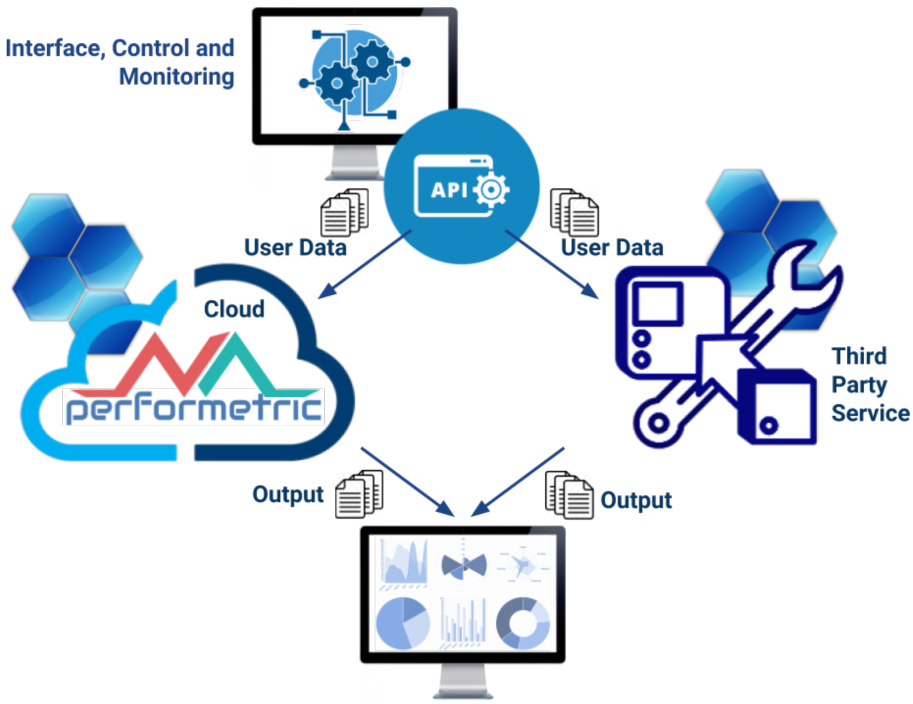


Figure 3: System Architecture

This system, shown in figure 3 is organized into several layers that separate the acquisition and the data processing tasks:

- **Data gathering** - The data gathering layer is responsible for the acquiring interface, control and monitoring data that characterizes the user in terms of the features studied, that describe their behavioural patterns;
- **Data Processing** - This layer processes and transforms the data to be sent to the next layer, synchronizing data from different sources and constructing the appropriate software objects to interpreting player game data from the third party services and the biometrics player data from Performetric to build the meta-data that will support decision-making.
- **Data access** - This layer is responsible for providing structured access to the data of each user and managing their complete information. It provides, not only, access to this data in real-time but also provides access to a behavioural historic and profile of each user, allowing studies within longer time frames;
- **Presentation** - This layer includes the mechanisms to build intuitive and visual representations of the users' reports and recommendations.

3.2.1 *Performetric Flux Diagram*

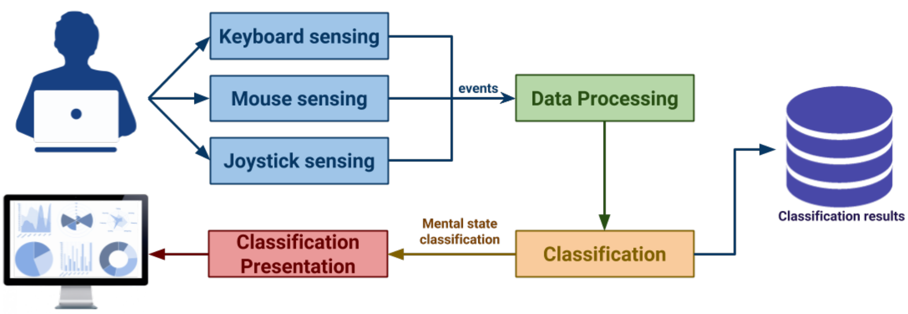


Figure 4: The flow of data in Performetric

The process of analysing and classifying the behaviours is detailed in the workflow depicted in Figure 4. It starts with the acquisition of data from the mouse, the keyboard and the joystick and continues with its processing and filtering in real time. The results of this classification are depicted graphically in real-time through the interfaces developed and are also stored in a database for future use.

Despite the complexness of the information compiled, it is shown, in a first instance, in a very minimal and intuitive interface. There is also no explicit or conscious interaction with the system: the events fired by the use of the mouse and the keyboard are stored and analyzed entirely in background. The whole system runs in background, and only the output (classified mental state) is shown, through a notification to the user.

3.2.2 *System Flux Diagram*

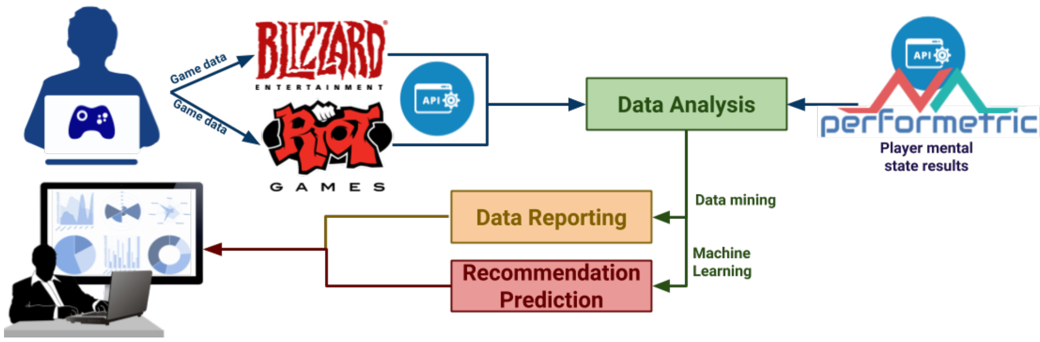


Figure 5: The system flow of data

As shown in figure 5 , demonstrating the flow of the system, during and after each game relevant data about its individual and team performance are stored. The regulators of these games (e.g. Riot and Blizzard) through their API allow obtaining this data.

In the data analysis phase the entire process of cleansing, transforming, and modeling of the game data is done in conjunction with the player's biometric data obtained during that match as described in the flow of figure 4.

After this sequence, data mining techniques are performed in order to generate reports of this data, as well as the resorting to ML in order to provide recommendations or forecasts for upcoming games. These final results are presented to the coach of the team through a UI platform.

4

DEVELOPMENT

4.1 DECISIONS

4.1.1 *Game*

In order to make possible the development of this thesis, the decision in choosing an Esports game for the case study was necessary to fulfill the following preconditions:

- Existence of teams and team play;
- Strong adhesion and worldwide recognition;
- Existence of professional competitions;
- Possibility of improving individual performance through training;
- Possibility of improving team performance through training;
- Possibility of a coach existence and team training;
- API service with the ability to provide complete and detailed data about the gameplay of specific players;
- Played by Performetric users previously identified as possible subjects for a case study.

After a close investigation of these requirements and their analysis, it was decided that the game LoL would be used to the development of the case study because it fulfilled all the requirements.

LoL Basics (RiotGames (2018))

In 2009, Riot Games released LoL (usually abbreviated by LoL) which is a Esports multiplayer online video game that has an active and widespread competitive scene. In North America and Europe, Riot Games organizes the League Championship Series (LCS), which consists of 10 professional teams in each continent. Similar regional competitions exist in China (LPL), South Korea (LCK), Taiwan/Hong Kong/Macau (LMS), and various other regions. These regional competitions culminate with the annual World Championship. The 2017 World Championship had 60 million unique viewers and a total prize pool of over 4 million USD.

Players compete in matches, lasting anywhere from 20 to 60 minutes on average. In each game mode, teams work together to achieve a victory condition, typically destroying the core building (called the Nexus) in the enemy team's base after bypassing a line of defensive structures called turrets, or towers.

In all game modes, players control characters called champions, chosen or assigned every match, who each have a set of unique abilities. Different champions suit different roles and strategies and begin every match at a low level, and then gain experience over the course of the match to achieve a maximum level of 18. Gaining champion levels in matches allows players to unlock their champion's special abilities and augment them in a number of ways unique to each character. If a champion loses all their health, they are defeated, but are automatically revived in their base after enough time passes. Players also begin each match with a low amount of gold, and can earn additional gold throughout the match in a variety of ways: by killing non-player characters known as minions and monsters; by killing or helping to kill enemy players; by destroying enemy structures; passively over time; and through unique item interactions or champion abilities. This gold can then be spent throughout the match to buy in-game items that further augment each champion's abilities and game play in a variety of ways. Champion experience, gold earned, and items bought are specific to each match and do not carry over to subsequent matches. Thus, all players begin each match on more-or-less equal footing relative to their opposing team.

Across matches, players also earn rewards that are applied to their account. Player accounts begin at level one and progress onward with games played. Player level is separate from character level; both a level 30 account and a level 5 account would begin at character level 1 at the start of a new game. Accounts are given rankings based on the Elo rating system (method for calculating the relative skill levels of players in zero-sum games), with proprietary adjustments. These ratings are used in automated matchmaking to make games with players of comparable skill level on each team.

Maps

LoL consists of three main maps that have different terrain, objectives and victory conditions, as well as varied summoner spells and items, in this study, it was analyzed the Summoner's Rift map, illustrated in figure 6

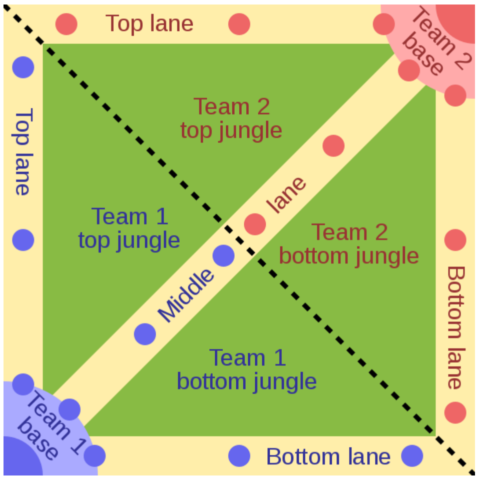


Figure 6: Summoner's Rift map

Summoner's Rift is the most popular map in LoL. On this map type, two teams of five players compete to destroy an enemy building called a Nexus, which is guarded by the enemy team and a number of defensive structures called turrets, or towers.

A simplified representation of Summoner's Rift. The yellow paths are the "lanes" where endless waves of troops known as minions march; blue and red dots are the defensive turrets that defend the lanes. Not pictured are the two turrets that flank each Nexus - the ultimate goal of the game, which are within each team's base in their corner. The dotted black line is the river that divides the sides.

One nexus is located in each enemy base on opposite sides of the map, in the lower-left and upper-right hand corners. These structures continually create weak non-player characters known as minions, which advance toward the enemy base along three paths:

top, middle, and bottom lanes. Players compete to advance these waves of minions into the enemy base, which allows them to destroy enemy structures and ultimately win the match. Between lanes are neutral areas of the map known as the 'jungle', arrayed in four quadrants. A shallow river divides the map between the teams, but doesn't actually impede movement; all champions can wade through it no differently than dry land.

Each team wishes to defend their own structures and destroy the other team's structures. These include:

- **Turrets** - Each lane is guarded by powerful defensive structures called turrets. Turrets deal exceptionally high damage and will attack enemy minions and players that approach them. Turrets prioritize enemy minions in their vicinity, but will immediately attack enemy players if they attack allied players. Thus, by advancing an allied minion wave into the range of a turret, a player can do damage to the structure without themselves being attacked. When destroyed, turrets provide gold and experience. Turrets that are destroyed are destroyed permanently for that match and will not respawn. Some turrets, depending on location, will regenerate health over time if they are damaged but not destroyed.
- **Inhibitor** - Each lane contains one Inhibitor. A lane's Inhibitor can be attacked after a team has destroyed the three turrets guarding its lane. Destroying an Inhibitor will cause the allied Nexus to spawn Super Minions, more powerful Minions that provide a buff to surrounding Minions. If destroyed, inhibitors will respawn after five minutes.
- **Nexus** - Each team has a Nexus that can only be damaged once all the turrets in a lane and that lane's inhibitor is destroyed. Destruction of the enemy's team Nexus ends the game.

Many of the details have changed over time; League is not a static game, with mechanics being both introduced and removed since launch in 2009.

Game Types

LoL includes several game types players can select. In this study, it was analysed the Ranked Matchmaking game type.

Ranked Matchmaking is available to players upon reaching account level 30. It uses a pre-made teams that must be of comparable Elo strength, so expert players and weak players are not allowed to team together in Ranked. After playing 10 or more Ranked games, accounts are given a public "rank" that roughly correlates with their Elo ranking.

Champions Types

There are currently 141 champions in LoL as of August 21, 2018. League divides its champion types up a number of ways. The most salient difference is the type of damage a champion deals; some champions deal largely physical damage, which is resisted by the armor stat, and other champions deal largely magic damage, which is resisted by the magic resistance stat. Some champions deal a combination of both and can choose which to emphasize; and some rare abilities deal 'true' damage which is not mitigable by either armor or magic resistance.

League Points

League system is a ranking system that matches players of a similar skill level to play with and against each other. It comprises seven tiers which indicate the skill level of players. Players within each division are ranked using a system of points called League Points (LP).

Players earn League Points when they win ranked games and lose them when they lose ranked games.

Riot Developer API

After exposing the basics of the game, we can list and explain the types of metrics used, corresponding to each game, which are possible with the implementation process described about the Riot Rest API data collection.

- **Game Duration** - In seconds;
- **Game Outcome** - The player and their team won or lost the game;
- **Champion** - Champion identifier used in game;
- **Kills** - A kill is the event of decreasing an enemy champion's health to zero while the enemy has no abilities or Items to prevent death.

- **Deaths** - Death occurs when a champion takes sufficient damage to be reduced to zero health.
- **Assists** - An assist is the action of helping an allied champion kill someone. You can either score an assist by hitting (without killing) the champion in the last 10 seconds before their death, or by contributing passively during this period of time.
- **KDA** - Ratio: (Kills + Assists) /Deaths
- **Gold Earned** - Total gold earned by the player in the game;
- **Gold Spend** - Total gold earned by the player in the game;
- **Total Damage Dealt** - Total Damage deducted, as a result of an offensive, on the enemies current health and structures;
- **Total Damage Taken** - Total Damage received on current health as a result of an offensive by the enemies;
- **Total Damage Dealt To Champions** - Total Damage deducted on enemies champions as a result of an offensive;
- **Longest Time Spent Living** - Maximum of consecutive seconds in which the player has not suffered any death
- **Vision Score** - Vision Score is a loose measurement of vision game contribution that indicates how much map vision a player provided to their team and removed from the opposing team.
- **Total Minions Killed** - Total number of enemies minions killed by the player.

From the exposed game metrics, the **KDA** and **Gold Earned** are the most important metrics that synthesize and define the performance of a player and a team in the game, since, in addition to being directly associated with the final result, when compared to the other players in the game itself, as well as in previous matches, can provide a good / bad match and a better / worse performance by the player or team.

Scrims

Scrim is the shortened word for "scrimmage", which usually means the teams will play against each other to practice. So it's basically a match between two teams who want to train.

The advantage of using this type of training is that the teams have the guarantee that they are playing against another team that is interested in the victory and that have trained in team for some time. Because games are personalized matches, players do not lose league points.

The disadvantage to this study is that the Riot API no longer makes the details of this type of games available, keeping them private. All game information, of this genre, performed would have to be manually reported by the coach in order to merge with the biometric performance data.

4.1.2 *Development and Case Study*

In order to test and validate the scientific evidence of this thesis, both in the development process and in the case study, it was necessary to decide the procedure indicated for each stage, respecting some necessary minimum requirements taking into account the chosen theme and game.

For the first phase, corresponding to the development process, it was decided to collect and observe individual data and dynamics of a player with a margin of progression to a professional level, fitting into practices of professional teams, such as daily training following a coach's instructions and/or analyst. This phase served to refine and prepare a more advanced case study.

For the second phase, corresponding to the realization of the case study was decided to look for a professional team to apply the development process to validate their possible production in the market.

4.1.3 *Company Context*

Since the development of this thesis was carried out under the supervision of a company and the subject of the study itself could result in a new product of its own, it was decided that the development process would take this into account, being worked on as a basis for a implementation of the system.

With this study, in addition to the possibility of extending the company's services in a new product, the existence of more gaming-related interaction data can help improve some aspects of the company's base product.

4.1.4 *Technologies*

The choice of technologies to be used in the implementation process also took into account the enterprise factor, since it was decided to use the company's current technologies in its development. The technologies used in the company presented complete to serve perfectly for the effect, not having any inconvenience of the need to resort to alternatives.

The main technologies used are presented below.

R

R is a highly extensible, simple and effective programming language and environment that provides a wide variety of statistical, graphical techniques and an integrated suite of software facilities for data manipulation, calculation and graphical display.

H2O

H2O.ai is an open source, in-memory, distributed, fast, and scalable machine learning and predictive analytics platform that allows building machine learning models, in cutting-edge Supervised and Unsupervised algorithms, on big data and provides an easy way to launch those models to production in an enterprise environment.

H2O's REST API allows access to all the capabilities of H2O from an external program or script via JSON over HTTP. The Rest API is used by H2O's web interface (Flow UI), R binding (H2O-R), and Python binding (H2O-Python).

4.2 IMPLEMENTATION

4.2.1 *Data Collection*

For the process of implementation of data collection of the stipulated game was used R. This process consisted of the search and storage of data of a particular player, from the moment of registration on the platform of Performetric. To do this, through a generated KEY API and the Endpoints of the platform https://developer.riotgames.com/ as a REST API, requests were made in R, using the httr package. These requests were collected in JSON format and stored in CSV format to facilitate manipulation.

Among the various data possibilities that could be collected are the following EndPoints:

- Collection of the basic information of the player through the username provided, these included his account identifier and current level in the game;
- Collection of game identifiers made since registering with Performetric through its account identifier;
- Collect detailed player performance data at the end of each game through its identifier;

To aggregate gaming metrics data with biometric mouse and keyboard performance data, it was necessary to resort to the Performetric REST API collecting and storing following the same methodology.

The requests would have to be made in the form of time interval being built in blocks of 5 minutes. Thus, for each game, biometric mouse and keyboard data were stored with the following time interval:

- **Begin**: 15 minutes before the start of the game;
- **End**: Sum of the start date of the game with the duration of the game and five minutes of tolerance in order to allow the collection of the last block in case the game duration was not a multiple of 5;

In addition to the abovementioned biometric data, the type of dominant task that the player was performing was also in the stored data blocks, in this case with the label ”game” it would be possible to filter the data of the collected interval, distinguishing whether they would be referring to or not a data during the game.

Throughout this document, the game data collected by the Riot API will be referred to as game metrics and the data collected by Performetric’s API as performance biometrics.

4.2.2 *Data Preprocessing*

In order to prepare the data in a possible and perceptible way to generate reports and apply machine learning, it was necessary to submit the collected data to Data mining techniques. The following steps are explained:

Data cleaning

The data from the Riot API did not have missing values, since they are quantitative values, so it was not necessary to treat it. In contrast, the data collected from Performetric deserved a special treatment, such as games without saved data blocks (the player could have used another computer without the software installed) were disregarded, as well as for the metrics that presented missing values (possible collection errors), alternative datasets were generated with the respective mean, mode and median relative to the type of task (game / not game) of the set of data collected in the game context.

Data transformation

Performance biometrics underwent the following transformations:

- Aggregation of the blocks before the game through the values (mean, maximum, minimum, initial, and variation);
- Aggregation of the game blocks through the values (mean, maximum, minimum, initial, last and of variation);

Data reduction

Game data has been filtered and reduced by game type and game mode ("Classic" and "Matched Game") to analyze only games with the same mode used in competitions. Games with a duration of less than 5 minutes were also disregarded because they do not represent a real scenario in a competition context.

Data Discretization

The date of the game was discretized by replacing its numeric attribute to a nominal one, belonging to a particular time of day (morning, noon, afternoon, evening, night or dawn) and a certain moment of the week (Monday to Weekend).

After these transformations, the game metrics and performance biometrics were linked together to form a single dataset.

Complementary datasets were also created with an aggregation of all games performed, per day, with the sum of the metrics of the game and the average of the performance biometrics.

4.2.3 *Statistical and graphical Reports*

After the data preprocessing process, it was possible to generate some statistical reports and graphs in *R*, through the use of the *ggplot2* package, comparing the performance of the player during the game with the performance biometric of interaction with the mouse and keyboard and the predicted mental fatigue state.

For game metrics with binary category distinction, such as the outcome of the game, the Mann-Whitney U test was performed that verified if the game metric selected in two samples of the same dataset, distinguished by their binary value, showed differences compared to performance biometrics.

Of all the possibilities of analysis, it was deepening and detailing, the cross-referencing of game metrics that presented a greater value in correlation module with performance biometrics. For this, several tests were performed using the *Pearson*, *Kendall* and *Spearman* correlations analyzing the various coefficients associated, and the study proceeded with the game metrics identified by the Pearson correlation.

After the selection of game metrics, reports were implemented with various types of graphs that showed the total relation or evolution over time between game metrics (Y-axis) and biometric performance (X-axis), as well as differences in biometric performance in a win vs. loss scenario.

With the existence of a team in the case study, graphics were implemented that presented comparisons of the biometric performance of a specific player with the rest of the team.

4.2.4 *Machine Learning*

After the process of Data mining and statistical analysis of game patterns, it was necessary to define a restricted set of relevant game metrics that could be predicted, based on a player's choice, before the game, in order to create a recommendation system using machine learning.

Its implementation was based on a supervised learning since it mapped the relations between an input provided with the respective output. From this learning and depending on the type of input variable of the game metric, resulted in the division between classification problems (mapping the input variables into distinct categories) or regression (mapping input variables into a continuous function).

The input variable (response) to be predicted would be one of the metrics of the selected restricted set and prediction variables would be the history of performance biometrics in the moments that preceded all the player's games, as well as the possible choices and configurations that the player took before each game. All other metrics in the game were ignored during the training process, as they could not be the basis to use in predicting another metric in a future game.

The concept of prediction was based on the following principle: "Based on my current interaction with my machine, translated through performance biometrics and this choice for the game, what is the predicted probability/value for this game metric?"). From this concept could easily be implemented a ranking system of the best choices to take based on a higher probability/value of success.

To materialize a model in machine learning to be able to realize these predictions, the following actions and tests were implemented using *H2O* software in *R* environment:

- Division of the dataset - tests of improvement in results using different approaches:
  - ***train*** (the sample of data used to fit the model), ***valid*** (the sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters.) and ***test*** (The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset.);
  - ***train with K-fold cross-validation*** (used to validate a model internally, i.e., estimate the model performance without having to sacrifice a validation split. and to avoid statistical issues with a validation split, especially for imbalanced data) and ***test***.
- Algorithms - test of improvement in results using different algorithms:
  - *Distributed Random Forest* (DRF);
  - *Generalized Linear Model* (GLM);
  - *Gradient Boosting Machine* (GBM);
  - *Deep Learning* (Neural Networks))
- Grid (Hyperparameter) Search - Using a random grid search, specifying a set of values for each hyperparameter to search over, H2O does uniformly from the set of all possible hyperparameters value combinations;
- Stopping criterion - Usage of a performance-metric-based stopping criterion, to search when the performance stops improving by a specified amount and control when the random grid search is completed;
- Stacked Ensemble (usage of multiple learning algorithms or models to obtain better predictive performance than could be obtained from any of the constituent learning algorithms)- tests of improvement in results using different sets:
  - Best five models, generated by the grid, with better predictive performance of an algorithm;

- Model with better predictive performance of each algorithm;
- Best three models, generated by the grid, with better predictive performance of each algorithm;

The use of this technique generated a model with better predictive performance, but it increased considerably and proportionally the response time needed with the increase of the set of algorithms and models.

At the end of the training process, the generated models were subjected to a test that consisted of predicting the value of the game metric, for which they were designed, in the test dataset. This procedure originated several metrics regarding the predictive performance that allowed to evaluate and to choose the model to use, within the set of metrics, were considered, mainly, the following ones:

- *Accuracy* - Percentage of correct predictions;
- *Logarithmic Loss (Logloss)* - quantifying the accuracy of a classifier by penalizing false classifications;
- *Root-mean-square error (RMSE)* - measure of the differences between values predicted and the values observed.

After selecting the best predictive performance, the software H2O allows saving in a binary format the considered model, allowing later loading in the same environment in order to carry out the case study

4.2.5 *Platform*

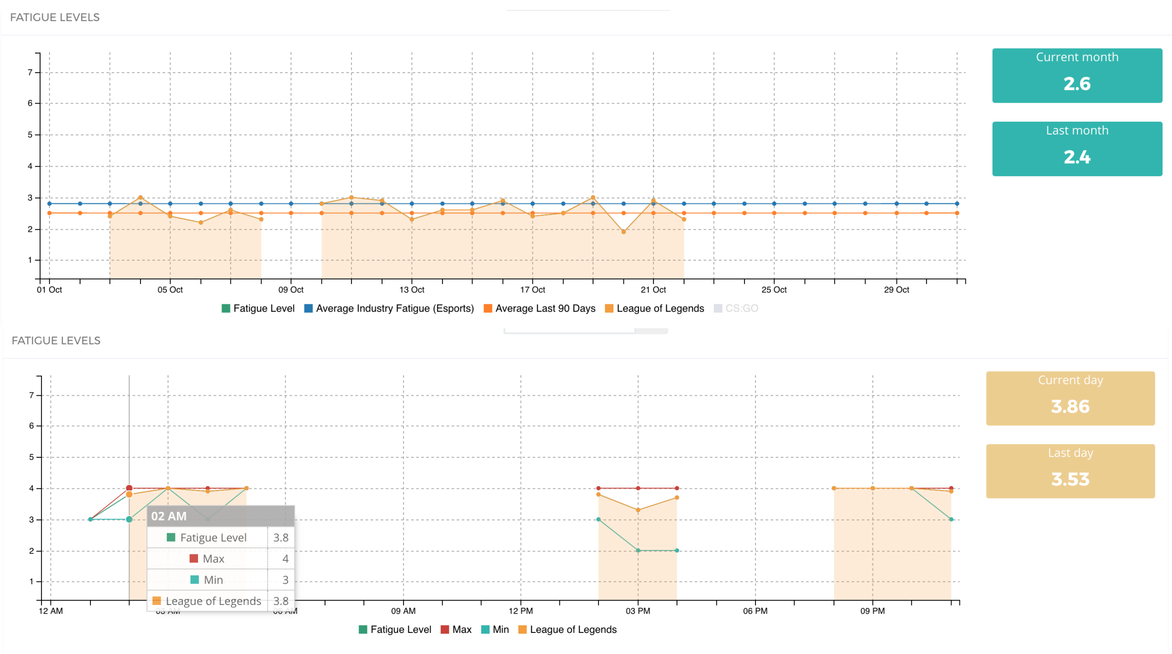


Figure 7: Platform: Fatigue Level records and play periods identification

The implementation of a platform, with teams formed by players, coaches and analysts as a target audience, was developed through the replication of the Performetric architecture for an independent system, with emphasis on graphical reporting and analysis of states of mental and biometric fatigue performance of players throughout their interaction with the computer.

The platform enables the management of the players' fatigue levels and their performance. The user (e. g. coach, analyst) can:

- See the overall status of the team regarding to fatigue levels, moments under fatigue (number of times the system detects fatigue in the player) and rest times (number of times that an player rest after a fatigue warning), like is shown in figure 7;
- See the periods in which the player was playing (figure 7);
- Check and manage players, allowing to view their profiles, assign them to a team, set as team coaches, disable or delete them;

- See the comparison between the player behavior biometrics with the rest of the team;
- See the comparison between the player behavior biometrics by a time period, shown in figura 8 ;
- Check team overall fatigue levels by hour, day, week and month;
- Check out which teams are overloaded with games (in the case of an association with several teams).

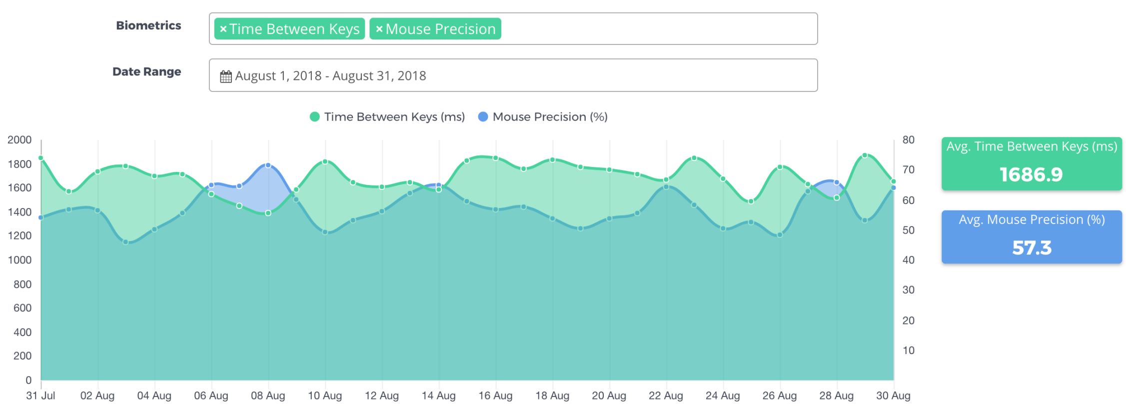


Figure 8: Platform: Behavioral biometrics in data range

The data concerning on LoL metrics were not included in the platform due to constraints of use *RIOT* API for commercial purposes. This makes it impossible the implementation of a real-time data collection requests. Despite that, sporadic requests were sufficient to be able to the accomplishment of a case study of this dissertation.

4.2.6 *Recommendation System*

In order to provide coaches and players with a forecasting service in the form of a recommendation system, it was used the package *Shiny* which makes possible to build interactive web apps straight from *R*.

The system has developed for a simple and intuitive interface to use, making this service possible to predict the *Game Result* as a percentage of probability of victory, from theoretically impossible (0%) to a certain victory (100%), and the prediction of *Gold Earned* per minute.

As mentioned in section 4.2.4, this service had into account the player's interaction with the computer in the last 10 to 15 minutes, the moment in time (Time of Day and Day of the Week) and the Performetric prediction on mental fatigue set in this period. When the player was not interacting with the computer, the system did not have enough data to make recommendation predictions, nor would it make sense.

It was made possible for users to specify a Player and a Champion in order to provide the prevision of that combination, or a more direct way, the ranking of the most likely champions to win the game and their associated gold-earnings forecast.

The aforementioned predictions were possible with the loading of the previously stored binary format ML models, through the use of the binding of the imported *H2O* environment in *R*.

4.3 OUTCOMES

The main results and their scientific evidence from this stage of development, to later carry out a case study, were obtained with the individual data collection of the semi-professional player of LoL:

Name: Artur Ribeiro

Residence: Braga, Portugal

Analyzed Games: 998

Occupation: Student and part-time player

Test period: Since October, 2017

Info: Artur, has more than 7000 hours playing LoL since he was 14 and is part of the *Doxa Gaming* team, currently in the 1st Portuguese division of the game. Since October, the Performetric system has been collecting his performance biometric data.

4.3.1 *Player Statistical and graphical Reports*

In order to verify different patterns of interaction, the Mann-Whitney U test was performed, which reported significant differences in performance biometrics compared to the final outcomes in all games collected. The table 1 shows the result of this test.

The *P-value* checks the performance biometrics statistic significant in the final results of the games answering this question: *If the groups are sampled from populations with identical distributions, what is the chance that random sampling would result in the mean ranks being as far apart (or more so) as observed in this experiment?*

Biometric	P-Value
KDTMean	0.57874169
MAMean	**0.04325705**
MAVar	**0.02880556**
MVMean	**0.03546299**
MVVar	**0.03546299**
TBCMean	0.08920955
TBCVar	0.57874169
DDCMean	0.43587218
DDCVar	0.39304813
DMSLean	0.24745069
DMSLVar	0.21756262
MousePrecision	0.79593626
ErrorPerKey	0.52884886

Biometric	P-Value
AEDMean	0.06301284
AEDVar	**0.03546299**
ADMSLMean	0.57874169
ADMSLVar	0.73936435
TBKVar	0.07525601
TBKMean	**0.04325705**
LeftClicks	0.73936435
RightClicks	**0.04325705**
KeysPressed	0.48125095
WVMean	0.35268137
MouseDistance	**0.01468964**
MouseExcessDistance	0.16549395

Table 1: Mann-Whitney U test results

As can be observed in table 1, some performance biometrics presented promising results for an analysis of evolution over time and possible subsequent work by the coach, since they indicated an influence on the final outcome of the player's games.

The radar chart of figure 9 graphically reinforces a possible influence of the performance biometrics identified in the final outcome of the analyzed player's games. In this, it is possible to verify the differences of the average of each biometric of performance in the games in which the player won (in green) of which the player lost (in red).

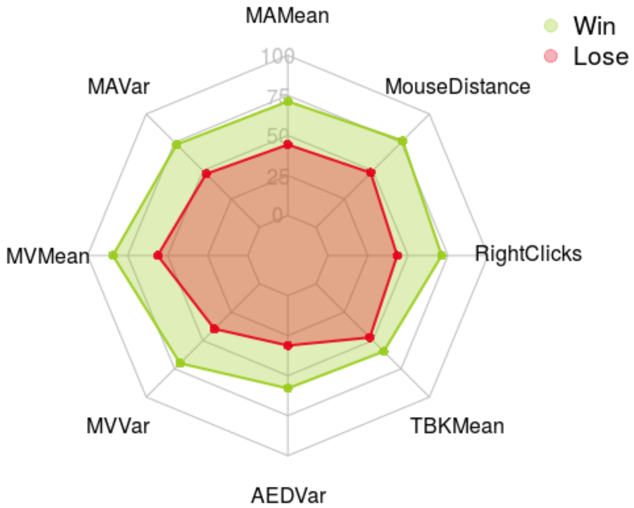


Figure 9: Comparison between performance biometrics and game outcome

The figure 10, depicts the player correlation coefficients of some game metrics with performance biometrics using Pearson's correlation.

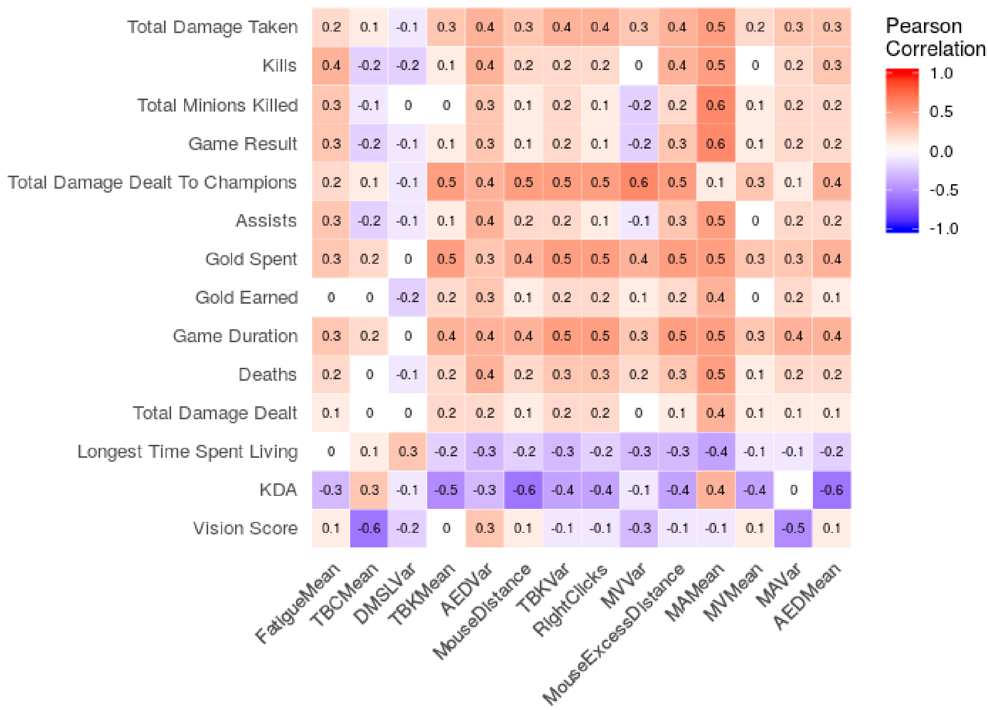


Figure 10: Correlation between game metrics and performance biometrics

As can be observed, in figure 10 chart, relations of greater proportional correlation through the red gradient and inversely proportional relations through the blue gradient. The more accentuated the color is, the greater the correlation. Following these correlations we can provide the player and/or trainer with detailed reports on the relationship between the game metrics and performance biometrics identified.

The player presents some interesting correlations, like the *Game Result* and *Total Minions Killed* with *Mean Mouse Acceleration*, and the *KDA* with *Mouse Distance* and *Mean Average Excess Distance between clicks*. Based on these correlations it is possible to detail the analysis with the relationship between game metrics and performance biometrics.

In the following figures are shown some analyzes of the relationship between game metrics and mental fatigue status.

In figure 11, we can see that the player has a lower percentage of game wins as his maximum mental fatigue reached during gameplay increases.

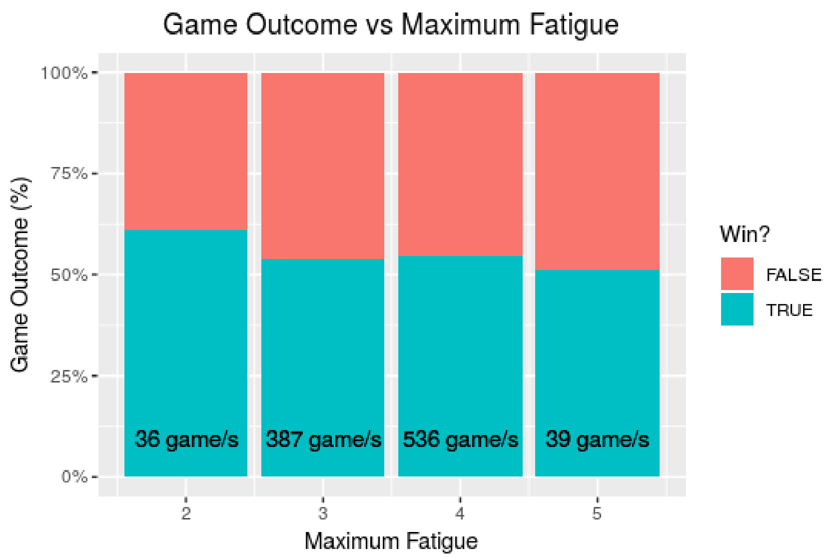


Figure 11: Percentage of game outcome by the Maximum state of fatigue

In Figure 12 charts, we can see a decrease in the average number of *Kills* and *Total Minions Killed* as the mean state of mental fatigue increases from level 3 to level 4 which can indicate a loss of performance in this metrics with the increase of the level of average mental fatigue. It also provides the indication of a low average of *Kills* and *Total Minions Killed* to low mean levels of mental fatigue, which can indicate a loss of performance in this metric in games that the player does not perform a warm-up.

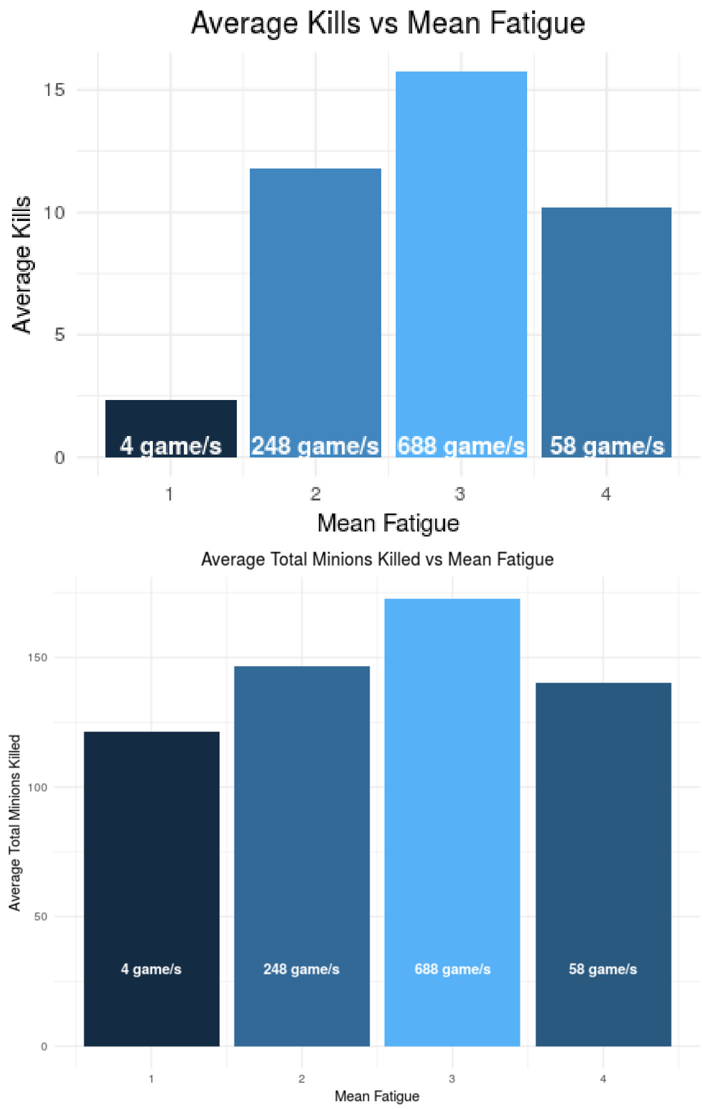


Figure 12: Average Kills and Total Minions Killed per Mean state of fatigue

In figure 13, it is possible to observe a hypothesis of relation between the average of the *KDA* obtained with the average level of mental fatigue presented by the player. The lowest values of *KDA* are visible for days with greater mental fatigue status presented.

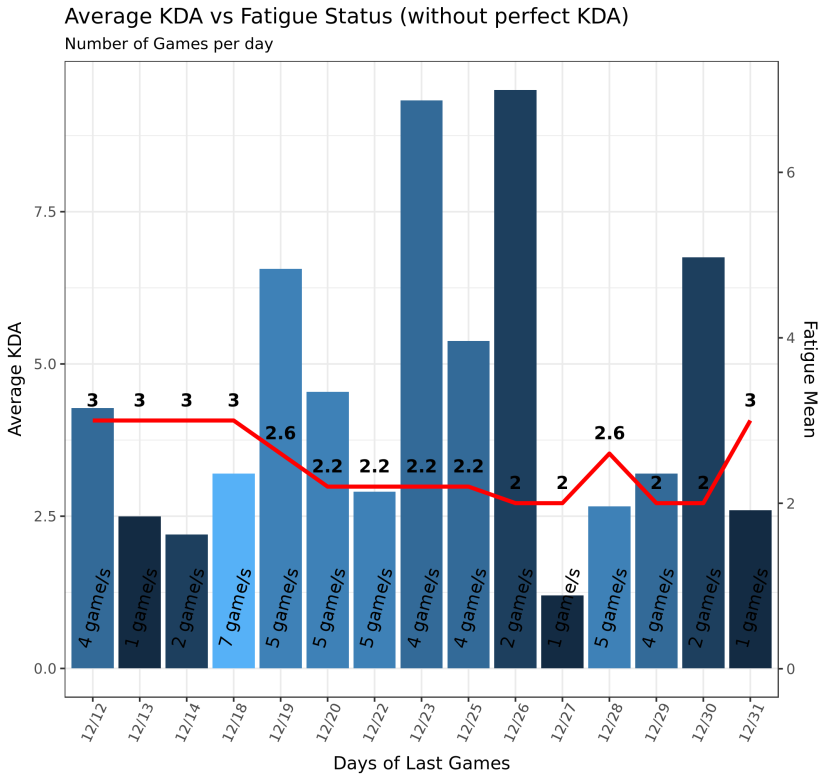


Figure 13: Average KDA day records per Fatigue Status

4.4 SUMMARY

This chapter explains the steps taken during the development phase, such as game and case study decisions, the technologies used and the implementation procedure of data collection, passing through preprocessing up until the use of machine learning. In the end an application analysis was exposed with a semi-professional player who served to identify the required features for the platform and refine the preparation of a case study with a professional team.

5 CASE STUDIES

As a case study, in an attempt to prove and validate the implementations of the development process in a real environment, was analyzed game metrics and performance biometrics data from an association with a team of professional LoL players, GGEA.

Test period: Since February to August, 2018

GGEA, is an organization owned by Infinite Esports & Entertainment alongside OpTic Gaming and Allegiance. Looking to do more than merely compete, the organization provides a curriculum for up-and-coming competitors to hone their skills with the hopes of developing talent into professional players.

Figure 14: GGEA LoL Players

5.1 EXPERIMENT SETUP

Players had to have the Performetric software installed and running on their machines where they trained and played LoL to collect enough data for training and creating *Game Result* and *Gold Earned* prediction models. As this study did not require a quick response in the predictions, was opted to build models with higher processing that could bring better performance.

After the building of the models in ML, a service on a platform, for the coach and players was provided. This platform with the recommendation system, used the models, to provide the probability of winning with the selection of a certain *Champion*, the ranking of *Champions* with greater probability of winning and the forecast of *Gold Earned* for the next near game.

Based on the development phase and the presented LoL concepts, the study with GGEA followed the following methods:

- Analysis of 20 team games (*scrim's*) with the recommendation system based on ML models (*Gold Earned* and *%Win by Champion*) during 3 weeks;
- Impact analysis of the mental fatigue in the individual performance on ranking points though the LP during a week;
- Impact analysis of the mental fatigue in individual performance (*Game Results*, *KDA*, *Gold Earned/min*) on the last 100 games (SOLO) of each player;
- Analysis and testing of the accuracy of the recommendation system based on ML models (*Gold Earned* and *%Win by Champion*).

Due to the fact that the team was in the middle of a process of replacing one of the players, this study only approached 4 of 5 team formation players.

5.1.1 *Prediction Machine Leaning Models*

Based on the games that the players have made since they installed the Performetric software, two types of prediction models were made for the team, as mentioned, using the techniques described in the machine learning section (4.2.4). The models used as input the interaction of the player with his computer and a particular *Champion* and obtained as output a prediction chances of victory and *Gold Earned*, as described in section 4.2.6.

Game Result Model

The *Game Result* prediction model is a classification problem. The performance of the stacked ensemble model formed by the chosen best 3 models in the *Grid of Hyperparameter Search* had the following metrics in a test dataset (not used and therefore unknown during the training).

Actual/Predicted	FALSE	TRUE	Error	Rate
FALSE	88	89	0.5028	89 / 177
TRUE	41	210	0.1633	41 / 251
Total	129	299	0.3037	130 / 428

Figure 15: *Game Result* Model performance

The model performed an accuracy metric of 70% in the test dataset, as this was a classification problem, the case study game result predictions had this into consideration.

Gold Earned Model

The *Gold Earned* prediction model is a regression problem. The performance of the stacked ensemble model formed by the chosen best 3 models in the *Grid of Hyperparameter Search* had the following metrics in a test dataset (not used and therefore unknown during the training).

The model performed an RMSE metric of 73 in the test dataset, as this was a regression problem, the case study game result predictions had this into consideration.

model	Stacked_GBM_DRF_Gold_Model
model_checksum	-3191438955292221952
frame	·
frame_checksum	0
description	·
model_category	Regression
scoring_time	1532624187163
predictions	·
MSE	5317.748645
RMSE	72.922895
nobs	428
custom_metric_name	·
custom_metric_value	0
r2	0.446450
mean_residual_deviance	5317.748645
mae	56.767450
rmsle	0.176672

Figure 16: *Game Earned* Model performance

5.2 RESULTS

The results and predictions of the 20 GGEA team's (*scrim*) games are shown in table 2. The values present in each column are:

- *"Gold/min"* - Gold per minute in the game from all players
- *"KDA"* - Average KDA ((Kills + Assists) / Deaths)) in the game from all players
- *"Result"* - Final game result (0 - The Team lost; 1 - The team Won)
- *"Predicted % of Win"* - Average predicted chances of victory from all team players
- *"Predicted Gold Earned"* - Average predicted *Gold Earned* from all team players

Game	Gold/min	KDA	Result	Predicted % of win	Predicted Gold Earned
1	1662.147	1.69	0	43%	1644
2	1771.828	3.05	0	51%	1627
3	2073.557	3.73	1	64%	1678
4	1548.56	1.09	0	56%	1521
5	2145.446	8.80	1	65%	1771
6	2049.434	9.00	1	58%	1735
7	1951.591	5.57	1	69%	1655
8	1641.853	1.77	0	54%	1625
9	1601.69	1.22	0	65%	1664
10	1468.353	0.20	0	57%	1672
11	1509.283	1.07	0	51%	1482
12	2003.175	9.13	1	78%	1818
13	1955.254	2.25	1	79%	1784
14	1561.249	0.57	0	63%	1563
15	2078.116	5.56	1	78%	1805
16	1665.919	1.67	0	72%	1615
17	1749.691	1.95	1	61%	1714
18	1729.107	1.62	1	76%	1810
19	1910.705	6.45	1	78%	1552
20	1458.601	0.38	0	58%	1538

Table 2: GGEA case study games results and predictions

5.2.1 *Combined Players analyses*

As can be seen by the correlation exposed in table 3, the models proved the accuracy and a correlation with the final results.

Correlation Coefficient Predictions and Real Results		
Gold	KDA	Result
0.7	0.4	0.7

Table 3: Correlation between predicted models and Real Results

The graph of figure 17 serves to prove that the results of the performance of the created *Game Result* model were close to the results in this test. The X-Axis represents the *Game Result* (0-Lost , 1-Win) and the Y-Axis represents the predicted chances of winning. Lower odds of victory are visible for actual results of defeat and odds are always higher than 50% for all victories.

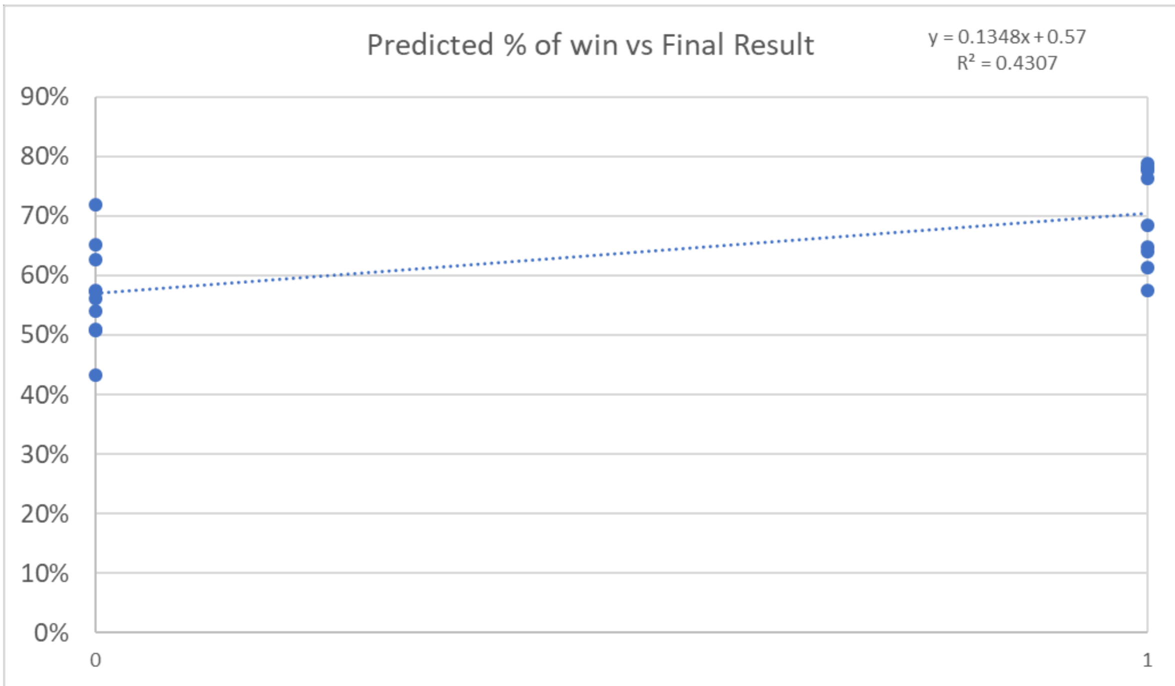


Figure 17: Predicted Game Result vs Real Result

The graphs of the figure 18 serve to prove that the results of the performance of the created *Gold Earned* model were close to the results of this test.

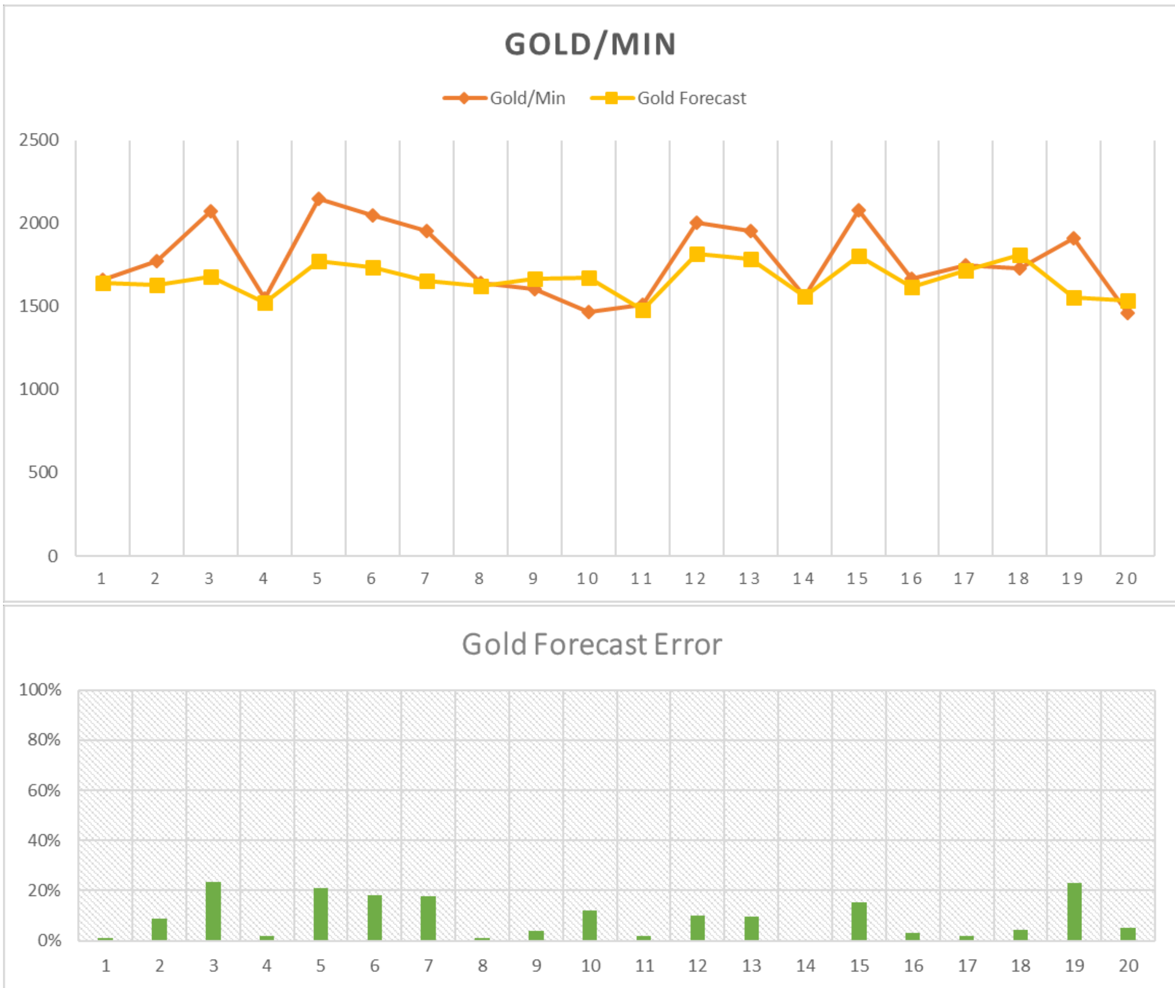


Figure 18: Predicted Gold Earned vs Real Gold Earned

In the chart above, we can see a comparison between the real average Gold Earned per Minute in the game (on the orange line) and the prediction (in yellow). The graph below shows the error percentage of the Gold Earned forecast model and as we can observe never reached a 30% error of the total value.

5.2.2 *Individual Players analyses*

For each player an individual study of the recommendation system and analyzes of some biometrics shown on the platform was performed to validate if these predictions were valid.

GGEA Strompest

Name: Lee Seung-min

Residency: North America

Trained Games in Models: 107

Occupation: Professional Player

Test period: Since February to August, 2018

Role: Mid laner

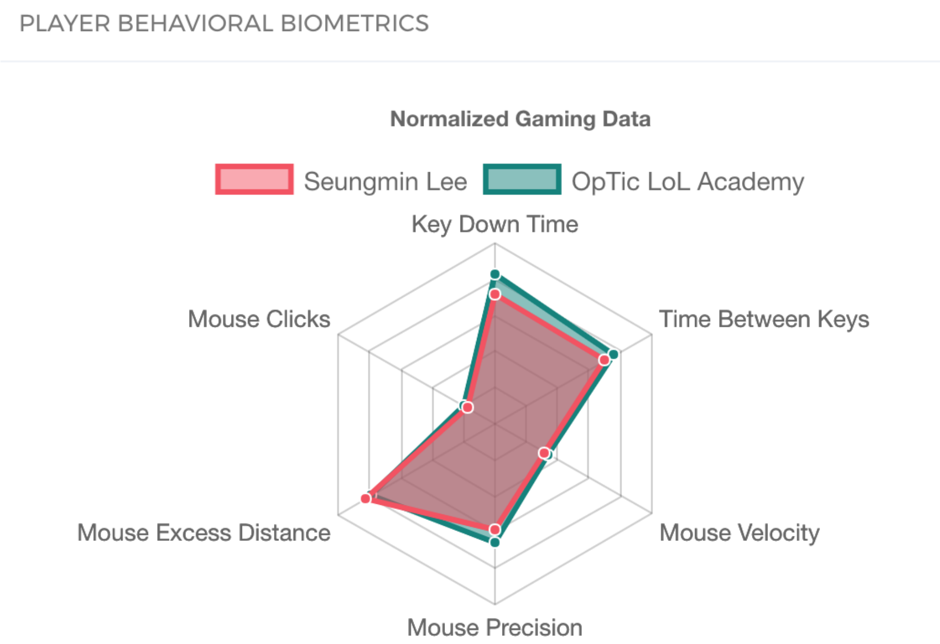
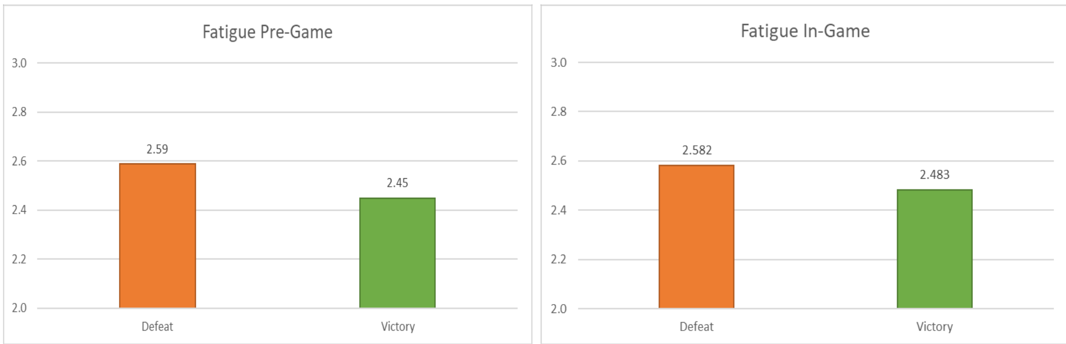


Figure 19: GGEA Strompest biometrics comparison

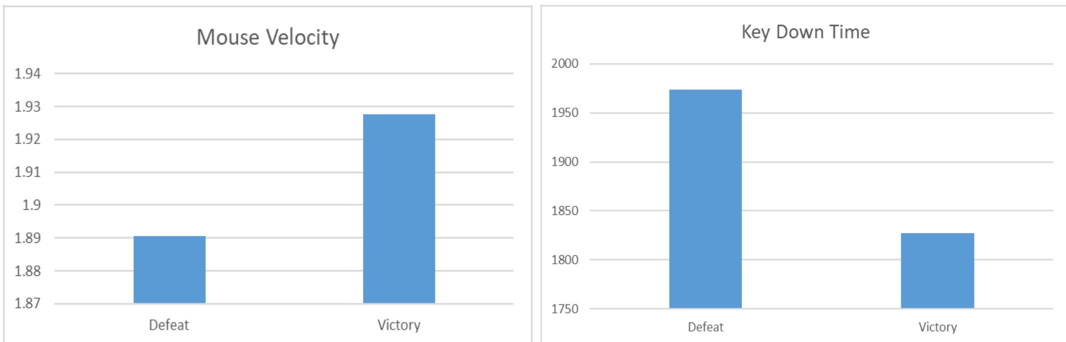
The player's performance biometrics, shown in the figure 19 chart, are similar to the rest of the team, with a slightly different in the *Key Down Time*.



(a) Pre-Game (b) In-Game

Figure 20: GGEA Strompest Average Fatigue Level per Game Result

In figure 20 charts, it's possible to observe a small difference in the pre-game and in-game average state of mental fatigue compared with the game results. This may prove a possible influence of mental fatigue on the player's game result. With this information, it would be possible to recommend, if it were possible, that the player takes a short break before starting a game. Also to notice a low average state of mental fatigue presented by the player in game situations, which can also prove the resistance, from this type of athletes, to mental fatigue in competitive situations (referred in section 2.5).



(a) Mouse Velocity (b) Key Down Time

Figure 21: GGEA Strompest In-Game Average Biometrics per Game Result

In figure 21 charts, it's possible to observe that the player has a higher average *Mouse Velocity* and lower average *Key Down Time* when he wins. With this information, the coach can use this biometric to measure the player's form or check if the player already presents values close to his average *Mouse Velocity* and *Key Down Time* during the warm-up.

Date	29/07	30/07	31/07	01/08	02/08	03/08	04/08	05/08	06/08	07/08	08/08
Fatigue	2.3	2.3	2.7	2.8	2.9	3.0	3.0	3.0	2.7	2.4	2.7
LP	735	610	541	551	540	557	578	580	651	651	651
Correlation Coefficient: -0.7											

Table 4: GGEA Strompest LP and Average Fatigue Level per Day in time period

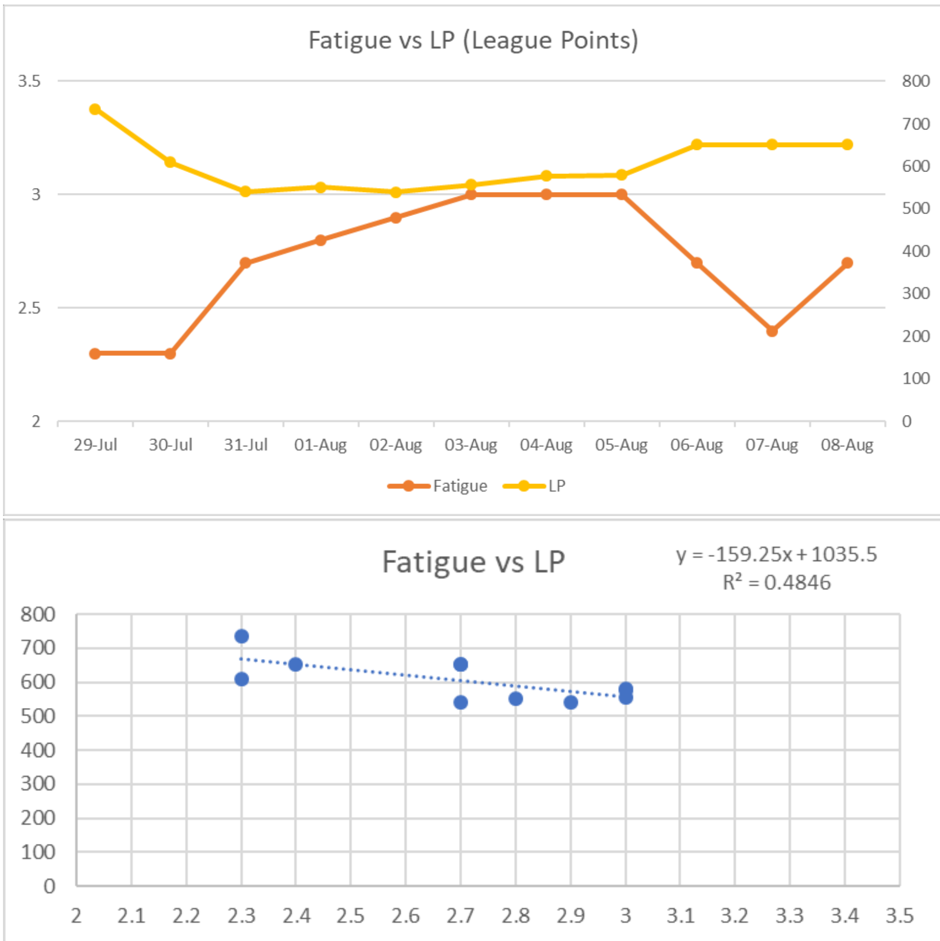


Figure 22: GGEA Strompest LP and Average fatigue Level per Day comparison

In figure 22 charts, based in table 4, it's possible to observe that a higher average mental fatigue level by day means fewer LP and it presents a strong negative correlation. With this information, the coach can establish rules of the maximum number of *SOLO* games that the player can perform per day.

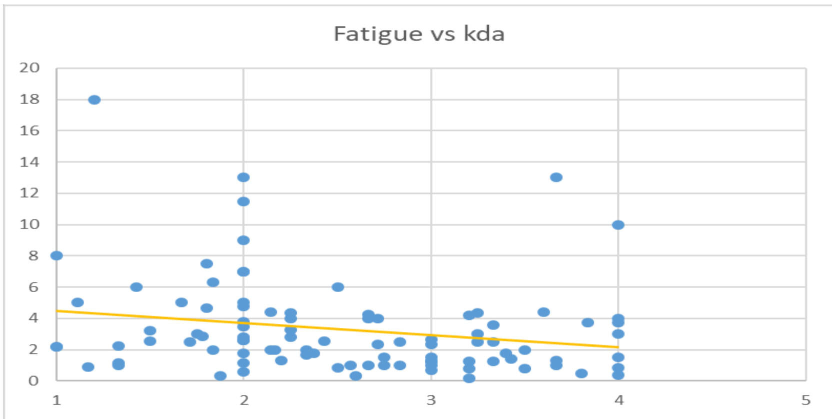


Figure 23: GGEA Strompest KDA per Mental Fatigue Level

In figure 23 chart, it's possible to observe that a higher average mental fatigue level revealed a lower *KDA* ratio. With this information, the coach can establish different tactics when the player presents in increasing level of mental fatigue during the game, such as a preference and greater caution in the defensive phase.

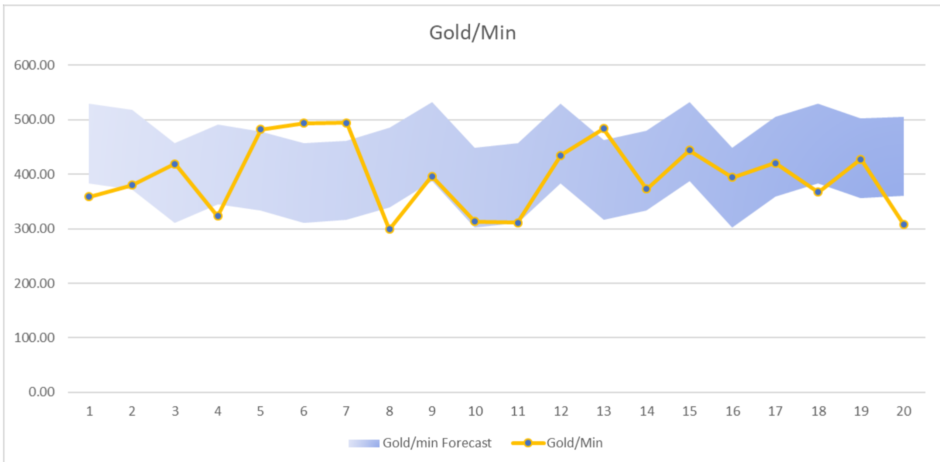


Figure 24: GGEA Strompest Real *Gold Earned* and Predicted *Gold Earned* comparison

In figure 24 chart, it's possible to observe that the *Gold Earned* per minute predicted for this player, when inserted in a range with the *Root-Mean-Square Error (RMSE)* (73 um), reported on its creation (e. g. *[Predicted - RMSE, Predicted + RMSE]*), was able to be accurate with the real value of *Gold Earned* over the 20 games reported. This forecast for the coach can be considered very useful since, as mentioned, is one of the most important game metrics that directly influence the outcome of the game.

GGEA Rodov

Name: Tom Rodov

Residency: North America

Trained Games in Models: 107

Occupation: Professional Player

Test period: Since February to August, 2018

Role: Top laner

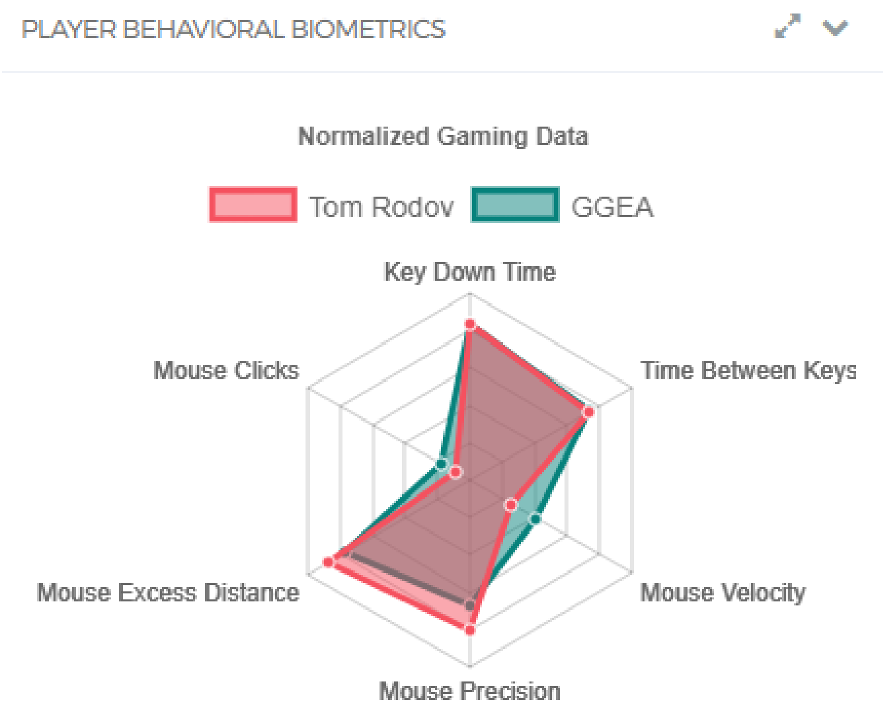
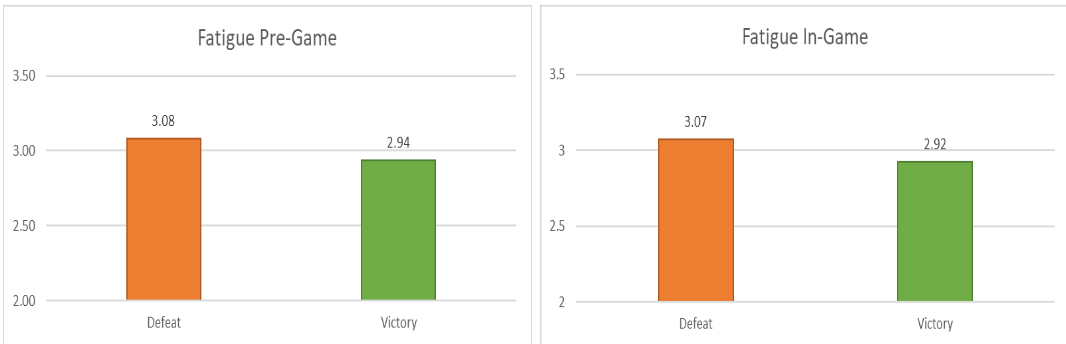


Figure 25: GGEA Rodov biometrics comparison

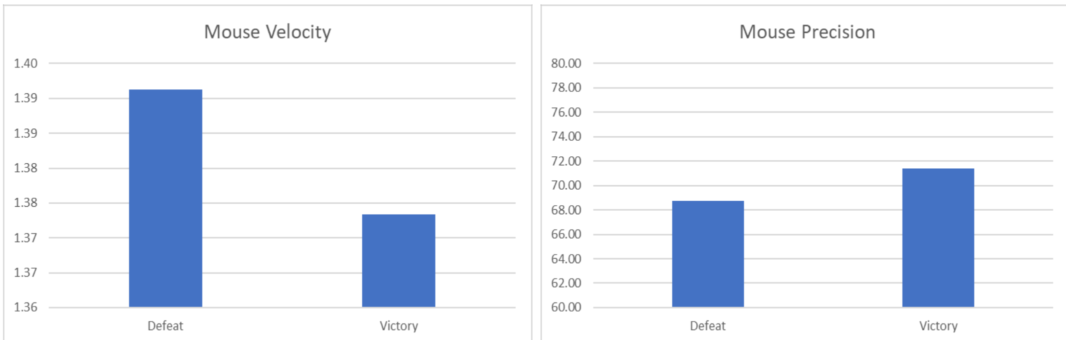
The player's performance biometrics, shown in the figure 25 chart, are similar to the rest of the team in regards to keyboard metrics. As for the biometrics of the mouse they differ from the rest of the team, which may indicate that the player has a different style of play from the rest of the team, for example, related to his role in the game or the possibility that he needs to improve some aspects in his interaction with the mouse.



(a) Pre-Game (b) In-Game

Figure 26: GGEA Rodov Average Fatigue Level per Game Result

In figure 26 charts, it's possible to observe a small difference in the pre-game and in-game average state of mental fatigue compared with the game results. This may prove a possible influence of mental fatigue on the player's game result. With this information, it would be possible to recommend, if it were possible, that the player takes a short break before starting a game.



(a) Mouse Velocity (b) Mouse Precision

Figure 27: GGEA Rodov In-Game Average Biometrics per Game Result

In figure 27 charts, it's possible to observe that the player has a lower average *Mouse Velocity* and higher average *Mouse Precision* when he wins. With this information, the coach can see if the player is in a nervous situation in the warm-up and control that situation, for example, when presenting *Mouse Velocity* higher or *Mouse Precision* lower than normal. The coach also can use this biometrics to measure the player's form or check if the player already presents values close to his average *Mouse Precision* and *Mouse Velocity* during the warm-up.

Date	29/07	30/07	31/07	01/08	02/08	03/08	04/08	05/08	06/08	07/08	08/08
Fatigue	3.2	2.7	2.6	3.1	3.1	3.2	3.2	3.2	2.6	2.4	3.0
LP	499	514	476	494	475	456	450	450	486	431	389
Correlation Coefficient: -0.1											

Table 5: GGEA Rodov LP and Average Fatigue Level per Day in time period

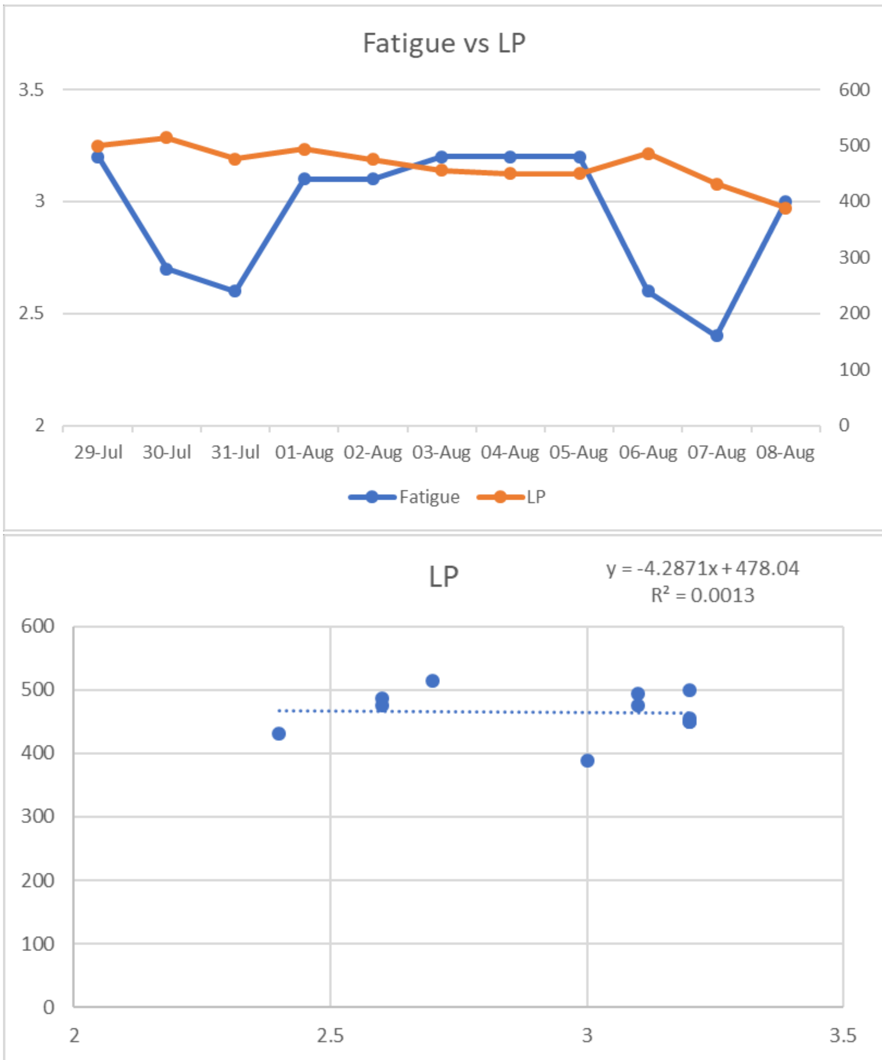


Figure 28: GGEA Rodov LP and Average fatigue Level per Day comparison

In figure 28 charts, based in table 5, it's possible to observe that a higher average mental fatigue level by day means fewer LP but, in this player case, it doesn't present a strong negative correlation. This may show a greater resistance of the player in the number of daily *SOLO* games that he can perform.

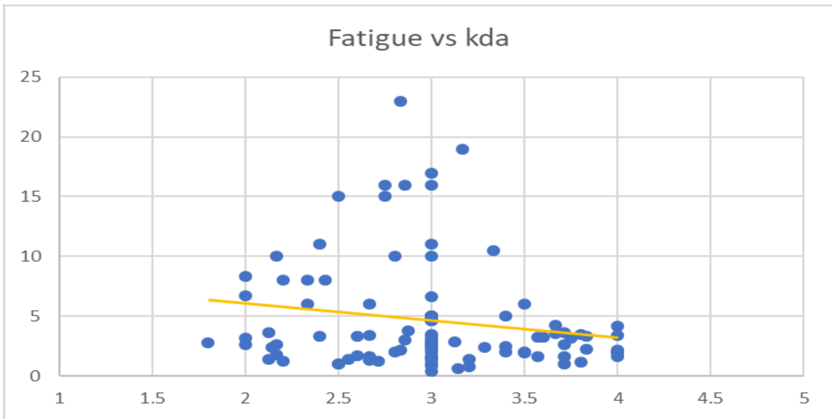


Figure 29: GGEA Rodov KDA per Mental Fatigue Level

In figure 29 chart, it's possible to observe that a higher average mental fatigue level revealed a lower *KDA* ratio. With this information, the coach can establish different tactics when the player presents in increasing level of mental fatigue during the game, such as a preference and greater caution in the defensive phase.

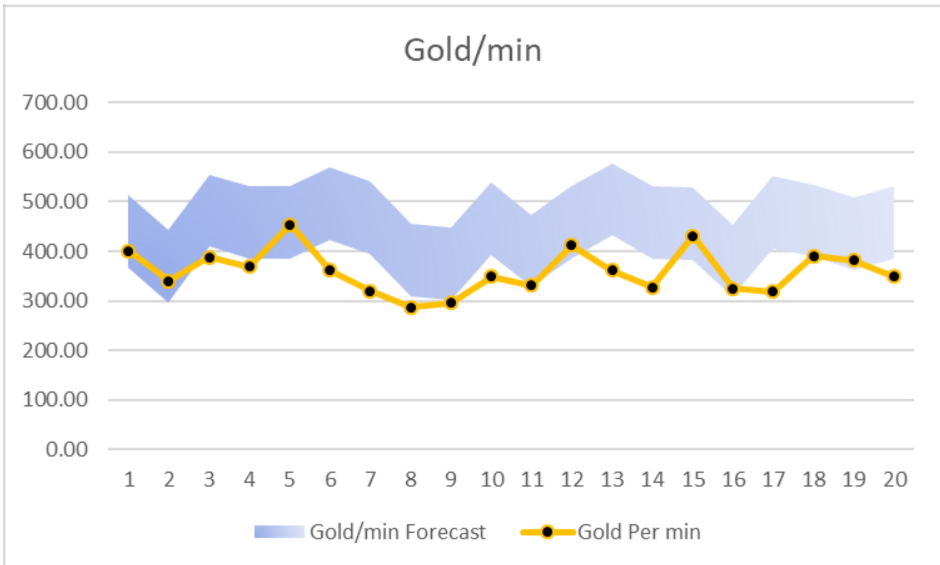


Figure 30: GGEA Rodov Real *Gold Earned* and Predicted *Gold Earned* comparison

In figure 30 chart, it's possible to observe that the *Gold Earned* per minute predicted for this player, when inserted in a range with the RMSE (73 um), reported on its creation, was able to be accurate with the real value of *Gold Earned* over the 20 games reported.

GGEA Neøø

Name: Toan Tran

Residency: North America

Trained Games in Models: 107

Occupation: Professional Player

Test period: Since February to August, 2018

Role: AD carry

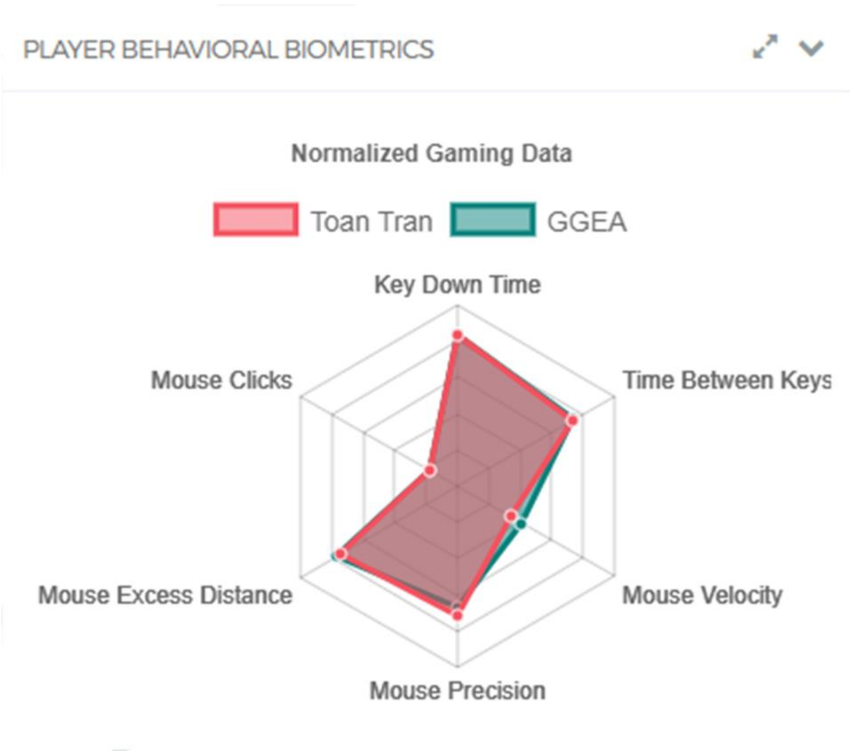
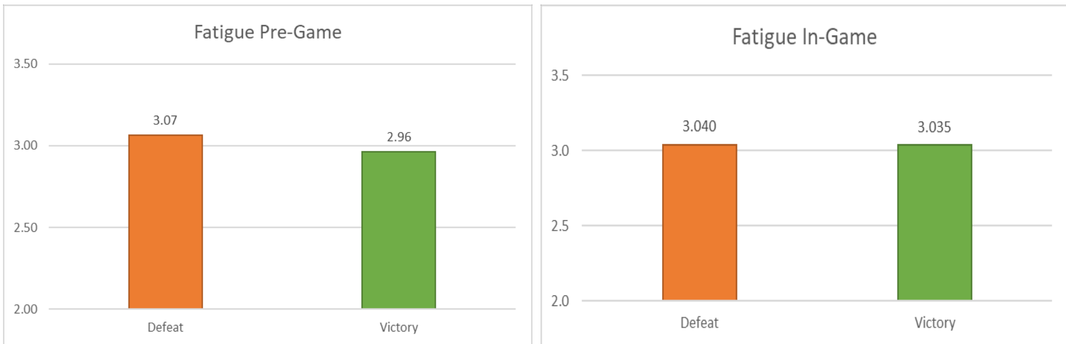


Figure 31: GGEA Neøø biometrics comparison

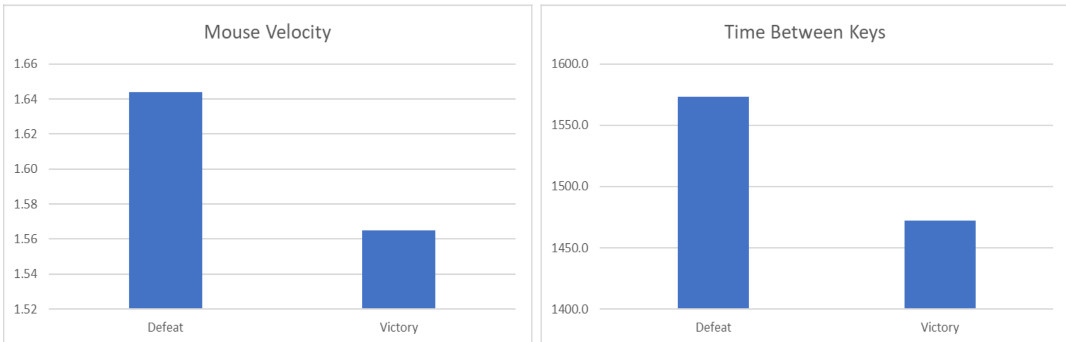
The player's performance biometrics, shown in the figure 31 chart, are similar to the rest of the team, with a slightly different in the *Mouse Velocity*.



(a) Pre-Game (b) In-Game

Figure 32: GGEA Neøø Average Fatigue Level per Game Result

In figure 32 charts, it's possible to observe that the player doesn't have a considerable difference in the in-game and a small difference in the average state of mental fatigue compared with the game results. This may tell that's no influence of mental fatigue on the player's game result.



(a) Mouse Velocity (b) Time Between Keys

Figure 33: GGEA Neøø In-Game Average Biometrics per Game Result

In figure 33 charts, it's possible to observe that the player has a lower average *Mouse Velocity* and *Time Between Keys* when he wins. With this information, the coach can see if the player is in a nervous situation in the warm-up and control that situation, for example, when presenting *Mouse velocity* and *Time Between Keys* higher than normal. The coach can also use this biometrics to measure the player's form or check if the player already presents values close to his average *Mouse Velocity* a*Time Between Keys* during the warm-up.

Date	29/07	30/07	31/07	01/08	02/08	03/08	04/08	05/08	06/08	07/08	08/08
Fatigue	2.5	2.2	2.2	2.3	2.5	2.7	2.5	2.8	2.0	2.0	2.2
LP	517	465	409	462	404	387	391	403	483	483	519
Correlation Coefficient: -0.7											

Table 6: GGEA Neøø LP and Average Fatigue Level per Day in time period

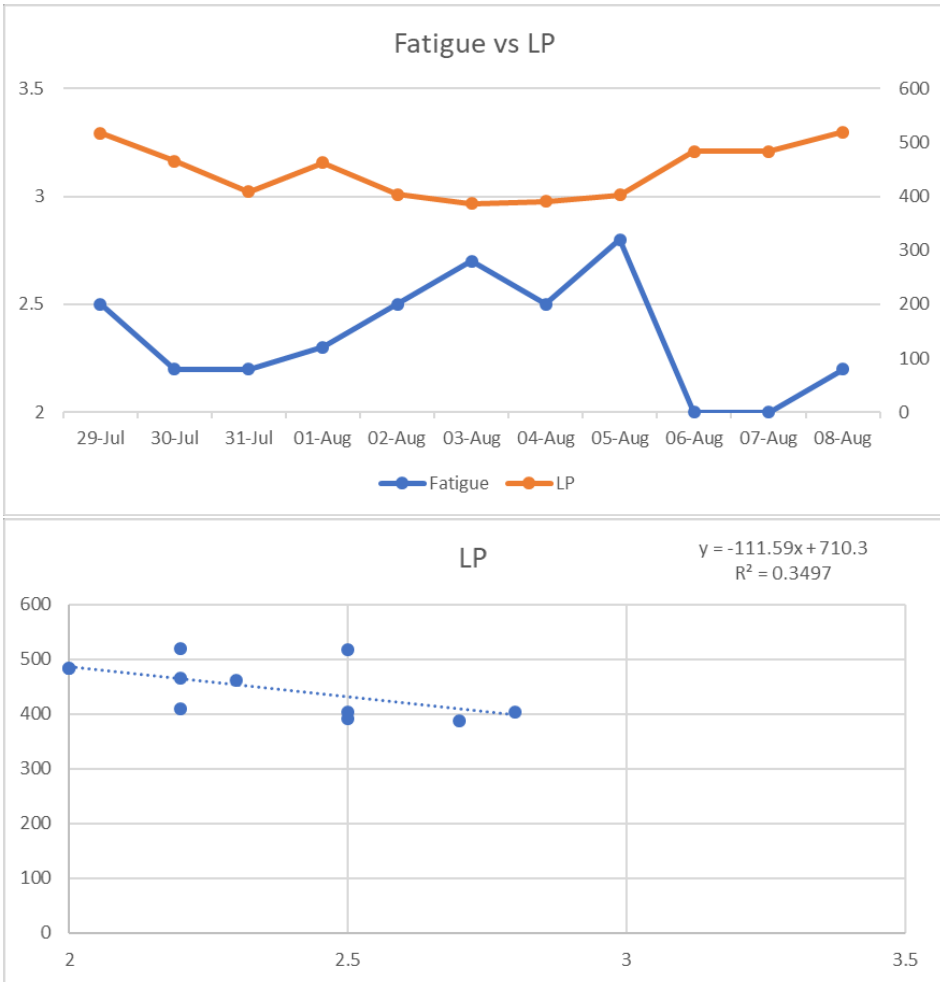


Figure 34: GGEA Neøø LP and Average fatigue Level per Day comparison

In figure 34 charts, based in table 6, it's possible to observe that a higher average mental fatigue level by day means fewer LP and it presents a strong negative correlation. With this information, the coach can establish rules of the maximum number of *SOLO* games that the player can perform per day.

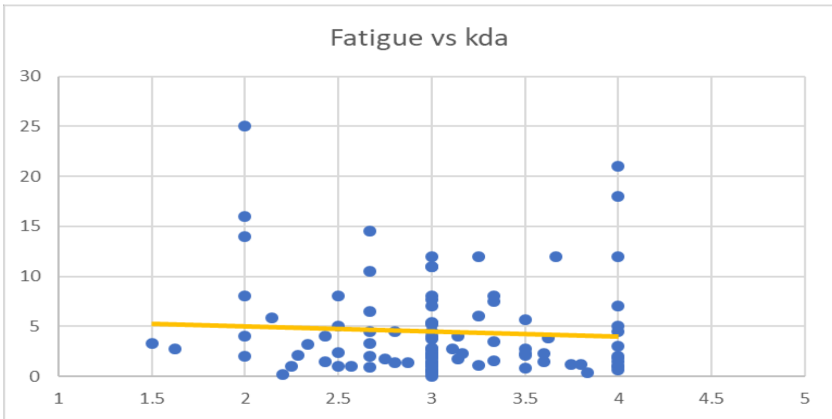


Figure 35: GGEA Neøø KDA per Mental Fatigue Level

In figure 35 chart, it's possible to observe that a higher average mental fatigue level revealed a lower *KDA* ratio. With this information, the coach can establish different tactics when the player presents in increasing level of mental fatigue during the game, such as a preference and greater caution in the defensive phase.

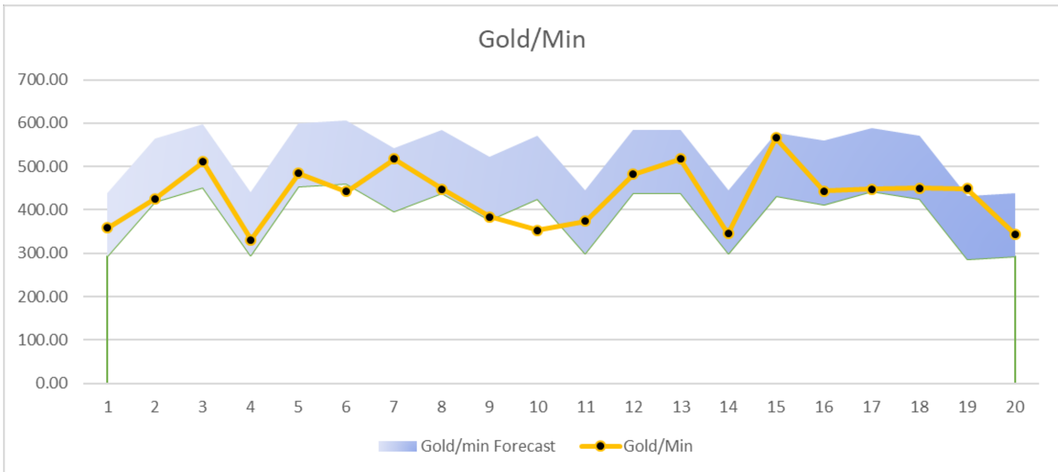


Figure 36: GGEA Neøø Real *Gold Earned* and Predicted *Gold Earned* comparison

In figure 36 chart, it's possible to observe that the *Gold Earned* per minute predicted for this player, when inserted in a range with the RMSE (73 um), reported on its creation, was able to be accurate with the real value of *Gold Earned* over the 20 games reported.

GGEA Abu222

Name: Ali Abou Elala

Residency: North America

Trained Games in Models: 107

Occupation: Professional Player

Test period: Since February to August, 2018

Role: Support

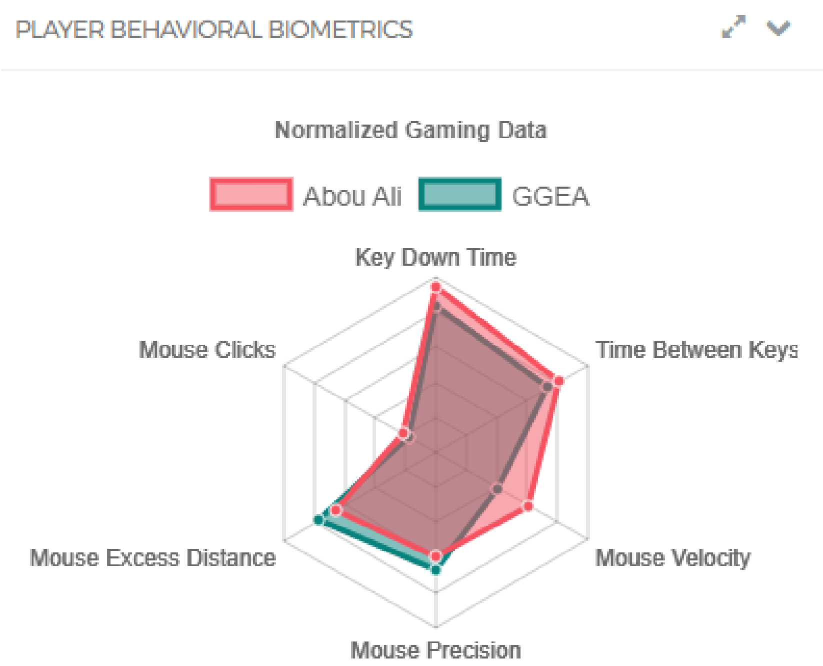
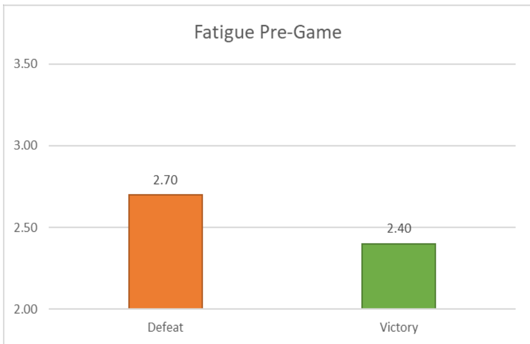
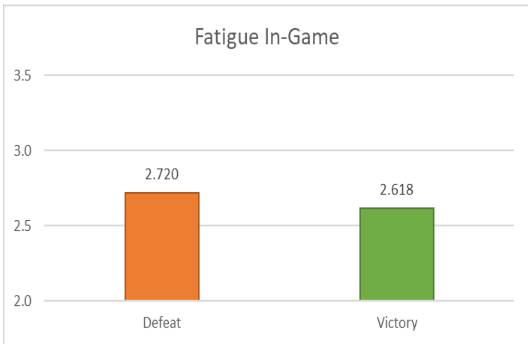


Figure 37: GGEA Abu222 biometrics comparison

The player's performance biometrics, shown in the figure 37 chart, has some similarities with the rest of the team. The player shows to be a bit slower than the rest of the team in the keyboard use, though it pays off with faster mouse interaction compared to the rest of the team. The coach, in the case of this player, can do a specific training to improve the speed in the usage of the keyboard if he figures out that these biometrics are affecting his performance.



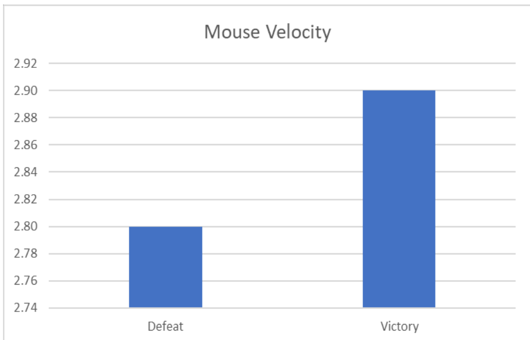
(a) Pre-Game



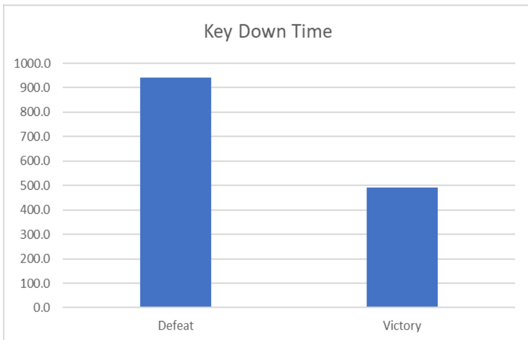
(b) In-Game

Figure 38: GGEA Abu222 Average Fatigue Level per Game Result

In figure 38 charts, it's possible to observe a small difference in the pre-game and in-game average state of mental fatigue compared with the game results. This may prove a possible influence of mental fatigue on the player's game result. Also to notice a low average state of mental fatigue presented by the player in game situations, which can also prove the resistance, from this type of athletes, to mental fatigue in competitive situations (referred in section 2.5).



(a) Mouse Velocity



(b) Key Down Time

Figure 39: GGEA Abu222 In-Game Average Biometrics per Game Result

In figure 39 charts, it's possible to observe that the player has a higher average *Mouse Velocity* and lower average *Key Down Time* when he wins. With this information, the coach can use this biometric to measure the player's form or check if the player already presents values close to his average *Mouse Velocity* and *Key Down Time* during the warm-up.

Date	29/07	30/07	31/07	01/08	02/08	03/08	04/08	05/08	06/08	07/08	08/08
Fatigue	2.7	2.8	2.3	3.0	3.4	2.8	3.0	2.4	2.0	2.5	3.0
LP	370	373	389	420	400	400	397	492	563	563	563
Correlation Coefficient: -0.5											

Table 7: GGEA Abu222 LP and Average Fatigue Level per Day in time period

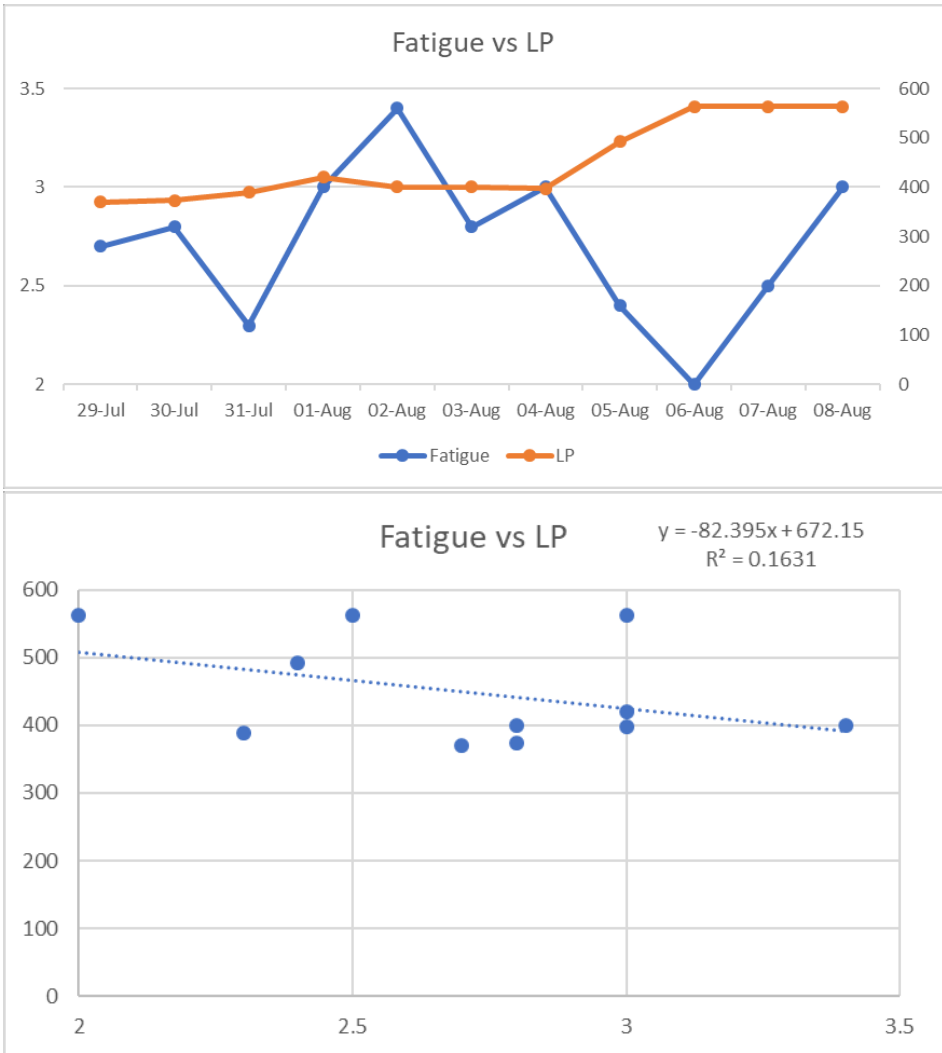


Figure 40: GGEA Abu222 LP and Average fatigue Level per Day comparison

In figure 40 charts, based on table 7, it's possible to observe that a higher average mental fatigue level by day means fewer LP and it presents a strong negative correlation. With this information, the coach can establish rules of the maximum number of *SOLO* games that the player can perform per day.

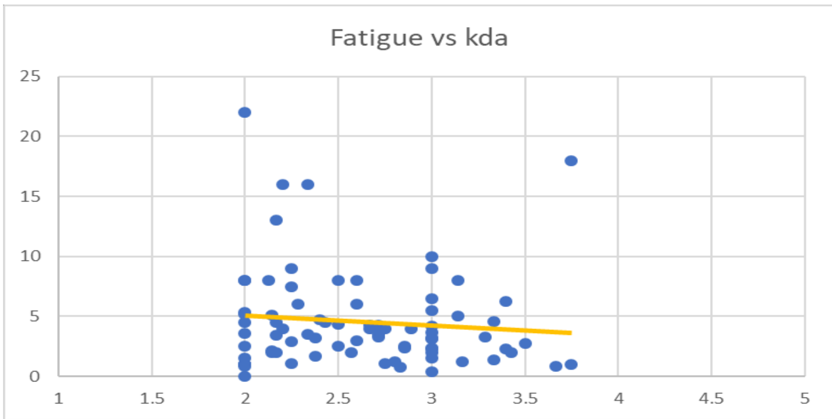


Figure 41: GGEA Abu222 KDA per Mental Fatigue Level

In figure 41 chart, it's possible to observe that a higher average mental fatigue level revealed a lower *KDA* ratio. With this information, the coach can establish different tactics when the player presents in increasing level of mental fatigue during the game, such as a preference and greater caution in the defensive phase.

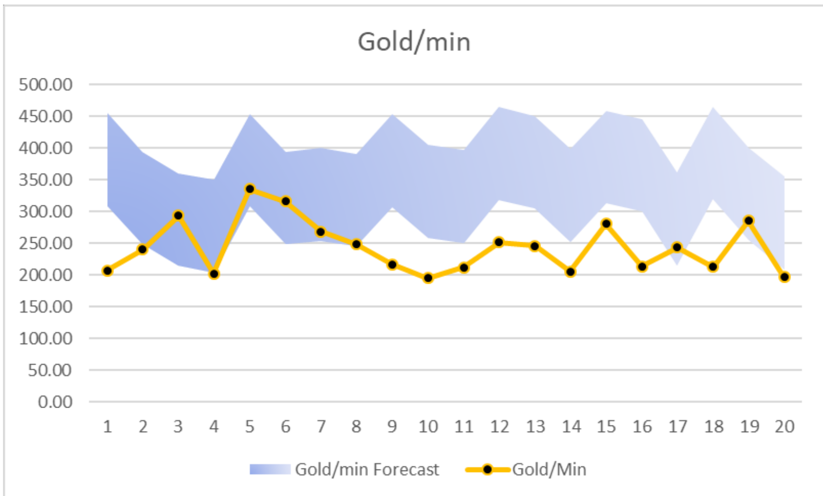


Figure 42: GGEA Abu222 Real *Gold Earned* and Predicted *Gold Earned* comparison

In figure 42 chart, it's possible to observe that the *Gold Earned* per minute predicted for this player, when inserted in a range with the RMSE (73 um), reported on its creation, was able to be accurate with the real value of *Gold Earned* over the 20 games reported.

5.3 DISCUSSION

With the analyses of the 20 GGEA team's (*scrim*) games predictions and 100 *SOLO* Games from each player it was able to detect and verify the impact of fatigue in individual performance in:

- Final *Game Result*;
- Game Performance (*KDA* and *Gold Earned* per minute);
- Ranking LP.

The biometric profile revealed what characteristics the player stands out and how this characteristic can make a difference in performance during the game. Monitoring and enhancement of these features can be used to improve player performance. With the existence of substitute players or more professional players from other teams it would be possible to compare the differences of performance biometrics taking into account the role of the player. It could be useful to see if any player fit into another role in the game for an improvement in their performance or as a team resource, for example, due to some injury of a team player.

The *Gold Earned* per minute prediction model revealed high accuracy in the real results and with the increase of the number of games in training it would be possible to improve even more the performance of the predictive model.

It has been proven that an recommendation system service can have a big impact on the final outcome of the game. In the warm-up phase, the coach can receive several real-time analyzes of the player's stats, preparing a personalized tactic based on his current interaction with the computer. Some additions to the training process of the models, although complicated, such as the selection of the opponent's Champions could make the models even more accurate. However the system should become easier to use, with the availability of automatic data collection of professional teams training games (*scrims*).

With an increase in the number of data with the collection of more games over time, it would be possible to develop models with less response time maintaining or even improving their forecast performance.

5.4 SUMMARY

In this chapter, there is a case of study with a professional LoL Esports team, the GGEA. This study involves the analysis of 20 games in team scrim and about 100 individual games (SOLO).

This team was given access to the Platform created, the *Performetric's* software for behavioral biometrics collection and a service with a system with recommendations to use in their future games.

The results showed an influence of mental fatigue on the results of the analyzed games and that the recommendation system was valid for the established predictions, being ready for application in other teams and a margin of improvement in these and new analyzes.

6

CONCLUSION

During this work, it was discussed the current status of Esports and how the management of performance and mental fatigue of the players could be made through the use of non-invasive technology. In this way, was chosen to use behavioral biometrics more specific through mouse dynamics and keyboard dynamics that allow tracking the actions of the player in full activity in the game.

Knowing that it is possible to analyze human performance through this information (Pimenta et al. (2014)), it was decided to analyze the impact of the different metrics in a game scenario, thus crossing human performance information with game performance information and validated the assumption that it is possible to measure human performance through behavioral biometrics, and more importantly, that these have a considerable impact on the player's performance.

In the final phase, it was decided to use the biometric information of the player with information acquired through the game to train models in ML that would be able to help the player with recommendations on the best pre-game choices, given his mental state and the current state of performance, as well as the requirement/complexity of some game features so that better results can be obtained even under conditions of greater wear or worse performance.

As a final result, it was possible to develop a human performance and fatigue management platform that has recommendations that can help Esports coaches and analysts optimize and manage their team with a scientific basis.

This results indicate that mental fatigue state influence the performance of a player in the course of a game, human performance through behavioral biometrics measures have impact on the player's performance and that AI can be used to find player game patterns and with that make predictions in future games.

6.1 Contributions

The main contributions of this work were:

- Fatigue and performance management platform in real time;
- System of recommendation based on the mental state of the player;
- Machine learning models capable of understanding the player's behavior in different scenarios and different configurations.

All the work done was deployed in the Performetric production environment and is currently used by professional teams as in the example of the presented case study.

6.2 Limitations and prospects for future work

As mentioned the implementation of this solution must transmit to the player confidence in its use ensuring that during a competitive game will not occur errors, distractions and loss of fluidity in his computer.

It will be necessary that the game producer continues providing data collection access regarding player performance metrics in his matches.

A recommendation system for a player requires a period of game data collection using the *Performetric* software in order to be able to create ML models. The accuracy of these models will increase over time with the increase in the number of games trained..

Although all the objectives proposed in this dissertation have been reached, new hypotheses and paths to follow have been raised as a continuation and improvement of the developed platform, with emphasis on the following points:

- Integration with new games, example CS:GO, Rainbow 6, FIFA/PES, Overwatch and Fortnite;
- Improvement of the final application to the player, so that individual can perform a self-training;
- Adaptation to helps non-team amateur players to quick reach the levels of a professional player;
- Development of an ML models creation system, automatic training and deploying from the continuous data collection.

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