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Football Selection Optimization through the Integration of Management Theories, AI and Multi-criteria Decision Making

Roukaya Ben Jeddou

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Law, Management, Economics, and Politics

Doctorate in Management Sciences

By

Ms. Ben Jeddou Roukaya

Football Selection Optimization through the Integration of Management Theories, AI and Multi-criteria Decision Making

Thesis presented and defended at Université de Bourgogne, UFR STAPS, 3 Allée des Stades Universitaires, 21000 Dijon, on 16 December 2024.

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Abstract

The research outlined in this thesis falls within the context of professional football club management, where establishing a balance between human and financial aspects is essential for long-term viability of sports organizations. In football management, the traditional methods of player selection have historically guided decision-making processes within clubs. This strategic decision-making process, which is often subjective and uncertain, can have a significant impact on the club's financial, economic and sporting situation.

As football is increasingly becoming a data-driven sport, there is a growing recognition that traditional approaches need to be complemented by scientific methods based on artificial intelligence and multi-criteria decision making approaches to optimize player selection and improve both sporting and financial performance. It is becoming increasingly important to find an optimal balance between sporting success and financial performance to optimize the results of a specific entity: the football club.

In this respect, the main purpose of this thesis is to propose a model that combines machine learning techniques with multi-criteria analysis methods to improve the efficiency and objectivity of the football player selection process, while taking into account financial and managerial considerations. Our first contribution is to prioritize the physical, technical, tactical, and behavioral criteria of players using Random Forest, Entropy, and CRITIC algorithms. The second contribution is to rank players based on their performance using the TOPSIS method.

To validate these contributions, we designed a decision support system that assists the sports decision maker by proposing players in order of performance. Our model does not aim to replace coaches but rather to integrate subjective and objective evaluations to provide a thorough understanding of the factors influencing sporting and managerial performance, thereby improving the accuracy of player selection. As football moves towards more data-oriented approaches, the combination of AI and MCDM can further optimize player selection processes by leveraging the benefits of objective data analysis and subjective expertise.

The results obtained show the effectiveness of our approach in improving the performance of football teams, especially when supported and promoted by emotional intelligence, which refers to the manager's ability to recognize the substantial state of the players.

Keywords: Sports performance optimization; Player selection; Football management; Data-driven decision making; Machine learning; Multi-criteria decision making

Résumé

Le travail de recherche décrit dans cette thèse s'inscrit dans le contexte de la gestion d'un club de football professionnel, où l'établissement d'un équilibre humain et financier est essentiel pour assurer la pérennité des organisations sportives. Dans le management du football, les méthodes traditionnelles de sélection des joueurs ont historiquement guidé le processus de prise de décision au niveau des clubs. Ce processus de décision stratégique, souvent subjectif et incertain, peut avoir un impact significatif sur les performances financières, économiques et sportives de l'équipe. Alors que le football évolue vers un sport plus axé sur les données, il est de plus en plus reconnu que les méthodes traditionnelles doivent être complétées par des méthodes scientifiques basées sur l'intelligence artificielle et le recours aux méthodes de prise de décision multi-critères pour optimiser la sélection des joueurs et améliorer les performances tant sportives que financières. Il devient essentiel de rechercher un équilibre optimal entre le rendement sportif et la performance financière afin d'optimiser les résultats d'une entité spécifique: le club de football.

À cet égard, l'objectif principal de cette thèse est de proposer un modèle qui combine les techniques de machine learning et les méthodes d'analyse multicritères pour améliorer l'efficacité et l'objectivité du processus de sélection des joueurs de football, tout en tenant compte des considérations financières et managériales. Notre première contribution est de prioriser les critères techniques, physiques, tactiques et comportementaux des joueurs en utilisant les algorithmes Random Forest, Entropy et CRITIC. La seconde contribution est de classer les joueurs selon leurs performances en se basant sur la méthode TOPSIS.

Afin valider ces contributions, nous avons créé un système d'aide à la décision permettant au décideur sportif de suggérer des joueurs en fonction de leurs performances. Notre modèle ne vise pas à remplacer les entraîneurs, mais plutôt à intégrer des évaluations subjectives et objectives pour permettre une compréhension approfondie des facteurs de performance sportive et managériale, améliorant ainsi la précision de la sélection des joueurs. Alors que le football s'oriente vers des approches plus axées sur les données, la combinaison de l'IA et du MCDM peut optimiser davantage les processus de sélection des joueurs, en tirant parti des avantages de l'analyse de données objective et de l'expertise subjective. Les résultats obtenus démontrent l'efficacité de notre approche dans l'amélioration des performances des équipes de football, particulièrement lorsqu'elle est soutenue et assistée par l'intelligence émotionnelle, à savoir la capacité du manager à détecter l'état substantiel du joueur. **Mots-clés:** Management du football; Sélection des joueurs; Prise de décision axée sur les données; Apprentissage automatique; Prise de décision multi-critères; Optimisation des performances sportives.

Statement

"The University does not intend to approve or disapprove of the opinions expressed in this thesis. These opinions are to be considered as those of the author alone."

Dedication

To my beloved daughter, Sarah, and my darling son, Mohamed Amine,
To my loving husband, Hichem, who has been my unfailing support and confidant,
To my dear brothers and sisters, whose encouragement has been invaluable,
In loving memory of my dear parents, who set me on the learning path.

This thesis is dedicated to all of you, with gratitude and love.

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List of Publications

- Ati, A., Bouchet, P., and Ben Jeddou, R. (2024). Using multi-criteria decision-making and machine learning for football player selection and performance prediction: a systematic review. *Data Science and Management*, 7(2):79-88.
- Ati, A., Bouchet, P., and Ben Jeddou, R. (2024). Decoding financial and sporting dynamics: A decade of French ‘Ligue 1’ clubs. Accepted to the IHSI 2025 8th International Conference on Intelligent Human Systems Integration (IHSI 2025), February 24-26, 2025, Sapienza Universita’ di Roma, Italy.
- Ati, A., Bouchet, P., and Ben Jeddou, R. (2024). Optimizing Football Player Selection Using Random Forest for Criterion Weighting and TOPSIS for Ranking. Submitted to the IEEE International Conference on Decision Aid and Artificial Intelligence, October 31, 2024, ALECSO Tunis, Tunisia.

List of Abbreviations

AFP	Agence France-Presse
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
CRITIC	CRiteria Importance Through Intercriteria Correlation
DEA	Data Envelopment Analysis
DM	Decision Maker
DMUs	Decision Making Units
DSS	Decision Support System
ELECTRE	Elimination Et Choix Traduisant la Realité
EPL	English Premier League
FFP	Financial Fair Play
JI	Jaccard Index
MCDM	Multi-Criteria Decision Making
PFC	Professional Football Club
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PSG	Paris Saint-Germain
SLR	Systematic Literature Review
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UEFA	Union européenne des associations de football

Chapter 1

Introduction

1.1 Overview of the thesis topic

In football management, traditional methods of player selection have historically guided decision-making processes within clubs. This often subjective and uncertain strategic decision-making process (Dadelo et al., 2014; Purwanto et al., 2018; Salles et al., 2019) can have a significant influence on the financial, economic and sporting performance of the team, directly influencing the outcome of the match. Bad decisions can lead to team failure, resulting in sports and financial losses. As football moves towards a more data-driven sport, it is increasingly recognized that traditional approaches need to be complemented by scientific methods and relying on artificial intelligence and the use of machine learning, to optimize the selection of players and improve the sports and financial performance of teams.

A major challenge in the selection of players is the large number of attributes each player has. On average, there are about forty, covering various technical, tactical, physical and behavioral aspects. Our aim is not to replace coaches, but rather to find an optimal balance between ownership and control, as defined by Berle-Means. It is about reconciling technical decisions with a double constraint: sporting performance on the one hand and financial performance on the other, for the purpose to optimize the results of a given entity: the football club. A professional football club is often seen as a lucrative organization in

which the principles of marketing, human resources management, economics and finance are rigorously applied. These fundamentals are inextricably linked to the player, who is the main product of this organization.

Even if we can minimize the degree of subjectivity in player selection, we cannot be completely objective. It is true that football is inherently a field in which both objective and subjective considerations play an important role. This is because football is based on a connection between the exact sciences, such as medicine, and the humanities, such as psychology and sociology.

To minimize the degree of subjectivism and base the decisions of technical staff in the selection of professional footballers on more objective scientific criteria, we begin our methodological approach with a systematic literature review (SLR) to better understand current practices in the selection of players for line-ups, recruitment and transfers in professional football. By examining existing research, we identify trends, gaps and opportunities in the field, which allows us to develop our methodology and analyze our findings. By linking the results of our SLR to sport management concepts, we aim to develop more effective selection strategies and support recruitment decisions in the professional football world.

Our model integrates a grid of player salaries and incorporates a complete list of player criteria or attributes. Specifically, we draw our information from a database of nearly twenty thousand professional players, tracing the sports and financial attributes of each player as well as data on nearly five hundred clubs. These player criteria cover various aspects such as technical ability, tactical, physical and behavioral attributes to provide a complete understanding of each player's capabilities and suitability for selection.

Through the application of supervised machine learning approaches and objective weighting, we assess and prioritize these criteria. In addition, we use multi-criteria decision-making techniques to assess players' performance by considering their specific positions within the club. By leveraging these concepts, we aim to optimize player selection processes, enabling clubs to strategically bring teams together and make hiring decisions that not only improve field performance but also align with overall organizational strategies,

financial objectives, and human resources management principles.

Before studying the modeling of our selection problem, it was imperative to consider the concepts and notions derived from management. Our preliminary investigation focused on understanding the relation between financial, managerial and sporting results. As part of our study, we explored a concrete case of the French professional league 'Ligue 1' to study the relationship between the financial performance of a club and its position in the league. We have shown that over the ten years of study, the best-placed clubs in the league have the highest incomes and vice versa. We also highlighted how this relationship can inform a strong prediction of club revenues and league rankings. Key variables such as broadcasting rights, sponsorship, gate receipts and total payroll appeared to be determining the financial performance of clubs.

By putting into perspective the significant relationship between sporting success and financial - managerial results, [Galariotis et al. \(2018\)](#), highlighted that the priority given to the selection and choice of players is paramount for clubs, supporters, owners, managers and coaches. The players, being the pivot of sporting success, naturally occupy a central place in the priorities of the clubs. Our research underscores the crucial importance of player selection within the broader context of the club's strategic vision and management practices, highlighting the need for informed decision-making in recruitment and team human resources management.

1.2 Organization of the thesis

In this section we give an overview of the structure of the thesis. As mentioned earlier, the aim of this research is to develop a decision support system based on the integration of machine learning techniques and multi-criteria decision making approaches, while considering human resources management, marketing and financial perspectives to evaluate the performance of professional football players. This integration explains the inherent uncertainty and complexity of the decision problems, which arises from the need to manage a large number of criteria distributed for each player position within his club. In order to

achieve this goal, the thesis is organized in the following way:

Chapter 2: Football player selection: a strategic approach to sports management

This chapter presents the general theoretical framework, motivations, contributions and research questions of the thesis. It provides an overview of the concepts and theories underlying the evaluation of player performance and decision-making process in professional football management, including considerations of human resources management, marketing and financial concepts.

Chapter 3: Systematic literature review on football player selection

This chapter examines the literature streams on football player selection, focusing on subjectivity in the player selection process, player selection aligned with management principles, and AI- and MCDM-assisted player selection. In addition, the research methodology is explained, including the planning, execution and reporting of the review.

Chapter 4: Professional football clubs performance and decision-making

This chapter discusses the production processes of professional football clubs. It covers the concept of the production function, measuring both playing and non-playing performance (inputs), and measuring sporting performance (output). The chapter also delves into decision-making as the core of the sport management process, involving strategic decision-making, tactical decision-making, and financial and human resources decision-making. Additionally, a case study on the French professional football 'Ligue 1' is presented.

Chapter 5: Theoretical foundations for integrating multi-criteria decision-making and machine learning in sport decision-making

This chapter covers the theoretical foundations of sports decision-making, including an introduction to decision-making theory and key principles and concepts of sports decision-making, along with a review of MCDM approaches. It also provides an overview of machine learning concepts, discussing types of ML algorithms, steps in ML modeling, and the

random forest algorithm. The chapter concludes with the application of ML and MCDM in sports decision-making.

Chapter 6: A Decision support system for football player selection based on ML and MCDM techniques

This chapter focuses on modeling the football player selection system. It addresses the identification of the football player selection problem and the weighting criteria by player position using the random forest algorithm and MCDM methods for objective weighting (CRITIC and entropy). The chapter also details the football player ranking based on the TOPSIS method. Finally, it includes an evaluation of the football player selection system through a comparative analysis with real match data and interpretations.

Chapter 7: Conclusions and future directions

This chapter provides a research summary, highlights the major contribution of the thesis, discusses its shortcomings, and offers recommendations for future research.

Chapter 2

Football player selection: A strategic approach in sports management

2.1 Introduction

The overall goal of this thesis is to advance the field of sport management by integrating theories of human resources management, ML, and MCDM methods into the process of selecting professional players for competitions, recruitment and transfers. Our goal is to improve the understanding and efficiency of player selection processes by applying artificial intelligence techniques based on economic and management theories.

To begin our analysis, we address the conceptual and theoretical framework of our research and examine key concepts from the fields of marketing, economics, human resources management and financial management strategies. In particular, we explore how the selection of professional football players can enrich the analysis, deepen the conceptualization and provide valuable insights into these theories. Moreover, our study will investigate how and to what extent managers take decisions on selection and recruitment by referring to financial and human resources management strategies. This question is underpinned by the agency theory formulated by [Berle and Means \(1991\)](#), which underlines the challenge of reconciling the interests of shareholders with those of managers (the agents). The separation of ownership and control inherent in modern companies leads to this agency problem, where shareholders delegate to managers the power to run the company or football club on their behalf. However, managers may prioritize their own interests, such as job security, personal wealth or power, over maximizing value for shareholders. Berle and Means underscored the necessity of implementing mechanisms to align the interests of executives with those of shareholders.

This theoretical foundation will guide us in reviewing decision-making in sports organizations and emphasize the importance of reducing agency problems through an improved process of player selection and organizational performance. This process will demonstrate the importance of selecting the right players. By demonstrating this relationship, we aim to underscore the significant impact that the selection of talented players can have on football performance and the financial outcomes of sports organizations.

This chapter provides a synopsis of the conceptual and theoretical framework that en-

compasses marketing, human resources, economic and financial management considerations related to player selection in professional sport. It also focuses on optimizing the player selection problem. Furthermore, the challenges and motivations associated with this process are discussed, contributions are outlined, and research questions are formulated to guide our investigation.

2.2 The conceptual and theoretical framework

Football has emerged as one of the most lucrative industries, with significant economic impact driven by factors such as sponsorships, TV rights, and player transfer (Szymanski and Kuypers, 1999; Morrow and Howieson, 2014). The professional football landscape in Europe has rapidly evolved in recent decades, particularly due to the prevalence of media rights contracts. Today, many professional football clubs operate as complex businesses, mainly dealing with financial and managerial issues (Arrondel and Duhautois, 2018; Galariotis et al., 2018; Memari et al., 2021). These clubs have become attractive investment opportunities for wealthy individuals and renowned corporations. The influence of football has expanded beyond the realms of sports to involve political, social, and cultural dimensions, focusing increasingly on financial gains and managerial strategies, thus transitioning from a simple sporting activity to a corporate business.

Today, football plays a decisive role as an economic engine in many countries. Television broadcasters, sponsors, the logistics industry, the advertising sector and governments all benefit greatly from its influence. This economic impact is undeniable and reflected in various aspects of society, from job creation to the generation of significant tax revenues. football creates thousands of jobs in areas such as logistics, television, advertising and stadium management. In addition to job creation, football also contributes to government revenue through taxes and industry-related fees. Football clubs play an essential role in promoting the image of cities, attracting investors and stimulating the local economy through national and international competitions. In short, football is more than just a game. It has become a powerful engine of economic development, creating significant

opportunities and contributing to economic growth.

The selection of players in the management of professional football clubs is a critical task that has a significant impact on financial and sporting performance. This task is usually performed by managers and coaches and involves strategic decisions to assemble the most competitive teams. However, these decisions go beyond purely sporting considerations and also include economic and organizational factors. To fully understand the importance of player selection in this context, the study of Berle-Means theory and human resources management proves instructive as it sheds light on the interaction between the legal power of shareholders and the operational authority of managers in large organizations.

This perspective highlights the intersection of economic and sporting interests in player selection and the potential impact of decisions at this level on the overall performance and financial stability of football clubs. By incorporating these concepts into our analysis of player selection, our goal is to offer a thorough insight into the challenges and opportunities facing professional football clubs, while exploring strategies to effectively balance sporting and financial objectives.

To establish the conceptual framework for this research, we draw on various theories of general business and sports management. Before turning to the empirical study, we will introduce in detail the concepts and terms that form the basis of the research. These concepts come from the most important economic and managerial theories.

The objective is to adapt these concepts to the context of football management. It is crucial to acknowledge and honor the distinctive characteristics of sports management to prevent misapplications. Key concepts and terms that will guide this research include marketing, human resources and financial management. The conceptual and theoretical framework of our research will be deepened through a description of the fundamentals associated with the management of professional football clubs, marketing strategies, human resources, and financial management approaches. These fundamentals are outlined in the following subsections.

2.2.1 Professional football club

A professional football club is often seen as a lucrative organization, where the principles of marketing, human resources management, economics, and finance are rigorously applied. These principles are intrinsically linked to the players, who represent the main product of this organization.

This undeniable economic impact is reflected in various aspects of society, from job creation to significant tax revenues. Football creates thousands of jobs in areas such as logistics, television, advertising, and stadium management. In addition, Football clubs significantly enhance the reputation and image of cities, attracting investors, and stimulating the local economy through national and international competitions. Football has become a powerful vector for economic development, offering significant opportunities and contributing to overall economic growth.

Given the substantial economic impact of a professional football club, It is crucial to recognize how it operates. The structure and governance of clubs are fundamental components that ensure effective management and performance on and off the field. Let us take a look at the organizational structure, governance, and managerial models that contribute to the success of a sports club.

2.2.1.1 Organizational structure

The structure of a professional football club is essential for its proper functioning and success on and off the pitch. Typically, a professional football club is organized into several departments or sectors that work together to achieve the club's sporting, financial and organizational goals. The following is a general description of the primary structural components of a professional football club (Fig. 2.1):

- *The management and administration:* Responsible for strategic decision-making, financial management, and general supervision of the club. This often includes positions such as the president, the Chief Executive Officer, and other board members.
- *Sports department:* Responsible for managing the football team, including player

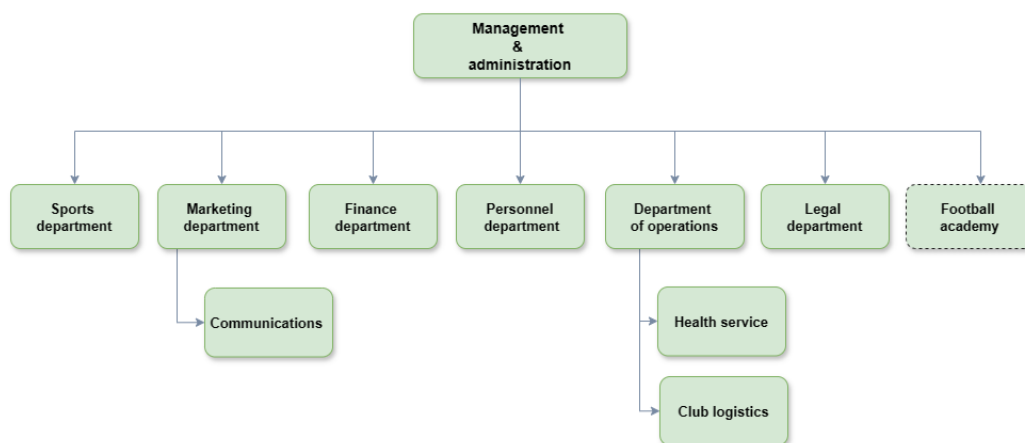


Figure 2.1: Proposed organizational structure of a football club

recruitment and training, match and training planning, and coordination of sporting activities within the club. These tasks are often carried out in collaboration with the coach or manager. Together, they identify recruits, plan training sessions, and ensure that players correspond to the team's style. The department also focuses on team cohesion and performance, which are essential for success on the field.

- *Marketing and sales department:* Responsible for promoting the club's brand image, ticket sales, sponsorship partnerships, merchandising and other initiatives aimed at maximizing the club's revenues.
- *Personnel department:* The human resources department handles the management of the club's staff, including player and staff contracts, and payroll.
- *Finance department:* Responsible for accounting, budget management, financial forecasting, and cash flow management of the club.
- *Communications department:* It manages the club's public relations, media relations, social networking, and other communication channels to maintain a positive public image and enhance the club's marketing strategy.
- *Department of operations:* It manages the club's facilities, match logistics, security, grounds maintenance, and oversees medical services to ensure the health and well-being of players.

- *Legal department:* It deals with legal and regulatory issues related to the operation of the club, including contracts, disputes, licenses, and other legal matters.
- *Football academy:* In addition to the professional team, many professional football clubs also have a football academy responsible for the training of young players and their eventual integration into the first team.

The organizational structure can vary from club to club based on factors such as size, budget, and specific objectives, as well as the governance and management models described below:

2.2.1.2 Governance structure

Governance is the structure that oversees the management and operation of the organization. It determines the organization's mission, policy and strategy. Governance is the responsibility of the Board of Directors, and focuses on long-term strategy and direction. The governance structure of a professional football club delineates how the club is operated, administered, and supported, and may vary based on the ownership structure and regulatory framework of the region in which it operates. As stated by [Michie and Oughton \(2005\)](#), corporate governance is paramount for English professional football clubs, especially given the challenging economic landscape surrounding the football industry. Recent studies have underscored the significance of good governance practices in ensuring effective club management and long-term survival. Two primary models, the European and American, are distinguishable:

European model: This model typically features a more traditional governance structure, with clubs often organized as associations or limited companies. Governance is overseen by a board of directors comprising elected or appointed members representing shareholders, supporters, and other stakeholders. This model is characterized by the following:

- The governance of professional football clubs in Europe is a complex and varied subject, with several key elements to consider. Unlike commercial enterprises, professional football clubs do not primarily aim for economic profitability but rather for

maximizing their sporting performance. Recruiting the best players leads to an arms race ("course aux armements") among the wealthiest clubs, resulting in inflation of salaries and transfer fees, which can cause financial difficulties for many European clubs (Andreff, 2007; Dermitt-Richard et al., 2019).

- Clubs often operate within the framework of a loosely defined budget constraint ("Contrainte budgétaire lâche" CBL), where despite recurrent deficits, they manage to secure external financing to avoid bankruptcy. Despite attempts at management control, many clubs in France and elsewhere in Europe face persistent financial difficulties, attributed to "poor governance" ("mauvaise gouvernance") characterized by a deficit that accumulates year after year (Dermitt-Richard et al., 2019).
- The concept of the Financial Fair Play, introduced by UEFA in mai 2010¹, also constitutes a key element of the governance of professional football clubs in Europe. The FFP aims to promote financial stability and long-term viability of clubs by regulating their expenditures relative to their revenues (Dimitropoulos and Scafarto, 2021). Clubs that fail to comply with FFP regulations are subject to sanctions, including fines and restrictions on player transfers. These sanctions are an integral component of the financial regulatory framework governing European professional football.
- Research has examined the impact of governance structures of European football clubs on their ability to generate funding and invest in players (Dermitt-Richard et al., 2019). Additionally, there is a joint manifesto on the governance of European football, aiming to reflect the rights of stakeholders in the professional football industry².
- The governance of professional football clubs in Europe is an ever-evolving field, with complex financial, sporting, and regulatory challenges that require ongoing attention (Drut and Raballand, 2010).

American model: In contrast, the American governance model tends to prioritize a business-oriented approach. Clubs may be owned and managed by private investors or

¹Source: www.uefa.com/FFP. Accessed on Mai 2023.

²Source: www.ffipro.org/media. Accessed on Mai 2023.

corporations, with a strong emphasis on financial profitability and maximizing shareholder value. The most important elements that distinguish this model are:

- The Major League Soccer (MLS)³ serves as the primary organizing body for professional football in the United States. It operates under a closed league model, meaning clubs do not have to fear relegation to a lower division, unlike the European system of promotion and relegation based on sporting performance.
- Ownership of MLS clubs is typically held by private investors, corporate groups, or individual owners, favoring a private ownership model rather than the cooperative model adopted by some European clubs owned by supporters.
- Each MLS club is managed by a board of directors or advisory board, responsible for strategic decisions, player recruitment, and financial management.
- The MLS is overseen by a central commission that establishes rules and regulations for the entire league. This commission, comprised of club representatives, MLS leadership, and other stakeholders, manages aspects such as broadcasting rights, player transfers, contracts, and financial matters.
- In contrast to many European clubs facing financial difficulties, the MLS has implemented salary cap rules to maintain a certain financial balance among clubs and prevent excessive spending. These rules limit player salaries and overall club expenses, thereby helping to prevent financial inequalities and ensure a degree of stability.
- The governance of professional football clubs in the United States is influenced by factors such as the closed league model, private ownership, central regulation, and budget constraints, thus distinctly differing from the European model (Dermitt-Richard et al., 2019).

A comparison of these models highlights significant differences in their respective approaches. The European model often seeks to balance various forces within the organiza-

³Source: www.fr.wikipedia.org/wiki/Major_League_Soccer. Accessed on April 17, 2024.

tion to optimize overall performance, valuing individual and cultural diversity as sources of creativity and innovation.

Conversely, the American model places greater emphasis on the market economy and shareholder value maximization, with management decisions often focused on satisfying shareholder interests. External governance mechanisms in the American model rely heavily on market control and legal system influence.

While the European and American governance models represent contrasting approaches to the management football clubs, both share the common goal of ensuring the success and sustainability of their respective organizations. However, beyond governance structures, another critical aspect of club management lies in the managerial model adopted by these clubs. This model delves into the day-to-day operations, decision-making processes, and strategic planning undertaken by club management to achieve their objectives. Let's now explore how the club management shapes the functioning and performance of professional football clubs.

2.2.1.3 Club management

Management focuses on the day-to-day operations of an organization. It incorporates planning, organizing, and coordinating resources to achieve specific objectives. Managers are responsible for the company's strategic and operational direction. Managing a professional football club is a complex task, requiring several challenges to be addressed. Here are some of the main issues facing club managers:

- **Financial pressure:** Clubs must constantly balance their revenues and expenses to maintain financial sustainability. Player salaries often represent a significant portion of expenses, making it crucial to maintain a stable financial balance.
- **Player management:** Recruiting, managing, and motivating players are essential elements for team success. Managing personalities, injuries, and transfers is a daily challenge for managers.
- **On-field performance:** Expectations from supporters, sponsors, and owners are high

when it comes to on-field results. Coaches must not only deliver positive outcomes but also develop an attractive style of play to maintain stakeholder interest and engagement.

- **Fan engagement:** Sustaining a loyal fan base is essential for financial stability and matchday atmosphere. Effective fan communication and relationship management are major challenges for clubs.
- **Regulatory compliance:** Clubs must adhere to regulations set by FIFA, UEFA, and national leagues. Sanctions for non-compliance can be severe, underlining the importance of regulatory compliance.

To better address the operational issues mentioned above, professional football clubs rely on key actors to ensure effective management and promote success.

Club owners/Board of directors:

- The club owner or board of directors provide strategic direction and oversees major decisions related to the club's operations. They are responsible for appointing key personnel such as the club manager and general manager. Their decisions impact the club's financial investments, long-term planning, and overall direction.

General managers/CEO:

- The general managers or chief executive officer (CEO) handle the administrative and operational aspects of the club.
- They oversee non-football-related operations such as finance, marketing, facilities management, and community engagement.
- The general managers ensure the smooth functioning of the club's business operations and implements strategies to enhance revenue generation and organizational efficiency.

Club Managers (Sporting directors):

- The club managers, also known as the sporting directors, are responsible for the management of the first team. They supervise player recruitment, team selection, tactics, and on-field performance. Beyond overseeing technical aspects of the game, managers handle transfers, contracts, player relations, media interactions, and fan engagement. Their involvement extends to long-term strategic planning, making them a vital component of the club's overall management structure. The manager works closely with the coaching staff and players to achieve sporting objectives set by the club.

Coaching staff:

- The coaching staff includes assistant coaches, goalkeeping coaches, and other specialists who work under the direction of the club manager. They are involved in training sessions, match preparation, and player development. The coaching team plays a crucial role in implementing the manager's tactical plans and ensuring the players' fitness and preparation. The coach, usually affiliated with the club's sports department, focuses on the team's performance on the pitch. Responsibilities include tactical preparation, player development, team selection, and training management.

Support staff:

- Support staff members include medical professionals, fitness trainers, physiotherapists, and sports scientists. They focus on player health, injury prevention, and physical conditioning to optimize player performance. Support staff work collaboratively with the coaching staff to maintain player fitness and well-being throughout the season.

Scouting staff:

- The scouting department is responsible for identifying and recruiting talented players to strengthen the squad. Scouts analyze player performance, assess potential transfer targets, and provide recommendations to the manager and recruitment team. The scouting department plays an essential role in building and maintaining a competitive team.

Figure 2.2 illustrates the information system of a professional football club, showcasing key actors responsible for addressing operational challenges and promoting success. It also shows the flow of information exchanged between strategic, tactical, and operational management subsystems, as well as communication with the external environment.

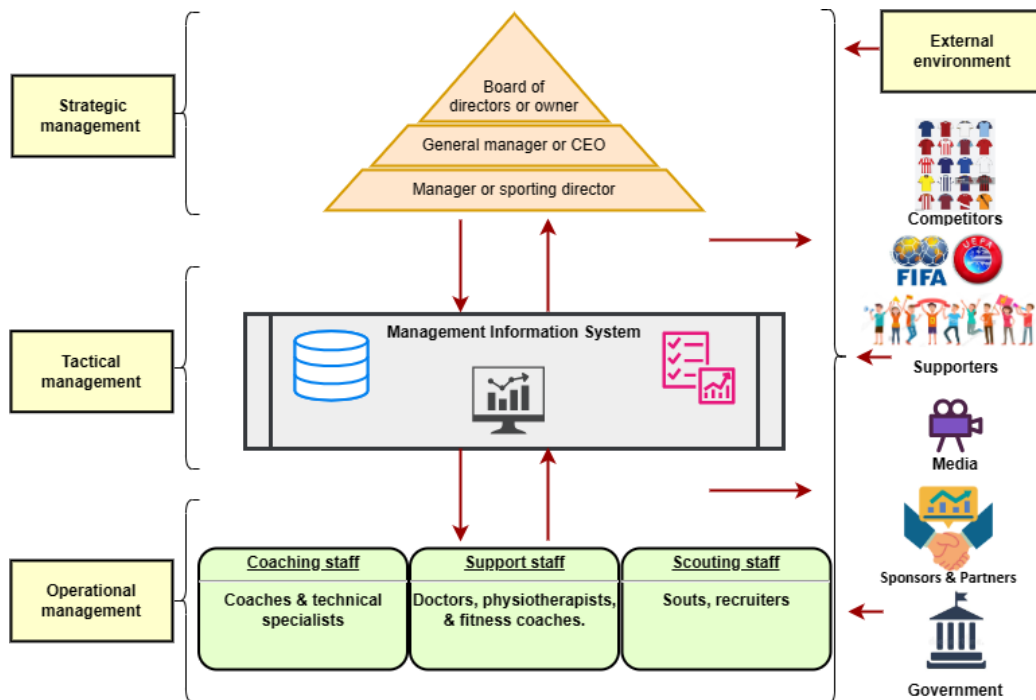


Figure 2.2: Professional football club information system (By the author)

Having described the organizational structure, governance, and management of a professional football club, we now have an insight into the inner workings of these dynamic organizations. Our attention now turns to another key aspect: the club's marketing strategy. This section examines football clubs' strategic initiatives to strengthen their brand presence, foster fan engagement, and optimize revenue channels.

2.2.2 Marketing strategy

Marketing is an essential area for any company that seeks to influence demand and achieve its goals. It is based on fundamental principles, including the 4Ps: product, price, place, and promotion (McCarthy, 1960).

2.2.2.1 Product

At the core of any marketing strategy lies a deep understanding of the product. It represents the company's offering to its customers. It is crucial to comprehend the product thoroughly: who needs it, why, and what are its distinctive features compared to competing products? This in-depth analysis helps define the product clearly and identify its positioning in the market. Moreover, it is vital to recognize that every product follows a life cycle, from conception to maturity.

Marketing strategies must adapt to each stage, whether emphasizing promotion and awareness during the launch of a new product, or prioritizing customer retention and continuous innovation for a mature product (Albrecht et al., 2023). In fact, innovation is actually the main vector of marketing; it links promotion and awareness. Production is essentially promoted by digital and numerical tool which are the fundamental referent of digital marketing. This latter is based on numerical and AI of product and promotion conception.

In the context of a football club, the product encompasses the entire team and each individual player. It is crucial to deeply understand the supporters' needs: why do they follow the team? What attracts them to the players and the game? The distinctive characteristics of the team and each player are essential in defining their positioning in the football market. Additionally, each player undergoes a lifecycle. From promising youth to peak performance on the field, and eventually decline, marketing strategies must adapt to each stage of a player's career.

The cornerstone of a professional football club is its players, who not only serve as a primary product, but also act as a central pivot around which all activities revolve. In player marketing, each player serves both as the product itself and as an important advertising platform. Their performance on the pitch, reputation, and influence on the team's results directly shape the club's image and reputation. However, the value of a player extends beyond the field, acting as a vector for various revenue streams and business opportunities.

The popularity of a player often leads to the creation and sale of merchandise bearing their name or image, such as jerseys, caps, posters, and toys, which become fan favorites

and additional sources of revenue for the club. Moreover, a star player's presence attracts media attention, business partners and sponsors, leading to sponsorship contracts, advertising campaigns, and licensing agreements that generate significant marketing revenue. In addition, a player's performance can have an impact on match attendance, as fans want to see their favorite player in action, increasing ticket sales and box office revenue. Furthermore, players attract not only fans but also media coverage and interest from investors, solidifying their role as primary drivers of the club's commercial activities.

2.2.2.2 Price

Once the product is ready, determining its price becomes a crucial step in the marketing strategy. It must be carefully aligned with the perceived value of customers and competition in the market, striking a delicate balance between maximizing revenues and maintaining competitiveness (Albrecht et al., 2023). Pricing strategies can vary based on several factors, including product market position, consumer demand, production costs, and other economic variables.

The price represents the monetary value that customers must pay to acquire the product or service, influencing not only customer perception but also company profitability. Proper pricing can attract and retain customers, ensuring the long-term financial viability of the business. Thus, price plays a pivotal role in marketing strategy and competitiveness, requiring in-depth analysis of market dynamics and customer needs.

In football, the "price" of players is an essential component of a club's management strategy. As emphasized by Müller et al. (2017), the cost of acquiring and maintaining players can greatly influence a club's finances and influence its competitiveness on the field. A player's market value is often influenced by various factors such as sport performance, growth potential, experience, age, field position, reputation, and even the context of the transfer market.

Stars usually have a higher economic value in terms of transfer and salary. Their presence can significantly boost ticket sales, TV contracts, and media exposure, thereby enhancing the club's financial standing and marketability. However, support players (water

carriers) may have lower economic value in terms of transfer and salary compared to stars, but they remain essential for the balance of the team.

Clubs must therefore perform a careful analysis to assess the real value of a player and determine a reasonable purchase or sale price. Player transfers can involve astronomical sums, as seen in high-profile transfers like Paul Pogba's move from Juventus to Manchester United for 105 million euros in 2016, or Kylian Mbappé's record-breaking transfer to Paris Saint-Germain for 180 million euros in 2017. Similarly, emerging talents like Endrick, a young Brazilian prodigy, command significant fees, such as his anticipated transfer to Real Madrid for 72 million euros in 2024⁴. These examples highlight the substantial financial investments associated with player transfers, especially for world-renowned players or promising young talents.

Clubs must be prepared to invest significant amounts of money to acquire the best talent available in the transfer market, in the hope of strengthening their team and competing at the highest level. At the same time, clubs also have to manage players' salaries, which often represent a large part of the club's expenses. Players' salaries can vary considerably depending on their experience, status, performance and competition in the player market. Clubs should establish fair and sustainable salary policies, ensuring that salaries remain competitive while preserving the financial stability of the club in the long term.

Clubs also set prices for match tickets and merchandise. These prices must be set to maximize revenue while remaining competitive in the marketplace. Strategies such as special offers, seasonal promotions and brand partnerships can also influence fans' purchasing decisions and stimulate merchandise sales. Indeed, appropriate pricing can help maximize club revenues while maintaining fan commitment and loyalty.

2.2.2.3 Place

Place, also known as placement or distribution, focuses on how the customer acquires the product. Marketers need to ask questions such as: where and how is the product available? Distribution channels, logistics and geographical availability are key elements to consider

⁴Football Transfers. www.footballtransfers.com. Accessed on March 27, 2023.

to ensure that the product reaches consumers effectively (Albrecht et al., 2023).

In the context of a football club, distribution is not limited only to the availability of merchandise or match tickets. It is also about making the team and players accessible to fans, whether physically or virtually. Distribution involves the availability of match tickets at various points of sale, such as the stadium ticket offices, the club's official shops, authorized dealers, and online platforms. It also involves the club's online presence through its official website, mobile apps, and social media platforms. These digital channels offer fans the opportunity to buy tickets, follow team news, interact with players, and even watch matches live, regardless of their geographical location. A well-designed digital distribution strategy can expand the club's reach beyond its local market and attract fans from around the world.

Additionally, the specificity of players, such as their unique skills and characteristics, adds another layer to the distribution aspect in football clubs. Unlike physical products that can be sold online, players cannot be sold directly through digital platforms. Instead, player distribution often involves transfer negotiations, contract agreements, and scouting processes conducted by club executives and agents. This aspect highlights the complexity of player management within the distribution framework of football clubs.

Moreover, distribution may also include participation in community events, signing sessions, and promotional tours, where players and the team can meet directly with supporters and strengthen ties with the local community. Thus, the distribution of the products derived from a football club can also be used to promote and support the social and humanitarian initiatives with which the players are associated, thus reinforcing the loyalty and commitment of the fans to the club and its values.

2.2.2.4 Promotion

Promotion encompasses advertising, public relations, and various other promotional strategies, such as print advertisements and television, internet and social media advertising, and participation in trade shows. A company's promotional endeavors aim to raise awareness of the product and elucidate the reasons why customers should opt for their product (Albrecht

et al., 2023).

In the dynamic world of football marketing, player promotion is a fundamental strategy, where clubs meticulously shape the image and visibility of their athletes to stimulate fan engagement, the growth of the brand and capture the attention of the media and investors.

- **Player branding:** creating a positive and consistent image for each player is crucial. This includes their behavior on the field, their interaction with fans, their involvement in the community, and their presence on social networks. Football clubs need to work closely with players to shape their public image and enhance their attractiveness.
- **Public relations:** It plays a key role in promoting players. The clubs organize press conferences, interviews and media events to introduce their players. Public relations help manage crises, respond to media requests and maintain transparent communication.
- **Digital marketing:** social media plays an important role in promoting players. Clubs create official profiles for players, share best moments, practice videos, interviews and behind-the-scenes content. Fans can directly connect with their favorite players via these platforms. It is important to note, however, that player promotion is not conducted online, as is the case with other products.
- **Partnerships and sponsorships:** players can serve as brand ambassadors. Clubs negotiate sponsorship agreements with companies to associate their brand with players. This may include agreements for advertisements, merchandise, and special events. Furthermore, it is essential to acknowledge the significance of athletes as ambassadors of goodwill and disseminators of values.

Players are often chosen not only for their skills on the field but also for their ability to convey human values and social ideals. For instance, some players may be designated as ambassadors for charities like UNICEF or other philanthropic initiatives, leveraging their influence to raise awareness for significant causes and mobilize funds for humanitarian projects. Similarly, a player who embodies national or regional values can become a sym-

bol of pride for their community, serving as a flag bearer on the international stage and strengthening the link between the club and its fans.

The marketing strategy of a professional football club is fundamentally centered around its players. They represent the main product and the central driving force behind the club's activities both on and off the field. Their performance, popularity, and influence play a significant role in shaping the club's brand image, strengthening fan loyalty, and driving revenue growth.

Given the strategic role that players occupy in the success of a football club, they need to be carefully selected and managed. This includes recruitment, team composition, and transfers, ensuring alignment with the club's objectives and competitiveness. Human resources management is essential to meet players' needs, including professional development, recruiting, selecting, developing, and overall management to ensure the club's sustainable success and growth.

2.2.3 Human resources management

In professional football, effective human resources management (HRM) is essential to build and maintain a successful team. This section explores the fundamental principles guiding human resources practices in football hiring, organizations, including criteria for evaluating players, and profiles of different types of players.

2.2.3.1 Fundamental principles

The fundamental principles of HRM, as outlined in [Pennaforte et al. \(2022e\)](#), provide an essential framework for the development, management, and optimization of human resources within an organization. For a professional football club, HRM includes recruiting, developing, and managing football players, with the objective of ensuring the club's long-term success.

In the context of a football club, HRM manifests in several key areas:

- **Recruitment of employees :** Recruitment, as defined by [Pennaforte et al. \(2022b\)](#), is the process of identifying, searching, filtering, and selecting qualified candidates

for vacant positions within an organization. Unlike traditional organizations, where employees are typically selected based on academic qualifications and professional experience, football players are recruited based on their skills, ages, and potential contribution to the team.

It's important to note that in football, players serve a dual role – they are not only the employees of the club but also the primary product on and off the field. Therefore, clubs must carefully evaluate players not only for their playing abilities but also for their marketability and contribution to the club's brand. This unique aspect of football recruitment emphasizes the importance of selecting players who not only excel in their performance but also align with the club's long-term objectives, especially that player can be employed by many different clubs.

- **Employee compensation:** The introduction of a fair and competitive remuneration policy that recognizes employees' contribution to the company. This can include competitive salaries, benefits, bonuses, performance incentives, and other forms of reward ([Pennaforte et al., 2022c](#)).

Football clubs offer players wages, benefits, and bonuses based on individual and collective performance. Players' employment contracts are often negotiated with their agents and may include specific clauses on compensation, bonuses, and benefits. However, the total wage bill is the largest expense for a football club, with the largest portion being player salaries. The salaries of star players are often much higher than those of supporting players.

In addition to traditional compensation, star players can also earn income through various channels such as social media, advertising, and sponsorship contracts. Wage is not always the determining factor in player contracts. Past experience has shown that some players prefer to stay with their club despite higher salaries offered elsewhere. Loyalty and love for a club are essential determinants in contracts, unlike non-sports activities.

- **Workforce planning and skills development:** This involves anticipating future

staffing needs and investing in developing employees' skills and knowledge to improve their performance and foster their professional growth (Pennaforte et al., 2022a). For football clubs, this means implementing various training programs, mentoring initiatives, leadership development activities, and other skills development opportunities. These efforts aim to maximize the potential of players to manage their career and ensure their continuous improvement. The club devotes resources to developing players' skills through a range of activities, including regular training sessions, specialized fitness programs, and customized workouts tailored to individual needs.

By investing in skills development, clubs aim to optimize player performance and contribute to their long-term success on and off the field. Moreover, clubs allocate resources to identify, recruit, and cultivate promising young players. These efforts aim to maximize the potential of the talents and prepare them for future roles within the club. By focusing on the development of young players, clubs not only strengthen their talent pool but also contribute to the sustainability and long-term success of the organization.

- **Improving working conditions:** Enhancing the working environment and conditions to ensure the well-being and satisfaction of employees. This includes providing adequate facilities, equipment, and support services (Pennaforte et al., 2022d). Football clubs prioritize maintaining positive relationships with players, fostering a conducive work environment, and treating players with respect and fairness. These efforts aim to strengthen team cohesion and enhance performance on the field. In traditional firms, employees have their careers and retirements managed by specialized organizations. Similarly, these same social security organizations handle health insurance and unemployment benefits.

In football, players and agents manage their careers and plan their retirements as there is no legal retirement age. As well, it is the responsibility of the clubs, the employers, to cover all medical expenses and ensure the players' well-being. Clubs often act as a second family to players, trying to create the best family environment

in terms of housing, facilities, memberships to various sports clubs, entertainment, and ensuring the education of children in the best schools.

Such a characterization of the fundamental principles of human resources, allows us to specify the main reference criteria for the evaluation of players. These latter are crucial in guiding the recruitment, development, and management of players within football clubs. By considering these elements, we can gain a better understanding of how human resources principles helps into the selection and management of football players.

2.2.3.2 Criteria selection in football management

Professional football players are characterized by a multitude of attributes or criteria that define their performance. In this section, we delimit the specific criteria used to evaluate football players. These criteria cover various dimensions, including physical, technical, tactical, behavioral, and goalkeeper attributes. They will help us assess player performance and serve as the basis for our multi-criteria analysis. Notably, our database includes over thirty-six distinct criteria for a thorough evaluation. For a concise overview, refer to [Table 2.1](#), which outlines these criteria alongside their detailed descriptions. These criteria are reflecting the classification based on FIFA Encyclopedia⁵.

Table 2.1: Definitions of criteria for football players

Criteria	Descriptions
Physical	
Acceleration	The increase in a player's running speed is influenced by their acceleration rate, which determines how quickly they can attain their maximum sprint speed.
Aggression	The aggression level of a player in tackling, pushing, and pulling.
Balance	A player's ability to remain upright and steady while running, carrying, and controlling the ball
Shot Power	The strength of a player's shots.

⁵Source: FIFA. www.fifplay.com/encyclopedia/player-attributes. Accessed on January 2023.

Table 2.1: Criteria definitions (Continued)

Criteria	Descriptions
Sprint Speed	Rate of a player's sprinting (running).
Stamina	A player's ability to sustain prolonged mental or physical effort over the course of a game.
Strength	The state or quality of being physically strong for a player.
Technical	
Agility	Indicates the speed and skill with which a player can control the ball.
Ball Control	The capability of a player to manage the ball on the field.
Crossing	The accuracy of a player's crossing.
Curve	The player's ability to curve the ball when shooting and passing.
Dribbling	The ability of a player to take the ball in front of an opponent while having control.
Finishing	The ability of a player to score.
Short Passing	Player's accuracy for short, precise passes during the game.
Tactical	
Interception	A player's capability to intercept the ball and catch the opposing team's passes
Jumping	A player's ability to jump from the surface for headers.
Long Passing	player's accuracy and ability to execute longer, more strategic passes across the field.
Long Shots	Player's precision for long-range shots distances.
Marking	A player's ability to mark an opponent and prevent him from gaining control of the ball.
Penalties	A player's precision on penalty kicks.
Positioning	A player's ability to position himself on the pitch.
Behavioral	

Table 2.1: Criteria definitions (Continued)

Criteria	Descriptions
Composure	A player's state of feeling calm and their ability to control frustration during matches.
Skill Moves	Special moves that players can perform with the ball. They are rated from one to five stars.
Sliding Tackle	A tackle in which the tackler uses their leg or legs to slide to their opponent's body and take the ball away from them.
Standing Tackle	A player's ability to make a standing tackle.
Vision	A player's mentally aware of his teammates' positioning to pass the ball to them.
Volleys	A player's ability to perform volleys.
Weak Foot	Shooting power and ball control for this player's other foot than his preferred foot.
Work Rate	The level of effort and activity a player puts in during a match, both defensively and offensively.
Goalkeeper	
GK Diving	A player's ability to dive as a goalkeeper.
GK Handling	A player's ability to manipulate and hold the ball using their hands as a goaltender.
GK Kicking	A player's ability to kick a ball as a goalkeeper.
GK Positioning	Goalkeeper positioning on the goal line.
GK Reflexes	A player's ability and speed of reaction to catch or save the ball as a goalkeeper.

These criteria are the main references for evaluating football players, understanding the profiles of players and their importance in professional football.

2.2.3.3 Player profiles management

Football, a team sport played by two opposing teams, consists of eleven players each. This includes ten outfielders and a goalkeeper. Those chosen to start a match are called starting line-up, distributed in several positions such as goalkeeper, defender, midfielder, and forward. Each position serves a specific role on the field (Hughes et al., 2012):

- **Goalkeeper:** stationed directly in front of the goal, the main duty of the goalkeeper is to stop the opposing team from scoring by saving shots and coordinating the defense.
- **Defender:** defenders play an important role in protecting the team's goal by intercepting passes, tackling opposing players, and clearing the ball out of the defensive area.
- **Midfielder:** midfielders operate in the middle of the field and serve as the link between defense and attack. They are responsible for controlling possession, distributing the ball, and supporting both offensive and defensive phases of play.
- **Forward:** forwards, also known as strikers, are positioned closest to the opponent's goal and are responsible for scoring goals. They use their speed, agility, and shooting ability to create scoring opportunities and convert chances into goals.

From these positions, except for the goalkeeper, emerge the terminologies "stars" and "water carriers", often used in the context of professional football to describe different types of players. In traditional businesses, employees in the same position and function typically receive the same wage. However, in football, the treatment varies depending on the status and importance of the player. Players are often classified as "stars" or "water carriers," even when they occupy the same position.

- The "**stars**" or elites are usually high-ranking players with exceptional skills on the pitch. They are in the public eye and receive great recognition from fans and the media. Their ability to score goals, make passes and influence the course of a game puts them at the top of the football hierarchy. These players benefit from high

salaries that reflect both their talent and their commercial power. Financially, the "stars" usually have a significant impact on the club's revenue. Their status as the best players attracts investors and sponsors, generates ticket and merchandise sales, and can lead to lucrative advertising contracts. The "stars" can also increase the market value of the club on the transfer market, by attracting the attention of big clubs and bringing in considerable sums of money in the event of a transfer.

- **"Water carriers"** or supporting players are often hard-working players who are tactically disciplined and willing to perform less glamorous tasks on the field for the sake of the team. They can be defensive midfielders or forwarders, side defenders or support players who provide constant support to their teammates. Despite relative lower salaries than the stars, their contribution to the balance and stability of the team is invaluable (Rosenior, 2017). Although they may not receive the same media attention as the "stars", their contribution remains valuable financially. Their commitment and hard work help maintain the stability of the team and preserve its reputation, which can have a positive impact on the club's incomes in the long run.

The attribute "skill moves", usually scored on a scale of 1 to 5, serves as a crucial indicator of a player's skill in performing technical and creative maneuvers on the field. Those with high scores in this attribute are often recognized as "stars", able to orchestrate goal opportunities and destabilize the opposing defense with their dribbling and agility.

Conversely, the "work rate" attribute rates a player's level of effort and activity during a game. Players with a high "work rate" are often identified as "water carriers" who are willing to put in sustained effort in defensive and support roles, thus strengthening the resilience and unity of the team. Players with a lower "work rate" can be referred to as "stars", compensating for their lower defensive activity with decisive contributions in the offensive phases of the game.

When selecting players, clubs must therefore skillfully navigate between these two profiles and strive for a balance that combines the individual talent of the stars with the collective commitment and teamwork of the water-carriers. This process of player selection and balancing player profiles underlines the fundamental principles of personnel management

in professional football.

By applying these human resources management principles appropriately, football clubs can maximize the potential of their players, strengthen their team and improve their performance on the pitch. In the context of football, human resources management includes the distinction between "star" and "water-carrying" players, as well as the importance of placing players in the right positions according to their specific skills and performance criteria.

First of all, the recruitment and selection of players must be conducted carefully, taking into account the proven recruitment theories. Football clubs often employ specialized recruiters for each position on the field, tasked with identifying players with the skills and qualities to excel in specific roles. In traditional businesses, a job offer is usually published to recruit new employees, while in football, clubs task their recruiters with headhunting: identifying stars and talents. That's why recruiters in football must have specialized skills. Once recruited, players sign contracts that govern their compensation and benefits.

Unlike other professional fields where compensation is often based on marginal productivity, salaries in football can be based on factors such as the player's reputation, experience, position on the field and competition in the player market. Furthermore, the special nature of football starts at a young age, with particular attention paid to the training of young players. Clubs invest in their training academies to develop the technical, tactical and mental skills of young talents so that they can later be integrated into a team.

Finally, the promotion and career management of players is also an important aspect of personnel management in football. Clubs can implement career development strategies to help players progress and reach their full potential. This can include additional training opportunities, mentoring sessions with more experienced players and promotions to leadership positions within the team.

The selection of football players, whether stars or water carriers, can have a significant impact on the result of a match and the financial situation of a club. Optimal player selection can improve on-field performance, which translates into wins, increased fan loyalty, higher ticket and merchandise sales, and better broadcast rights. On the other hand,

poor player selection can lead to poor performance, resulting in losses, reduced fan interest, lower revenue and potential financial pressure on the club. It should be noted that the recruitment of talented players can alter the balance between sporting performance and financial success.

2.2.4 Financial management

Mobilizing financial resources is crucial for the economic stability and growth of professional football clubs. In this section, we explore the various revenue sources and expenses involved in the financial management of football clubs.

2.2.4.1 Revenue sources of professional football clubs

Governments and private companies are investing in the development of sports infrastructure, such as stadiums, training centers, and related facilities. These investments not only benefit football clubs, but also create employment opportunities and stimulate the local economy. Governments, private companies, and individual investors play a significant role in supporting the financial needs of football clubs through various sources of revenue. These sources of revenue include:

- **Partnerships and sponsorship:** Football clubs establish partnerships with local and international companies, allowing sponsors to finance teams in exchange for visibility on jerseys, advertising spots, and media platforms. Sponsorship contracts contribute significantly to the revenue generation of clubs.
- **Match revenues:** Revenue from ticket sales or gate receipts and hospitality packages during matches are essential income sources for football clubs. The size and popularity of the club, as well as the competitiveness of the league, influence match-day revenues.
- **Broadcasting rights:** Broadcasting rights agreements with television networks and streaming platforms generate substantial revenues for football clubs. Broadcast rights are often sold to networks for live coverage of matches and exclusive content.

- **Player transfers:** Transfers of players between clubs involve significant sums of money, with transfer fees contributing to the revenue of selling clubs. Successful player development and scouting strategies can lead to lucrative transfer deals, providing clubs with additional funds for investment.

As an example, Figure 2.3 illustrates the total net income, encompassing transfer operations, of French 'Ligue 1' football clubs from the seasons 2017-2018 to 2021-2022. Notably, broadcast rights appear to be a major contributor, accounting for more than 30% of the league's total revenue.

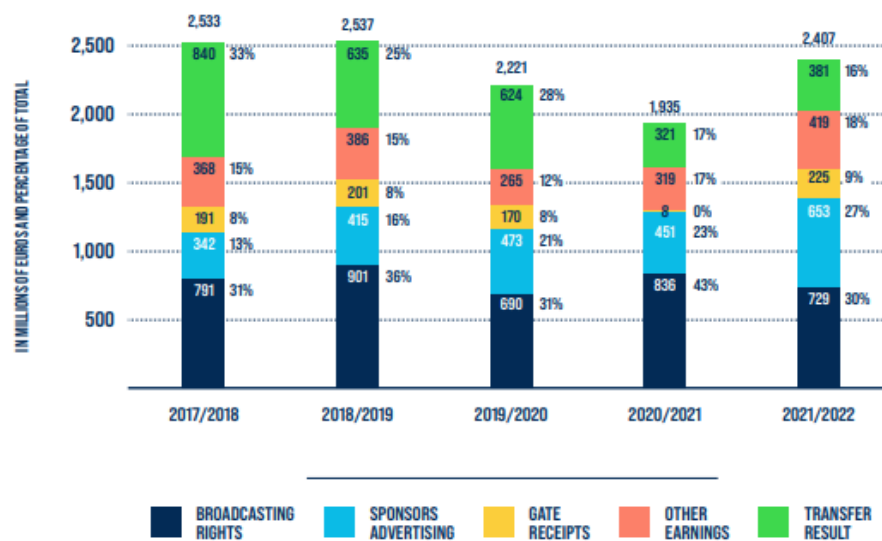


Figure 2.3: Evolution of total revenue of French 'Ligue 1'
Source: DNCG (2021)

2.2.4.2 Expenses and investment of professional football clubs

While revenue generation is vital, effective financial management also involves careful allocation of resources and investments in key areas to ensure sustainability and long-term success. Expenses and investments in professional football clubs include:

- **Player salaries and transfer fees:** Player salaries constitute the main portion of a club's expenses. Clubs must budget for player salaries and allocate funds for transfer fees when acquiring new players. Balancing player wages with the club's financial capabilities is crucial to maintaining financial stability.

- **Operating expenses:** Operating expenses include various costs related to the management of the club, including staff salaries, travel expenses, and administrative overheads. Controlling operating expenses is essential to effectively manage financial resources.
- **Infrastructure investment:** Investment in sports infrastructure, such as stadium upgrades, training facilities, and youth academies, is essential for the long-term development of football clubs. These investments enhance the club's facilities and contribute to overall success on and off the field.
- **Scouting and Recruitment:** Investment in scouting and recruitment strategies is vital for identifying and acquiring talented players. Clubs allocate funds for scouting trips, player assessments, and recruitment staff to strengthen their squads and maintain competitiveness.
- **Marketing and Promotion:** Clubs invest in marketing and promotional activities to enhance their brand visibility, attract sponsors, and engage fans. Marketing expenses include advertising campaigns, social media outreach, and fan engagement initiatives.

Figure 2.4 provides an overview of the operating expenses of French 'Ligue 1' from the 2017-2018 to 2021-2022. The total payroll, which includes player and staff salaries, appears to be a significant contributor, accounting for 47% of the league's total spending for the 2021-2022 season.

By strategically managing expenses and investments, and maximizing revenue opportunities, professional football clubs can achieve financial sustainability and success in the dynamic and highly competitive football industry.

After delving into the concepts of marketing, human resources, and financial management within professional football clubs, it becomes clear that resources optimization plays a significant role in the success and longevity of an organization. As clubs strive to maintain a delicate balance between maximizing on-field performance and financial stability off the field, one aspect emerges as particularly critical: *player selection*. Transitioning from

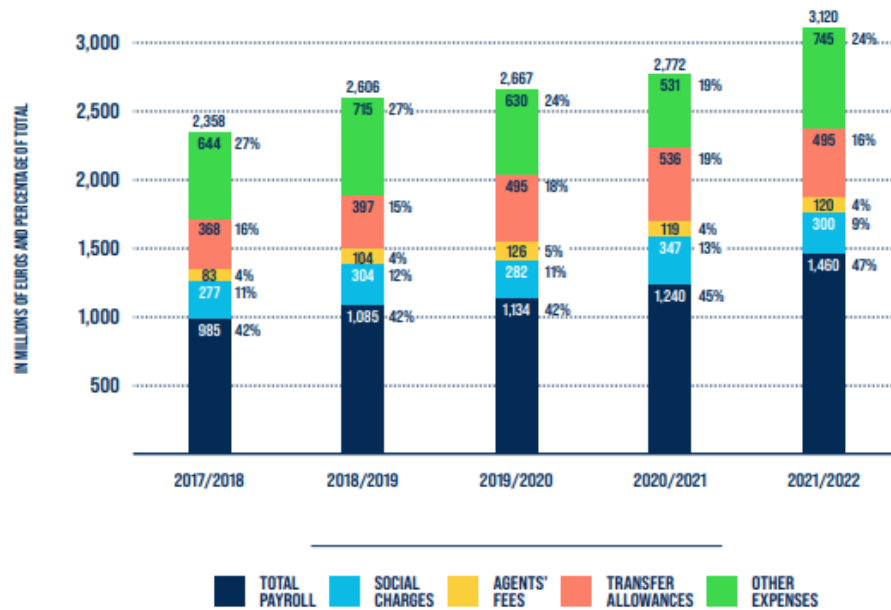


Figure 2.4: Evolution of operating expenses of French 'Ligue 1'
Source: [DNCG \(2021\)](#)

the conceptual and theoretical framework established previously, we now delve into the challenges and motivations of player selection problem.

2.3 Optimizing player selection problem

According to [Stephenson \(2012\)](#)⁶, player recruitment is considered one of the most important operational tasks for an elite football club. Ineffective recruitment can lead to significant costs in terms of performance, results, wages and transfer fees, thereby reducing the potential return on investment for clubs. The operational and strategic approaches of the recruitment and talent development departments can have an impact on the club's activities and ultimate success, both on and off the pitch.

An effective strategy for selecting players for line-up, recruitment and transfer must be based on choosing the best-suited player for the appropriate position and role. This strategy should take into account concepts of personnel management, especially player salaries and the multitude of player attributes that need to be analyzed and evaluated simultaneously.

⁶Author referenced in Lawlor et al. (2021): p. 59

2.3.1 Challenges and motivations

In the management of professional football clubs, achieving a financial balance between revenue and expenditure is essential to the sustainability of the organization. Similarly, establishing an optimal balance in team composition between "water carriers" and "stars" is crucial to maximizing sporting performance and maintaining team cohesion. To ensure this financial and human balance, it is essential to minimize the subjectivity of decisions made by coaches and managers when selecting players. This means adopting more objective, scientific methods rather than relying solely on subjective experiences and impressions.

Although existing research has highlighted the importance of player selection for team performance, there remains a significant lack of understanding the impact of this selection process on the sporting performance and financial success of football clubs. Traditional methods of player selection, often subjective, limit coaches' ability to compare and combine multiple criteria objectively, the result will be a potential biases and sub-optimal decisions.

The comparison of multiple players with various attributes can be influenced by varying degrees of subjectivity among technical staff. Some coaches may rely on their own experience, personal preferences, and intuition to evaluate players, thus introducing subjective biases into the selection process [Miller et al. \(2015\)](#). Their assessment can be influenced by factors such as the player's reputation, past performances, or even considerations unrelated to on-field performance.

The proof of this subjectivity can be found in the long list of football flops. The analysis of players can be influenced by personal judgments of their character, attitude or suitability for the team's strategy. Despite coaches' efforts to apply more objective methods, it remains a challenge to prioritize a large number of criteria and compare players with almost similar performances. When several players have comparable characteristics, the final decision may be based on subjective aspects such as the coach's intuition, confidence in the player or perception of his growth potential.

In addition, more and more clubs are hiring analysts whose main task is to evaluate

player performance criteria described in the human resources management subsection. However, it should be noted that these analysts often tend to focus solely on football-related criteria, thus neglecting extra-sporting aspects such as off-field behavior and conduct. This one-sided approach can sometimes lead to costly mistakes, as illustrated by PSG's acquisition of Neymar, where non-sporting considerations may have been overlooked, with negative consequences for the club and highlighting the difference between "tops" and "flops" in the world of professional football. An example of this is the transfer of Neymar to PSG from FC Barcelona in August 2017 for the astronomical sum of 222 million euros⁷. While this transfer shook the football world, unfortunately, it has not always lived up to this colossal amount.

However, the advent of real-time data analytics presents an opportunity for transformation in the field of player selection. With instant data availability, players' databases can be updated continuously, providing us with the latest information for our analysis and allowing us to make informed decisions about selecting players for specific tasks. The integration of artificial intelligence technologies further improves decision-making. AI algorithms are capable of analyzing large amounts of player data, identifying complex patterns, and providing information that coaches can ignore. By leveraging the power of AI, coaches can complement their expertise with data-driven recommendations, improving the objectivity and accuracy of player selection.

It is from this perspective that the degree of error inherent in the subjectivity of technical staff is minimized. Such minimization results in better efficiency of the line-ups, recruitment processes and transfers while avoiding flops. Our main objective is to maximize sports performance by seeking objectivity, facilitated by the use of artificial intelligence, machine learning and multi-criteria decision making methods.

It's important to underline that our goal is not to replace the technical staff but rather to complement the player selection process while respecting the autonomy of coaches' decisions. By exploring innovative approaches to solving the player selection problem using real-time data, based on the integration of supervised machine learning and multi-

⁷Source: Sporting News. www.sportingnews.com. Accessed on March 2023.

criteria decision making.

Our aim is to provide football clubs some tools and strategies necessary to optimize team composition, maximize performance, and achieve lasting success in the highly competitive landscape of professional football. Moreover, by minimizing subjectivity through the selection of talented players, we seek to reduce the financial imbalance often caused by the high wages of certain stars. Furthermore, the selection of an optimal team on the field can be ensured by maintaining a balance between "water carriers" and "stars" based on footballistics considerations.

2.3.2 Contributions

In response to the need highlighted in the previous arguments, this thesis attempts to establish a decision-making model, taking advantage of machine learning algorithms and multi-criteria decision-making methods. The aim is to provide experts and decision makers with a decision support tool to address the challenge of selecting high-performing football players, whether they are classified as "stars" or "water carriers". The optimal selection involves also to strive for a financial equilibrium between expenses and revenues within a professional club, by minimizing the wages, highest charges for clubs. This requires informing decision makers about the true value of salaries through supervised learning, given that deficits in certain clubs have been observed, often attributed to high wages.

By integrating advanced techniques such as artificial intelligence and multi-criteria decision making, both sporting and financial results can be significantly improved. Careful selection of players based on objective criteria and thorough scientist analysis is important not only to protect the interests of the club's decision makers, but also to meet the expectations of shareholders who support the organization financially. By revisiting the principles of sports management with innovative AI-based methods and multi-criteria models, football clubs can improve their overall performance and ensure sustainable success. This approach not only helps to achieve sports goals, but also maximizes financial returns and provides an optimal investment outcome for all stakeholders who invest in the success of the club.

In modern football management, where data-driven decisions are increasingly prevalent, our research aims to address the challenges and opportunities associated with player selection. Specifically, we seek to develop a decision support tool for selecting players and substitutes that optimize on-field performance and consequently improve the financial outcomes of football clubs. Moreover, our decision support system can benefit decision makers in player recruitment and transfer operations by offering the capability to oversee multiple professional clubs and various player positions.

The selection process in multi-player sports like football presents a complex multi-criteria problem. Attributes assigned to players, based on their positions within a football team, are prioritized using machine learning algorithm: Random Forest and objective multi-criteria methods namely CRITIC and ENTROPY. Random Forest method weighs attributes based on players' wage predictions, implicitly reflecting expert judgment. Conversely, the other two methods offer more objective attribute weighting, particularly useful when decision makers have conflicting opinions about criteria importance. Following the weighting phase based on one of the three methods mentioned, we will proceed to the evaluation phase of alternatives, which consists of evaluating the players according to their position in the club. In this phase, we will use the TOPSIS method (Technique of order preference by similarity with the ideal solution) to classify players according to their performance and suitability.

Our contribution is based on the fusion of three distinct weight allocation methods with the TOPSIS multi-criteria approach. Through the integration of these methodologies, we try to provide a more objective framework for evaluating player selection in the field of football management. To validate this contribution, we have developed an interactive platform specifically designed to meet the requirements of experts in the field, ensuring ease of use and promoting data-driven decision-making. This interface allows decision makers to have a complete vision of the performance of the players they have at their disposal, with their different attributes, taking into account the subtleties of player selection, thus increasing the effectiveness of their strategic decisions.

In the first phase of development of our model, we try to offer experts and decision

makers the opportunity to actively intervene by updating the database with recent data instantly retrieved from current matches. This data captures the player's current performance metrics, injury history, and compatibility with the team's tactical framework, allowing a real-time evaluation of their performance.

The field of sports has become increasingly rich in instant data thanks to advances in big data and artificial intelligence. The tracking devices and sensors built into players' equipment provide detailed information about their activity on the field, such as distance traveled, speed, successful passes, duels won, and much more. By integrating this real-time data into our model, we enable decision makers to have an accurate and up-to-date view of player performance. This allows them to make relevant decisions about team composition, in-game tactical changes, and even long-term recruitment strategies.

The result of this weighting phase will be provided both digitally and visually. Decision makers will receive numerical values indicating the weight of each attribute, which will facilitate accurate comparisons. Graphic representations will be available to provide decision makers with a visual comparison of the importance of each attribute. This dual presentation ensures clarity and enhances the ability of decision makers to analyze the relative importance of each attribute, allowing for more effective decision-making in player selection.

Second, our system integrates the knowledge and experience of experts and decision makers into the process of assessing and weighing criteria. Unlike a black box approach, our model functions as an interactive interface, involving decision makers in the process of evaluating player performance. This involvement is facilitated by allowing decision makers to choose a different club from their own club and the position of a player when they wish to recruit from another professional club. In addition, the model allows decision makers to add or remove criteria or attributes for evaluating players if they consider them important or irrelevant to a given position.

Furthermore, we will offer decision makers three weighting methods to provide them with different techniques for evaluating this delicate phase in our modeling process. The first method relies on machine learning and weights the attributes based on the salaries of

players specified by experts and managers, as well as the football market. This approach implicitly incorporates the opinions of experts. In contrast, the other two methods weigh the criteria in a more objective manner, relying on the relationships that exist between the criteria themselves, particularly useful when decision makers have conflicted views.

By integrating the preferences of experts and decision makers, our model becomes more adaptable and reflects real-world considerations. This interactive approach promotes transparency and collaboration, allowing decision makers to make optimal choices based on their specific needs and objectives when selecting the best players for a competition or recruitment. In summary, the key contributions of this thesis are:

- The implementation of a model that integrates machine learning, CRITIC or ENTROPY, and TOPSIS methods for the selection of football players, as well as the characterization, for each club and each position, relevant criteria for this selection process. This approach incorporates concepts from human resource management and finance to ensure an understanding of player selection processes in labor market, professional football clubs.
- Application of the proposed model to real football matches, to compare and validate the reliability of the model.
- Interpret and explain the results in reference to these concepts and theories. It is also important to confront our results to real selections made by sports decision makers in real matches.

[Figure 2.5](#) provides an overview of the various stages involved in modeling our research work on the player selection process. This process involves the assessment and ranking of players based on established criteria, which are weighted using various methods. It aligns closely with the fundamental principles of human resource management. The process includes composing for line-up, recruiting, and transferring players, all of which are key aspects of human resources management within our framework.

The use of a decision matrix to evaluate and rank players based on these criteria and weights means designing and controlling the process of player selection, which is a key

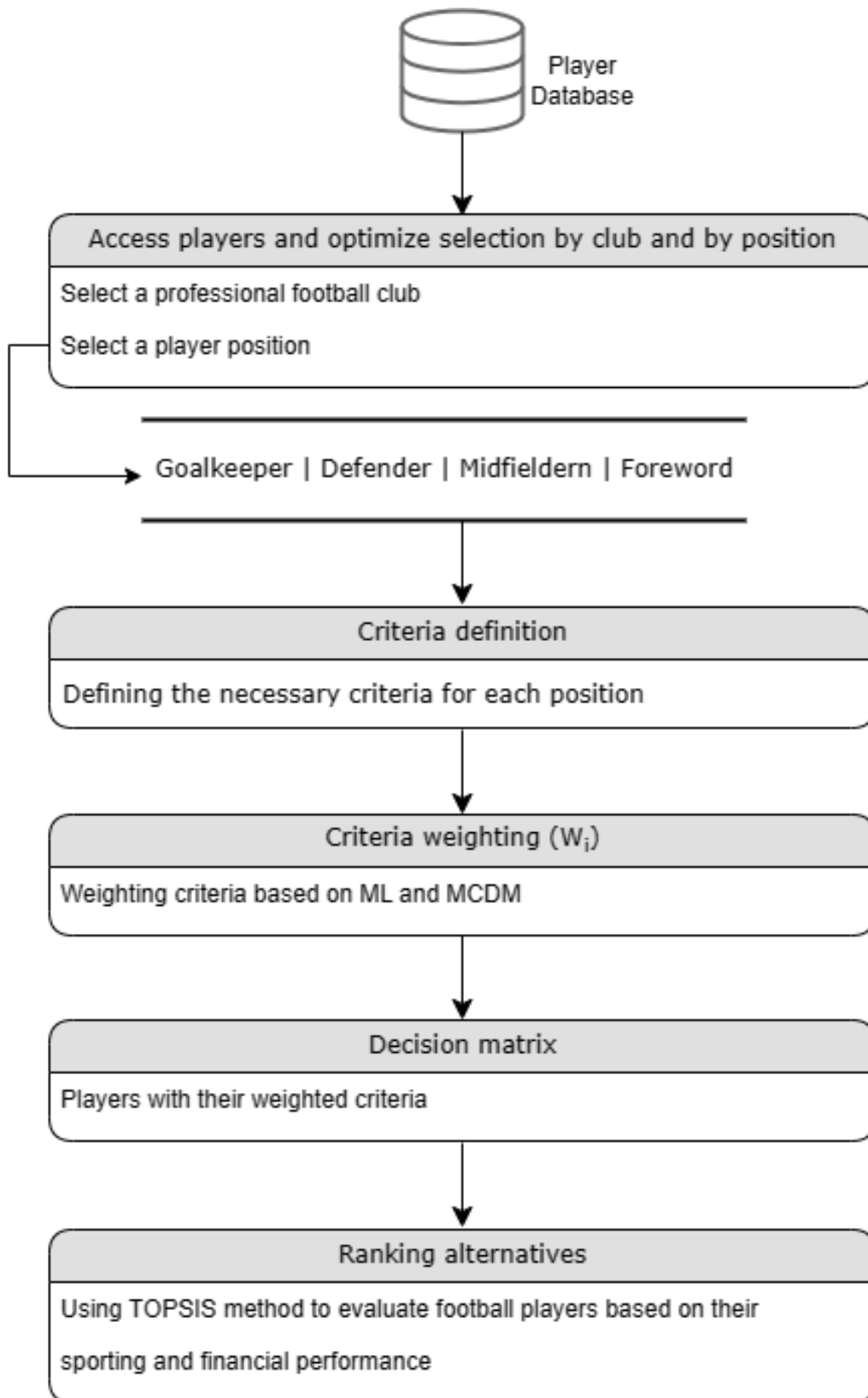


Figure 2.5: The process of player selection

operation in football clubs. Finally, the result, a ranking of players based on financial and sporting success, ties back to the overall aim of our research, which is to contribute to the understanding of sports management, particularly football, by relying on existing economic and managerial theories while respecting the specificities of this field.

To build our model we will follow these three key phases:

- 1- Identification of the problems: This initial phase consists in identifying the specific needs and challenges of the football club, including the definition of the position for which the players must be selected, collecting relevant data containing player performance data, and establishing player evaluation criteria.
- 2- Criteria weighting: In this phase, we use various methods such as machine learning, CRITIC or ENTROPY to assign weights to the identified criteria. This step ensures that each criterion is well considered and weighted according to its relative importance in the player selection process.
- 3- Evaluation of alternatives: The final phase consists of evaluating the available player alternatives using the TOPSIS method. Considering the weighted criteria, this step facilitates the comparison and ranking of players according to their suitability for the specified positions within the football club.

In light of the aforementioned considerations, this research aims to explore the role of a decision-making model in the player selection process within professional football clubs. Specifically, our objectives are to:

- Review and analyze existing literature to gain insights into the process of assessing and selecting football players, considering both managerial and economic perspectives.
- Define and analyze the primary criteria involved in football selection problems, considering expert feedback and data from Kaggle (2016-2022).
- Evaluate various supervised learning algorithms and decision-making methods available to sports decision-makers, comparing their utility, outcomes, and validity.

- Develop a comprehensive decision support tool integrating technical, human resources, and financial aspects to aid decision makers in selecting players for matches, recruitment, and transfer operations.
- Apply the developed model to real-world scenarios, examining its effectiveness in the context of prominent football championships and with well-known players as case studies, while considering human resources and financial implications.
- Compare the outcomes generated by our decision support system with real selections made by sports decision makers in real matches.

To achieve these objectives, it is recommended to consider the following hypotheses and research questions:

2.3.3 Research questions

An hypothesis is a set of principles or rules. To validate its truthfulness, it must be confronted with reality by raising a set of questions related to the inherent eventualities of the hypothesis. This is the purpose of this section, where we will test the following hypotheses and questions:

- *H1: "The selection of the starting lineup, recruitment and transfer based on the integrated model, incorporating machine learning techniques and MCDM approaches, contribute effectively to yield optimal results."*
- *H2: "The integrated model can be effectively applied and helpful in the current football landscape."*
- *H3: "The integrated model departs from conventional selection methods, offering a more scientific, comprehensive, and efficient approach to player selection".*
- *H4: "the scope of MCDM goes beyond the sports dimension; it extends to the financial and managerial aspects"*

This thesis proposes that the application of multi-criteria decision-making approaches incorporating machine learning techniques will facilitate more effective resolution of the complexities inherent in player selection and football management. The TOPSIS method, in particular, can assist multiple decision makers in enhancing their decision-making processes by identifying high-performing players and avoiding potential managerial and financial missteps.

To align with the above objectives and assess the proposed hypotheses, it is crucial to develop specific research questions that will serve as the guiding framework for our study. Each hypothesis or question should arise from a research axis raised in the theoretical part and address an issue presented in a section or part of the thesis. Hence, the following research questions have informed our investigation:

- *RQ 1: What is the contribution of the literature to the review and study of the relationship between managerial, financial, and sports performance?*
- *RQ 2: What are the main criteria for selecting football players?*
- *RQ 3: What are the add value, applicability and usefulness of machine learning and MCDM approaches in the football player selection process?*
- *RQ 4: How to build a decision support model combining MCDM approaches and machine learning algorithms by integrating all technical, managerial, and financial variables to help decision makers select the best players for a match?*

These research questions will be analyzed in detail in the next chapter, which focuses on the systematic literature review (SLR) of player selection.

2.4 Conclusion

This chapter has delineated the conceptual framework for our research, elucidating key concepts derived from marketing strategy, human resources and financial management. These concepts provide a theoretical foundation for comprehending the intricate dynamics

of player selection in professional football. Furthermore, the chapter underscores the evolution of football as an economic enterprise, where clubs function as complex organizations requiring strategic decision-making in player selection.

By integrating economic and managerial theories, our research aims to minimize and mitigate subjectivity in decision-making processes by shedding light on how football clubs can optimize player selection to achieve both athletic success and financial stability. It is imperative to strike a balance in human resources between "stars" and "water carriers," ensuring equitable treatment and fostering team cohesion. Additionally, maintaining financial equilibrium between revenues and expenditures is vital to safeguarding the interests of shareholders and club management actors, thereby addressing agency problems inherent in football governance structures.

The examination of player profiles and their impact in professional football underscores the multifaceted nature of player selection, involving physical, technical, tactical, and behavioral attributes. Through empirical investigation and the application of machine learning algorithms and multi-criteria decision models, we aim to address the research questions and hypotheses outlined in this chapter. Ultimately, our objective is to contribute to the advancement of knowledge in the realm of sports management and decision-making science, while providing actionable information for football clubs to effectively manage the complexities of player selection.

Our contribution does not represent a break with studies addressing our problem from the sporting, financial and managerial perspectives. Instead, our research will be based on an intersection of literature combining sport and management. What distinguishes our contribution is the application and use of AI and MCDM methods to assist decision-making in this area. To do this, we will first conduct a systematic literature review for the selection of football players.

Chapter 3

Systematic literature review for the selection of football players

3.1 Introduction

Football has been one of the world's most influential and popular sports for over a century. For the past thirty years, it has also become one of the most lucrative industries, with a significant managerial and financial impact on sponsorship, broadcasting, and transfers of players (Müller et al., 2017; Rohde and Breuer, 2017). Many professional football clubs operate as complex businesses with a primary focus on financial issues (Morrow and Howieson, 2014).

In a football match, decision makers, including coaches, managers, and technical staff, play a pivotal role in assembling the team lineup, drawing on technical and tactical factors (Carmichael et al., 2000). However, this process has traditionally relied on intuition and common sense rather than rigorous scientific methods (Boon and Sierksma, 2003; Dadelo et al., 2014; Purwanto et al., 2018; Salles et al., 2019).

The complexity of player selection necessitates the consideration of numerous qualitative and quantitative criteria, presenting a significant challenge for decision makers (Tavana et al., 2013; Nasiri et al., 2018a). While other fields have adopted methods such as multi-criteria decision-making, football has been slower to adopt such approaches. By combining MCDM with machine learning algorithms, decision makers can make more objective and data-driven player selections, which could transform the way football teams are assembled and managed.

In this chapter, we undertake a systematic literature review to explore the various factors influencing football player selection. We begin by examining existing literature streams on football player selection, focusing on the subjectivity of player selection, player selection aligned with management principles, and AI and MCDM assisted player selection. Following this, we outline the research methodology employed in performing our systematic literature review, including our search strategy, criteria for inclusion and exclusion of studies, data extraction process, and quality assessment. Finally, we present a discussion of the key findings from our systematic literature review and draw conclusions regarding the current state of knowledge in football player selection.

3.2 Literature streams on football player selection

In this section, we explore various streams of literature that contribute to our understanding of football player selection. We begin by examining works that have shed light on the inherent subjectivity in the player selection process. Next, we delve into how player selection aligns with management principles, aiming to optimize team composition for success on and off the field. Finally, our focus shifts to the integration of artificial intelligence and multi-criteria decision-making techniques to enhance objective player selection processes, incorporating both the subjective expertise of club decision makers and financial - managerial considerations.

3.2.1 Subjectivity in player selection process

The issue of subjectivity in the decision-making process of football player selection is a crucial aspect of professional club operations. The recruiting of talented staff represents a major challenge for these clubs, particularly concerning lineup composition, recruitment, and transfers.

Traditionally, football environments are often characterized by opacity and a reluctance to openly share details of recruitment methods (Parker, 2000). In the absence of solid economic considerations, technical staff were often free to choose players based solely on football-specific criteria such as technical skills, physical fitness, and previous experience, thus neglecting financial and managerial constraints. This approach, although often based on the experience and expertise of the coaches, could be limited by personal biases or individual preferences (Furley and Memmert, 2016; Reeves et al., 2019). Moreover, the pressure to achieve immediate results on the field sometimes led coaches to favor established players, at the expense of the long-term development of the team.

As pointed out by Lawlor et al. (2021), the literature on football recruiting reveals the uncertainty inherent in decision-making, where recruiters often act on impressions rather than factual data. Several authors have discussed the concept of subjectivity in the selection of players by the coaching staff. Indeed, coaches often base their decisions on training and

recruitment on criteria that are less scientific and more subjective. [Dadelo et al. \(2014\)](#) argues that professional sports often rely on subjective assessments for player selection and team management. This decision, made subjectively by the coach, can greatly influence the success of the team on and off the field. Likewise, [Purwanto et al. \(2018\)](#) highlights the important role of coaches in the selection of players, particularly in determining the starting line-up. This decision, made subjectively by the coach, can greatly influence the success of the team on the field. However, the subjective nature of this decision-making process can lead to perceptions of a lack of transparency and fairness, with the coach often being most to blame in case of defeat.

[Ozceylan \(2016\)](#) underscores the critical importance of effective team formation in sports, highlighting the significant repercussions of poor player selection decisions. Emphasizing the subjective nature of traditional methods, Ozceylan advocates for the adoption of scientific approaches to enhance objectivity and efficiency in team management.

[Salles et al. \(2019\)](#) emphasizes the challenges inherent in team formation in football, underlining the susceptibility to failures due to subjective decisions. The authors suggest that the use of quantitative methods can address these challenges and provide more effective outcomes for football clubs.

[Tavana et al. \(2013\)](#) point up the scarcity of structured methodologies in sports science to aid coaches in the process of player selection and team formation. Their findings underscore the need for further exploration and development of analytical approaches to optimize this process, addressing inherent complexities effectively.

The selection of players in football remains a complex process, characterized by the need for coaches to evaluate a large number of sporting parameters and deal with different potential scenarios. According to [Miller et al. \(2015\)](#), when faced with real-world decisions, scouts and coaches cannot necessarily consider all relevant elements impartially. Instead, they resort in part to heuristic reasoning. This subjectivity, as evidenced by the frequency of flops and sporting defeats in critical matches, raises an agency problem where decision makers may create an imbalance issue between control and ownership principles: the coaching staff may prioritize their own interests to the detriment of shareholders' inter-

ests.

To remedy this imbalance, the decision-making process needs to be complemented by financial and managerial considerations. This meant that crucial aspects such as compatibility with the club's overall strategy, budget constraints, and long-term profitability were not always adequately considered in the player selection process. As a result, player selection relied primarily on football-specific criteria, without fully considering broader considerations related to managing a professional football team.

3.2.2 Player selection aligned with management principles

As part of its evolution, football is now recognized as an economic activity in its own right. This recognition has led to a significant transformation in the way players are selected, from a traditionally subjective approach to a more objective one aligned with the principles of human resource and financial management.

In order to minimize the subjective bias observed among elite club recruiters, [Lawlor et al. \(2021\)](#) highlights the need for specific training for recruiters, a key element of human resource management, emphasizing the importance of professional development in this area. Consequently, clubs can not only improve their sporting performance, but also their operational efficiency and long-term sustainability when they integrate management principles into their approach to recruitment.

The focus on effective human resource management in football has led clubs to a paradigm shift from simply selecting a team to running a real business. Selection decisions, be they line-up, recruitment or transfers, are now made in the light of the club's long-term objectives, as well as the budgetary and financial constraints it faces. This involves a more in-depth analysis of player performance, based on objective, measurable criteria such as match statistics, training data and physical assessments.

The commercial pressures and intense competition in professional football have driven clubs to professionalize their organizational structures and management practices increasingly. According to [Parnell et al. \(2018\)](#), this development is aimed at improving clubs' competitiveness in the labor market, where success is financially rewarded and failure can

be costly. The emergence of the role of sports director represents a strategy aimed at improving performance on and off the pitch, while maintaining the organization's influence and control. This professionalization is also reflected in the player selection process, as clubs adopt more strategic approaches to recruiting and developing their squad. Thus, to remain competitive, player selection must align with the management principles guiding the increasing professionalization of clubs.

Similarly, [Gammelsæter and Jakobsen \(2008\)](#) note the significant impact of increasing commercialization and competition in professional football on clubs' organizational approaches, philosophies and practices. This observation underlines the importance of clubs adapting to the changing industry environment, where commercial pressures predominate in the decision-making process. In this changing context, it is crucial to align player selection strategies with club management principles in order to remain competitive and maintain sustainable performance.

As a result, player selection has become an integral part of the overall club management process, with the focus on optimizing sporting performance while ensuring long-term financial sustainability. Selection decisions are now made by a multi-disciplinary team of coaches, sporting directors, data analysts and financial managers, working together to achieve the club's strategic objectives. This transition to a more objective approach, based on the principles of management and finance, has enabled clubs to better manage their resources and optimize their performance both on the field and financially. This reflects a growing recognition of football as a business enterprise, where player selection decisions play a crucial role in the achievement of long-term objectives and the overall success of the club.

Aligning player selection with management principles represents a fundamental step in the evolution of professional football as a business. By adopting a more scientific approaches, clubs can optimize their sporting performance while ensuring their financial and managerial sustainability. However, as we move towards more rigorous, data-driven management in the player selection process, new opportunities are also emerging through the use of technologies based on artificial intelligence and multi-criteria decision making meth-

ods. In the following section, we explore how these innovative tools can help to further improve the player selection process, offering a more efficient and informed approach for professional clubs.

3.2.3 AI and MCDM assisted player selection

The selection process in football has evolved significantly, with researchers advocating for a multidimensional assessment that combines both objective and subjective evaluations. This approach has been increasingly recognized as essential for effectively monitoring and developing young talented athletes (Dugdale et al., 2020; Williams et al., 2020). However, despite this progress, there remains a notable insufficiency in the literature concerning the integration of artificial intelligence, particularly supervised learning techniques, and multi-criteria decision-making methods.

While AI has seen widespread application in various fields, its specific utilization in the football player selection process needs to be explored more within existing academic research. Likewise, the potential of MCDM methods, which offer a structured framework for evaluating player attributes across multiple dimensions, has yet to be fully leveraged in football talent identification and recruitment practices. This gap underscores the need for further research to explore and develop these areas, including financial and managerial considerations, to enhance the effectiveness and objectivity of football player selection processes.

Recent studies have highlighted the benefits of integrating subjective assessments, such as coach evaluations, with objective performance data. For instance, Sieghartsleitner et al. (2019) found that a combination of subjective coach assessments during matches, alongside objective measures of performance, more accurately predicted future player status, compared to relying solely on objective data. Our approach aligns with this framework, as we aim to provide club decision makers with a decision support tool centered on the user experience.

This tool exploits machine learning techniques and multi-criteria decision-making methods, focusing on human and financial resources management concepts relating to our selec-

tion of professional football players. We also draw on the experience and professionalism of these decision makers to enrich our approach and ensure its relevance to the club's operational context. Indeed, AI can only optimize selection if it is strongly supported and assisted by emotional intelligence: the manager's ability to detect the player's substantial state of mind.

This integration of subjective and objective assessments enables an in-depth understanding of sporting and managerial performance factors, enhancing the accuracy of player selection and financial predictions. As football moves towards more data-driven approaches, the combination of AI and MCDM can further optimize player selection processes, leveraging the benefits of both objective data analysis and subjective expertise.

Concurrently, machine learning based on large datasets, such as football data, has the potential to offer detailed predictions of player performance through models like neural networks and random forests ([Azeman et al., 2021](#)). However, the potential fusion of MCDM for selection and machine learning for predictive analysis remains an under-explored area of research. Addressing this research gap is critical and serves as the motivation for conducting this systematic literature review (SLR). This study provides a research review to improve the evaluation and selection process of football players. Therefore, this study aims to review and organize the literature on decision-making analysis and machine learning by performing an SLR.

To fill this gap in research, we conducted a systematic literature review. This review aims to refine the process of evaluating and selecting football players by organizing and analyzing existing literature on decision-making analysis and machine learning. Moving forward, we'll delve into the research methodology, outlining the protocol used to plan and execute our study.

3.3 Research methodology

The present study follows an SLR protocol based on Kitchenham's guidelines ([Kitchenham and Charters, 2007](#)). [Figure 3.1](#) shows three sequential plans reflecting the components of

the SLR: planning, conducting, and reporting the review.

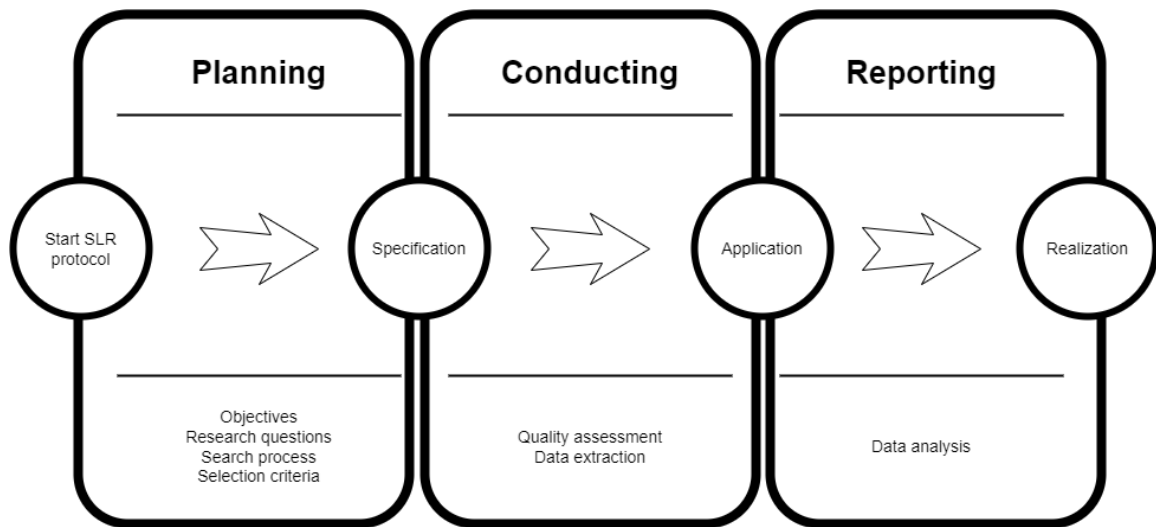


Figure 3.1: SLR general process

3.3.1 Planning the review

The purpose of the planning phase is to specify the following steps: determine the objectives of a review, set the research questions (four research questions are selected), perform a search process using using keywords to download relevant articles from selected digital libraries, and identify the selection criteria.

Objectives:

This study examines research into decision-making and machine learning when evaluating and selecting players, considering their playing attributes (physical, technical, tactical and behavioral criteria) and how this process influences managerial-financial and sporting performance. Player selection is a major challenge for all clubs, as it involves multiple criteria that need to be evaluated simultaneously. Hence, the process of hiring and line-ups must respect many sports and financial considerations. We aim to assess the main criteria by which decision makers set line-ups and predict the impact of their choice on sport and financial performance. To this end, decision-making methods may help decision makers recruit and select the best players, and machine learning algorithms would be appropriate

for predicting sporting and financial performances following this selection. Therefore, we provide an SLR of books and papers published in journals and conference proceedings related to our research topic.

Research questions:

After determining the purpose and motivation of our research, the SLR proposes a process to answer the following research questions.

RQ 1 *What is the contribution of the literature to the review and study of the relationship between managerial-financial and sports performance?* Financial and managerial successes are not the main objective, and football performance remains the primary goal. These two goals are mutually linked, and each determines the other. Football and financial success depend on hiring strategies and players' lineups.

RQ 2 *What are the main criteria and sub-criteria for football players?* In addition to preparing the team to participate in competitions, the coach's role is to select the starting range among the players in the hired stock, based on factors such as physics, technique, tactics and behavior.

RQ 3 *What are the add value, applicability and usefulness of machine learning and MCDM approaches in the football player selection process?* The efficiency of sports clubs is influenced by the talents of players and coaches. Indeed, the most essential elements for a sports organization are the sporting resources that constitute its human capital. MCDM approaches could be useful in supporting decision makers and providing more objective decisions. The objective of our study is to examine the applicability and usefulness of machine learning and MCDM approaches in the football player selection process.

RQ 4 *How to build a decision support model combining MCDM approaches and machine learning algorithms by integrating all technical, managerial, and financial variables to help decision makers select the best players for a match?*

Search process:

To plan the SLR process, an appropriate mechanism must be adopted to ensure the retrieval of relevant studies from selected digital libraries. A systematic mechanism is used to gather the most relevant articles by formulating a set of specific keywords. These data are then used to search peer-reviewed digital libraries for research articles. In the proposed SLR, several keywords are related to the analysis and applicability of multi-criteria decision models and machine learning in sports, mainly football, based on the above research questions.

However, following a search strategy that identifies the most relevant documents is essential. To ensure the quality of the articles, the search focused on various electronic databases: IEEExplore, SpringerLink, ScienceDirect, Taylor and Francis, and Wiley Online Library. These are the most frequently used libraries and are known to publish high-quality materials. The authors use specific keywords to search for relevant articles in these libraries. The keywords are selected based on the proposed research questions. A search string *S* is formulated to interact with the libraries (Table 3.1). The first attempt in this search process has yielded the following results: IEEE →802, ScienceDirect →1432, Springer →398, Taylor and Francis →221, and Wiley Online Library→137. To refine the results we assigned a subset of keywords (*S*₁,*S*₂, *S*₃, *S*₄) to each research question. Given the large amount of information generated by different digital libraries, they cannot be included in the proposed SLR. A process for selecting criteria, followed by the analysis and assessment of each article, should be developed.

Selection criteria:

Selection criteria are specified to refine the search results, namely, the inclusion and exclusion criteria. Given the large volume of published research, it is crucial to establish boundaries for a thorough and detailed literature review. We focus on the period between 2018 and 2023, sufficiently long to observe critical trends related to our research topic. Table 3.2 summarizes the essential inclusion and exclusion criteria for the proposed SLR.

Table 3.1: List of keywords selected for search process

Research questions	Keywords for search process
The whole topic	S = (“Multi-criteria Decision Making”) AND (“machine learning”) AND (“selection”)
RQ 1	S1 = (“football” OR “soccer”) AND (“management” OR “managerial”) AND (“financial sporting performance”)
RQ 2	S2 = (“football” OR “soccer”) AND (“player”) AND (“criteria” OR “attribute”)
RQ 3	S3 = (“Multi-criteria Decision Making”) AND (“selection problems”)
RQ 4	S4 = (“Multi-criteria Decision Making”) AND (“prediction”) AND (“machine learning”) AND (“football player selection”)

Table 3.2: Inclusion / Exclusion criteria

Inclusion criteria
<ul style="list-style-type: none"> - Published between 2018 and 2023 - English language - Provide good knowledge of the formulated research questions - Content of the paper Provide satisfactory information of the main topic and research questions
Exclusion criteria
<ul style="list-style-type: none"> - Published outside the 2018-2023 period - Content of the paper not providing satisfactory information of the main topic and research questions - Informal literature surveys - Duplicate papers

3.3.2 Conducting the review

Once the research protocol is completed, we may proceed with the review and apply what we have specified in the planning phase. The process is iterative (Figure 3.2), and the first primary study is performed on search string S. For greater relevance, we use a search string for each research question (Table 3.3). Second, the inclusion/exclusion criteria are applied to a subset of primary studies (Table 3.4). Third, the remaining studies are analyzed in depth and filtered by title and paper keywords, abstracts, and content (Table 3.5). Each digital library is searched separately. Finally, the articles collected from the five databases are imported into the Zotero reference management software (Zotero Community, 2022) to check for duplicates. Consequently, only 66 relevant documents (journal articles, conference papers, and book sections) that fit our topics and answer our research questions are identified. Figures 3.3 and 3.4 show the research trends in the selected period and the percentage of digital libraries, respectively.

Table 3.3: Search process based on research questions

Digital libraries	S1	S2	S3	S4	Total
IEEE	52	33	3	13	101
ScienceDirect	614	64	29	6	713
Springer	233	94	50	19	396
Taylor and Francis	147	86	3	33	269
Wiley Online Library	288	14	2	29	333

Table 3.4: Search process with inclusion/exclusion criteria

Digital libraries	Journal papers	Conference papers	Book	Total
IEEE	1	21	-	22
ScienceDirect	54	-	3	58
Springer	36	4	7	47
Taylor and Francis	32	-	-	32
Wiley Online Library	22	-	1	23



Figure 3.2: Review process

Study quality assessment:

The study quality phase aims to assess the quality of the primary studies. Each article is evaluated separately to ensure that it targets the research objective. We refer to the data analysis, figures, tables, and appendixes for analyzing and collecting data from each paper.

Data extraction:

The data extraction process extracts items from the 66 included studies and collects all information required to answer the research questions related to our topics. An extracted data form (Table 3.6) is developed to collect data items from each primary study. This process is the object of a meticulous examination by the authors to verify the consistency

Table 3.5: Filtering papers by title and paper keywords, abstract, and contents

Digital libraries	Title and paper keywords	Abstract	Content
IEEE	30	28	22
ScienceDirect	31	28	20
Springer	10	8	7
Taylor and Francis	11	11	9
Wiley Online Library	10	10	8
Total	92	85	66

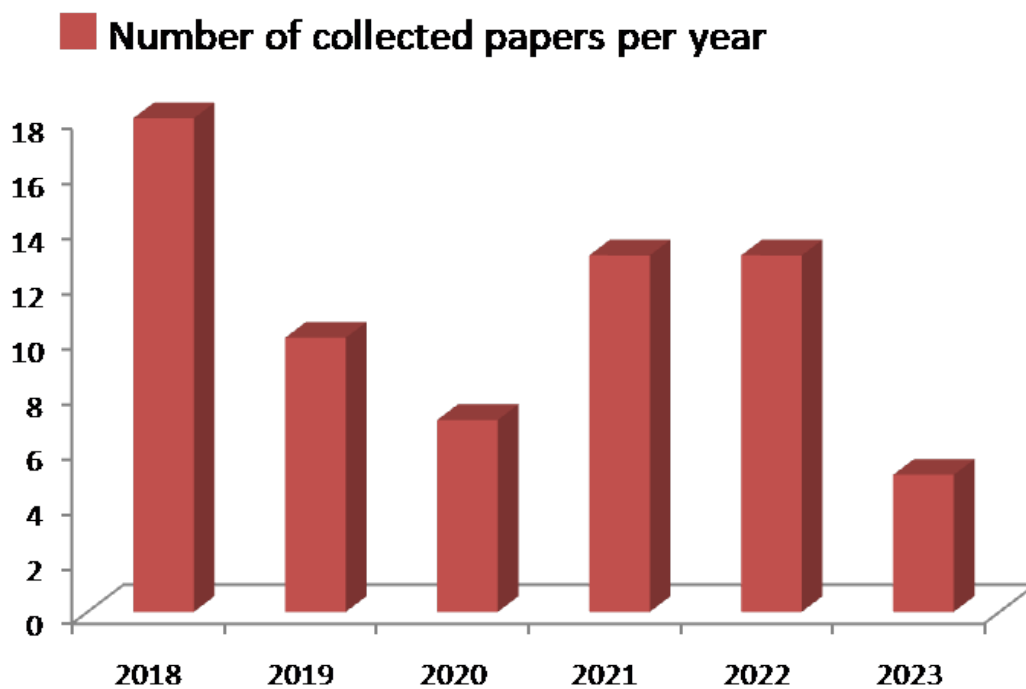


Figure 3.3: Research trends 2018–2023

of the inclusion/exclusion decisions and ensure the quality of the selected studies (Table 3.7).

We also consider books and book sections on sports management and decision-making: (Dobson and Goddard, 2004; Ishizaka and Nemery, 2013; Katzenbach, 2009; Katzenbach and Smith, 1993; Saaty, 1996; Saaty and Vargas, 1982; Tzeng and Huang, 2011). We thoroughly review articles that answer three or more research questions. However, by focusing on these articles, we delve into studies with higher levels of complexity and depth. It is essential to note that our approach does not diminish the importance of articles that

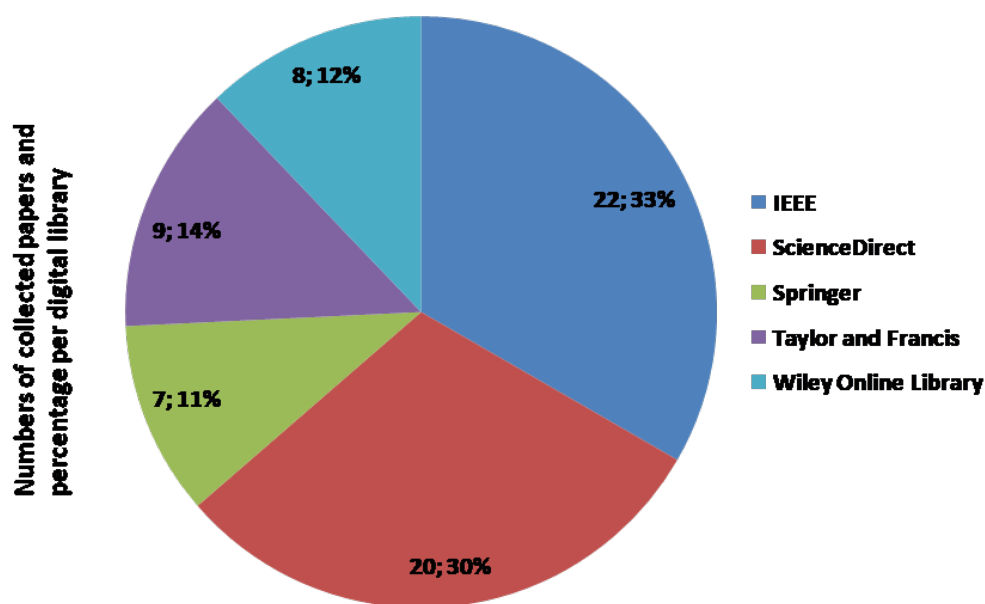


Figure 3.4: Contribution share of each database

address fewer research questions. Such studies can be valuable and insightful and often shed light on certain aspects of the topic. We also try to find articles on subjects not from the period selected for the proposed SLR, to avoid omitting any relevant and useful articles. To this end, we use the Connected Papers website ([Tarnavsky et al., 2023](#)), a visual tool that helps researchers. We identify academic articles relevant to our research areas. Some of these documents are considered in the reporting phase even if they do not fall within the selected period.

Table 3.6: Data extraction form

Data item	Description
Ref.	Reference ID/Number of the paper under
Study year	Year of publication
RQ 1	Does the paper relate to our RQ 1?
RQ 2	Does the paper relate to our RQ 2?
RQ 3	Does the paper relate to our RQ 3?
RQ 4	Does the paper address RQ 4?
Case Study	Does the Study Apply any Case?
DataBase	Does the paper include dataset from any DataBase?

3.3.3 Results: Reporting the literature review

The reporting phase is designed to analyze and implement a literature review that addresses the research questions related to our topics. This phase addresses 66 studies from the conducting process and other works related to the main papers. Subsection (1) reports the contribution of the literature to the study of the relationship between managerial and financial performance and sports performance (RQ 1). Subsection (2) describes the main criteria and sub-criteria related to the football players involved in the selection problem (RQ 2). Subsection (3) presents the decision-making methods used to assist decision makers in solving selection problems, referring to player criteria and sub-criteria (RQ 3). Subsection (4) highlights models that integrate all technical and economic variables to help decision makers select the best players for a game (RQ 4).

(1) *RQ 1: What is the contribution of the literature to the review and study of the relationship between managerial-financial and sporting performance?*

A team's success may be defined by its results and how managers organize and manage a football club. Several parameters must be considered during the decision-making analysis. According to Rohde and Breuer (2018), the managerial-financial process is an investment activity in a club organization where footballers represent a major asset. Furthermore, Flegl et al. (2018) highlight that personnel selection in organizations is typically challenging. This process becomes even more complex in large and diverse organizations where different departments may pursue conflicting objectives. Contradictions between a higher income, promoting sports, and providing a good show can be targets. As many areas may be involved in the selection process, it can become complex and challenging. Therefore, Samur (2018) suggests that football organizations can be broken down into critical processes that can be managed easily. The study underlines the importance of financial transfers generated by sporting success to all club activity areas in a balanced manner.

Gonçalves et al. (2020) measure economic-financial performance in football clubs using indicators like net revenue and revenue from broadcasting, matchday, commercial activities, and player sales. Through panel data analysis, they discover a positive and sig-

nificant relationship between team performance and the clubs' economic and financial performance in the following year. Similarly, [Barros \(2006\)](#) examines the relationship between football success, financial management, and performance of clubs. The study concludes that the financial crisis in the Portuguese first division may be imputed to mismanagement. [Ribeiro and Lima \(2012\)](#) analyze the relationship between the distribution of players' salaries and the effectiveness of clubs, and how sports performance and financial performance can mutually impact each other. Clubs should structure salaries to achieve optimal salary ranking to induce player effort. [Alaminos et al. \(2020\)](#) emphasize that the financial success of football clubs has become essential in ensuring their long-term solvency and viability. Therefore, theoretical and practical considerations reveal that financial, sporting, and business elements must be included to properly manage the club's finances and analyze potential revenues. They use neural networks to study the financial success of European football clubs. Their results show that a club's financial performance is influenced by its liquidity, leverage, and sports performance.

[Seungbum and Ross \(2012\)](#) identify the decision-making factors affecting sports sponsorship in a global market context. Sports teams with star players or coaches increase the club's attractiveness. [Trequattrini et al. \(2012\)](#) propose a methodology for estimating the economic value of professional football players in the event of a purchase or sale. [Dimitropoulos and Scafarto \(2021\)](#) study the relationship between Greek football clubs' athletic and financial performance. They deduce that sports and financial performance are linked through investments in players. [Frick and Simmons \(2008\)](#) establish a positive correlation between spending on team payroll (managerial compensation) and team performance. Using stochastic analysis, they demonstrated that playing and coaching inputs contribute to team success in the league. [Boon and Sierksma \(2003\)](#) discuss in their model how to support the design of optimal teams and assesses the value-added of a team's potential. New team members in football and volleyball support the idea that hiring new players to improve a team's quality is one of the difficulties in sports and human resources management.

Based on these studies, we conclude that financial and sporting performances are two major factors in club success; hence, several playing and non-playing criteria should be

analyzed to improve the player selection process.

Table 3.7: Summary of the reviewed literature

References	RQ 1	RQ2	RQ3	RQ4	Case study	Data Source
Xia et al. (2018)	✓	-	-	-	✓	National Football League & National Basketball Association
Blanco et al. (2018)	✓	-	✓	✓	✓	Spanish ACB Basketball League
Lepschy et al. (2018)	✓	-	-	-	-	-
Flegl et al. (2018)	✓	✓	✓	✓	✓	sofifa
Danisik et al. (2018)	✓	✓	✓	-	-	-
Purwanto et al. (2018)	-	✓	✓	✓	✓	interviews
Pariath et al. (2018)	✓	✓	-	-	-	-
Rohde and Breuer (2018)	✓	-	-	-	✓	Big five clubs owners from 2003 to 2014
Samur (2018)	✓	-	-	-	-	-
Hervert-Escobar et al. (2018)	✓	✓	-	-	✓	FIFA world cup 2018
Wajdi et al. (2018)	-	-	✓	-	-	-
Buhagiar et al. (2018)	✓	-	-	-	-	-
Galarotis et al. (2018)	-	-	✓	✓	-	-
Chatterjee et al. (2018)	-	-	✓	✓	✓	ABP (Media company in India)
Farshidi et al. (2018)	-	-	✓	✓	✓	Software companies
Nasiri et al. (2018b)	✓	✓	✓	✓	✓	Questionnaire
Chen et al. (2018)	-	-	✓	✓	✓	Location Selection
Purwanto et al. (2018)	-	-	-	✓	-	Wysout (soccer-logs)

Continued on next page

Table 3.7: Summary of the reviewed literature (Continued)

References	RQ 1	RQ2	RQ3	RQ4	Case study	Data Source
Bhat et al. (2019)	✓	-	-	✓	-	-
Shahriar et al. (2019)	-	✓	✓	✓	✓	Bangladesh Soccer Team
Mohanta et al. (2019)	-	-	✓	✓	-	-
Nsolo et al. (2018)	-	-	-	✓	✓	WhoScored - Opta
Ouahli and Cherkaoui (2019)	-	-	✓	✓	✓	-
Patnaik et al. (2019)	-	✓	-	-	✓	OPTA
Saeed et al. (2019)	-	-	✓	-	-	-
Gu et al. (2019)	✓	-	-	-	✓	Major League Soccer from 2004 to 2015
Gomez-Gonzalez et al. (2019)	-	-	✓	✓	-	-
Kizielewicz and Dobryakova (2020)	-	✓	✓	✓	✓	American/Canadian basketball league NBA
Alaminos et al. (2020)	✓	-	-	-	-	-
Cacho-Elizondo (2020)	-	✓	-	-	-	-
Gonçalves et al. (2020)	✓	-	-	-	✓	Brazilian sports clubs from 2013 to 2017
Yang et al. (2020)	-	✓	✓	✓	-	-
Valenti et al. (2020)	✓	-	-	-	✓	Data from 55 UEFA members from 2011-2017
Salih et al. (2020)	-	✓	✓	✓	✓	Data from Raheela et al. (2016)

Continued on next page

Table 3.7: Summary of the reviewed literature (Continued)

References	RQ 1	RQ2	RQ3	RQ4	Case study	Data Source
Di Simone and Zarnardi (2020)	✓	-	-	-	✓	European football companies (59 firms from 2013 to 2018)
Romero et al. (2021)	-	✓	✓	✓	✓	2018 European Men's Handball Championship
Bai and Bai (2021)	-	✓	-	-	-	-
Manish. et al. (2021)	✓	✓	-	-	-	-
Dimitropoulos and Scafarto (2021)	✓	-	-	-	-	-
Azeman et al. (2021)	-	✓	✓	✓	✓	English Premier League Season 2005-2006
Rahman and Asadujjaman (2021)	-	-	✓	✓	-	-
Wieckowski and Watróbski (2021)	-	-	✓	✓	✓	Formula 1
Zhao et al. (2021)	-	-	-	✓	✓	Sofifa
Aydemir et al. (2021)	✓	✓	✓	-	-	-
Li et al. (2021)	✓	✓	-	-	✓	National Basketball Association 2012 to 2015
Fry et al. (2021)	✓	-	-	-	-	-
Kaczynska et al. (2021)	-	-	✓	✓	✓	ratings.fide.com (chess)
Yelmikheiev and Norek (2021)	-	-	✓	✓	-	-

Continued on next page

Table 3.7: Summary of the reviewed literature (Continued)

References	RQ 1	RQ2	RQ3	RQ4	Case study	Data Source
Garcia-del-Barrío and Agnese (2022)	✓	-	-	-	✓	Premier League, La Liga, Serie A, and Ligue 1, from 2010 to 2019
Steve Arrul et al. (2022)	✓	-	-	-	✓	FIFA 2019
Morciano et al. (2022)	✓	✓	-	-	-	-
Rose et al. (2022)	✓	-	-	-	-	-
Jenifer and Sundarraj. (2022)	-	-	✓	✓	-	-
Datta and Rudra (2022)	✓	✓	✓	-	-	-
Parida et al. (2022)	✓	✓	✓	-	✓	Football Club Barcelona
Hu and Fu (2022)	-	-	-	✓	✓	Premier League & La Liga data
Karakaya et al. (2022)	-	✓	✓	-	-	-
Mahmood et al. (2021)	✓	-	-	-	✓	National Basketball Association
Ribeiro et al. (2022)	✓	✓	-	-	✓	Portuguese First League from 2016 to 2018
Manju and Philip (2023)	-	-	✓	✓	✓	Dataset of cricket matches 2008-2022
Peddi and Jain (2023)	-	✓	✓	✓	✓	Historical data
Athish V et al. (2023)	-	-	✓	✓	✓	kaggle.com-Sofifa.com

Continued on next page

Table 3.7: Summary of the reviewed literature (Continued)

References	RQ 1	RQ2	RQ3	RQ4	Case study	Data Source
Joe Anand et al. (2023)	-	-	✓	-	-	-
McHale and Holmes (2023)	✓	✓	✓	-	✓	transfermarkt.com, In-stat, sofifa.com

(2) *RQ 2: What are the main criteria and sub-criteria for selecting football players?*

The selection of a football player includes many performance attributes, also known as criteria, such as technical, physical, mental, and behavioral attributes that have emerged from Big Data technologies. Due to the increasing amount and different types of sports data, Big Data has become a challenge [Bai and Bai \(2021\)](#). Specialized companies such as OPTA, FIFA, and the websites of the official leagues provide an exponential number of datasets for Big Data research related to football analytics, focusing on individual player characteristics ([Cacho-Elizondo, 2020](#); [Raheela et al., 2016](#)). In selecting the best player, [Nikjo et al. \(2015\)](#) define six criteria after consulting ten experts and three decision-makers. These criteria include technical and tactical skills, experience in professional play, average number of goals scored per game, and overall ability to coordinate with the team, moral and behavioral features, and social prestige.

[Ozceylan \(2016\)](#) provides a set of criteria based on the position of players within a football team: Goalkeeper, Fullback, Central Defense, Central Midfield, Winger and Forward Center. The study describes a set of specific criteria for goalkeepers, such as one-on-ones and aerial abilities, and general criteria for all positions, such as anticipation, agility, and first touch. [Purwanto et al. \(2018\)](#) discuss a selection method for starting a line-up based on the physical, technical, tactical, and mental criteria. Sub-criteria such as agility, dribbling, ball control, and positional play, have also been studied to develop a system for line-up selection, where technical ability and physical strength are two most significant factors.

Qader et al. (2017) present a methodology for evaluating and ranking football players based on anthropometric, fitness, and ability tests. Tavana et al. (2013) propose 18 evaluation criteria (e.g. heading, jumping, and reading the game) that are usually considered by coaches when making team selections. The selection process includes four defenders, four midfielders, and two forwards. Nasiri et al. (2018a) examine several criteria and sub-criteria considered necessary by experts and the literature for evaluating football players. The study also describes the existing relationships between different sub-criteria. For independent criteria such as passing, dependent criteria exist, such as creativity, reading the game, reaction, speed, and both feet. It is worth noting that the talents of players and coaches influence the effectiveness of sports clubs. The essential elements for a sports organization are the athletic resources that constitute its human capital. Therefore, many authors place players at the center of their studies. Therefore, both player recruitment and team line-up selection are critical for maximizing profits and victory Carmichael et al. (2000); Charnes et al. (1978). Consequently, sports management requires decision-making based on scientific research that supports and informs decision makers of the most effective strategies to improve team performance and profitability.

(3) *RQ 3: What are the existing decision-making methods in which sports decision makers compare the usefulness, results, and validity of several MCDM methods?* Several MCDM methods have been reported in the literature. Following Ishizaka and Nemery (2013), these methods are classified into three main categories.

- Full aggregation approach: this method assumes compensable scores. The analytic hierarchy process (AHP) implemented by Saaty and Vargas (1982) and the analytic network process (ANP) extended from the AHP to consider the interdependent relationships between criteria and sub-criteria belong to this approach (Saaty, 1996).
- Outranking approach: this method assumes that a good score cannot compensate for a bad score. Methods belonging to this approach include The elimination and selection from the reality (ELimination Et Choix Traduisant la REalité, ELECTRE) (Roy, 1968) and the Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) (Mareschal et al., 1984).

- Goal or reference level approach: this method defines a goal for each criterion, and then identifies the options closest to the ideal reference level or goal. This approach includes the technique for order preferences by similarity to an ideal solution (TOPSIS) proposed by (Hwang and Yoon, 1981) to identify the best alternative based on the concept of the compromise solution, and data envelopment analysis (DEA) formulated by (Charnes et al., 1978) to evaluate the performance of decision-making units (DMU) that convert multiple inputs into multiple outputs.

This research aims to review articles that demonstrate the application of multiple criteria decision-making methods in sports, with a specific focus on football player selection. (Table 3.8). Mavi et al. (2012) assess the sporting performance of 18 professional football teams in the German Bundesliga by gathering data for the 1999/2000 season. Seungbum and Ross (2012) rank the criteria and sub-criteria to identify the decision making factors in sports sponsorship in the global market context. Blanco et al. (2018) apply a multi-criteria outranking methodology to the Spanish ACB Basketball League, using as alternatives the potential players and as criteria different efficiency indices.

According to Ozceylan (2016), the top-performing players in Turkish football clubs are selected for inclusion in the team. In the first phase, the Analytic Hierarchic Process attributes weight to each criterion based on the player's position. In the second phase, a scalar is established from zero to one, and an integer linear programming model is developed using the former weights of the player attributes. Dey et al. (2011) content that the performance of fast-bowlers and spinners of Cricket Indian Premier League is based on their economy rate, bowling average, and bowling strike rate, using AHP-TOPSIS and AHP-COPRAS (complex proportional assessment) approaches.

Bozbura et al. (2008) ranks six national basketball association (NBA) players according to their proximity to the ideal solution given by the TOPSIS method. Dadelo et al. (2014) develop an integrated model of TOPSIS and expert judgment to ensure greater efficiency in the assessment, rating, and selection of 18 basketball players. Nasiri et al. (2018a) propose an integrated approach combining MCDM analysis and mathematical programming to support decision makers through the process of building a football team. Nikjo et al. (2015)

select the best players from a sports team. AHP prioritizes each criterion, and extended TOPSIS is applied for weighing decision-makers and ranking alternatives. [Purwanto et al. \(2018\)](#) develop a system to select the starting line-up of football players based on the AHP method, in which technical ability and physical strength are the two critical factors for line-up selection.

[Raheela et al. \(2016\)](#) propose a method for evaluating and ranking 24 football players in the same team using MCDM, where players are selected according to several physical fitness indicators, such as 30-m speed running. [Balli and Korukoğlu \(2014\)](#) applies a fuzzy multi-attribute decision-making algorithm based on the fuzzy-AHP and TOPSIS methods to develop a decision support framework for selecting eligible basketball players in Türkiye. The findings of this SLR contribute to a deeper understanding of several MCDM methods used in sports.

Table 3.8: Summary of studies related to our [RQ3](#)

Methods- References	Category	Application	Goal	Criteria (Sub-criteria)
Fuzzy-COMET Wieckowski and Watróbski (2021)	•Goal or reference level	Predicting the chances of overtaking during pit stops in Formula 1 races by using fuzzy COmbined MEAsurement Techniques	Predicting the chances of overtaking	Drivers' gap; Tyres; Distance; Pit stop; Driver experience; team ranking

Continued on next page

Methods- References	Category	Application	Goal	Criteria (Sub-criteria)
Ouahli and Cherkaoui (2019)	•Full aggregation	Selecting team performance in industrial and safety critical systems	Team performance	Individual performance (Personal factors, skills, vigilance, Motivations); Job attributes (Criticality, Activity impact, Safety Impact); Team attributes (Communication, Pattern of distribution, Team experience, Global synergy) distribution)
Fuzzy-ANP-PROMETHEE II-DEA Nasiri et al. (2018b)	•Full aggregation •Outranking •Goal or reference level	An integrated approach that combines MCDM analysis and mathematical programming to support the decision maker during the football transfer season	Status of the players owned by the club (sale, stay)	Technical ability - Mental ability - Physical ability (Study the relationship between sub-criteria)
AHP Purwanto et al. (2018)	•Full aggregation	Selection starting lineup of football players based on their position.	Starting lineup selection	Physical, technical, tactical, mental

Continued on next page

Methods-References	Category	Application	Goal	Criteria (Sub-criteria)
PROMETHEE I-PROMETHEE II Blanco et al. (2018)	•Outranking	Applying a multi-criteria outranking methodology on the Spanish ACB Basketball League using as alternatives the potential players and as criteria different efficiency indices.	Ranking basketball players	6 efficiency indices (such as Ratio of points scored by the player with respect to the number of minutes played)
AHP-TOPSIS Flegl et al. (2018)	•Full aggregation •Goal or reference level	Selecting football players based on Multi-criteria Decision Analysis with the integration of qualitative and quantitative data	Team selection	several attributes are given by player's position such as: Finishing, Crossing, Agility, ball control, Acceleration, Vision, Sprint, speed, Dribbling...
TOPSIS Qader et al. (2017)	•Goal or reference level	Assessing 24 football players belonging in the same team using a MCDM.	Ranking football players	Anthropometric, fitness, skills
AHP-linear programming model Ozceylan (2016)	•Full aggregation •Goal or reference level	Determining top performers players for inclusion in the team	Selection of top performers	Criteria for goalkeepers, defensive centres, midfielder centres, wings, forward centers

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Methods-References	Category	Application	Goal	Criteria (Sub-criteria)
AHP-TOPSIS Nikjo et al. (2015)	•Full aggregation •Goal or reference level	Selecting best player in a sport team.	Ranking best player	6 criteria among them: The average number of goals scored per game (due to the Post) and Social prestige (popularity)
TOPSIS Dadelo et al. (2014)	•Goal or reference level	Ranking 18 basketball players from the best to the worst	Players starting the game	23 physical criteria , classified into 4 groups of competences (Body Size and Composition, Speed and Quickness, Power, Aerobic Endurance)
Fuzzy Inference System Tavana et al. (2013)	• Full aggregation	Selecting player for a football team by position: defenders, midfielders, forwards	Football player selection by position	Heading, jumping, Shoot, Short, passing, Crossing, Ball control, Dribbling, Finishing, Speed, Creativity, Create goal, scoring, position, Tackling, Both feet, stamina, Height, providing through (long) pass, Technical ability, Create attacking opportunities, Read the game

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Methods- References	Category	Application	Goal	Criteria (Sub-criteria)
AHP- TOPSIS Mavi et al. (2012)	•Full aggregation •Goal or reference level	Mesuring the sporting performance of 18 professional football teams	Best team	Players' annual wages, Coach's monthly wage, Points, Spectators, Stadium utilization, Total revenues)
AHP Seungbum and Ross (2012)	•Full aggregation	Ranking criteria and sub-criteria to Identify the decision making factors of sport sponsorship in the global market context	Evaluating weights of factors affecting sport sponsorship decision	Sport team factors (Media exposure opportunity, Sponsorship fit, Team image, Fan base strength, Star coach/player, Team on-field performance, Hospitality opportunity, Facility average attendance), Country factors (Interest level in sport, Political and economic state), Environment factors (Competitors Ambush marketing, League authority over sponsorship)
AHP- TOPSIS AHP- COPRAS Dey et al. (2011)	•Full aggregation •Goal or reference level	Measuring the performance of Fast-bowlers and Spinners of Cricket	Ranking of faster-bowlers and spinners	Economy rate, bowling average, bowling strike rate

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Methods- References	Category	Application	Goal	Criteria (Sub-criteria)
TOPSIS Bozbura et al. (2008)	•Goal or reference level	Ranking the six NBA (National Basketball Association) players according to their proximities to ideal solution given by TOPSIS method.	Ranking player to transfer	Rebounds per game, Points per game, Blocks per game, Age, Player Salary, Assists per game

(4) *RQ4: How to build a decision support model combining MCDM approaches and machine learning algorithms by integrating all technical and economic variables to help decision makers select the best players for a game?*

Our model leverages machine learning algorithms to predict players' performances, encompassing both sporting and financial aspects, by analyzing historical data sourced from official club websites. Subsequently, a set of criteria and sub-criteria is assessed and weighted utilizing a MCDM method. This weighted evaluation is then applied to rank football players for inclusion in the line-ups using a suitable MCDM methodology. This approach not only enhances the accuracy of player selection but also ensures that both qualitative and quantitative factors are considered in the decision-making process. By integrating advanced analytical techniques, our model provides a comprehensive solution to optimize team composition and improve overall performance. This model enables a complete analysis, integrating the power of machine learning algorithms and multi-criteria decision-making concepts.

This research question focuses on studies (samples) that construct a model to select or rank the best players ([Table 3.9](#)). Such models exemplify the application of sophisticated methodologies in evaluating player potential and optimizing team strategies.

Table 3.9: A sample of studies related to RQ4

References	Model/System	Application
Feng et al. (2010)	multiobjective 0–1 programming model and an improved NSGA-II algorithm	Proposed method to select the members of a cross-functional team. They considered both the individual performance of candidates and the collaborative performance between candidates. They developed a multiobjective 0–1 programming model and improved the nondominated sorting genetic algorithm II (INSGA-II) to solve The member selection problem.
Tavana et al. (2013)	Two-phase framework	Proposed a two-stage framework for player selection and team formation in football: first a fuzzy ranking method, then evaluation of alternative combinations of selected layers using a fuzzy inference system (FIS). This framework is illustrated with a case study using real data from a professional football team.
Balli and Korukoğlu (2014)	Fuzzy decision support framework	Developed a fuzzy multiattribute decision-making algorithm for the selection problem of basketball players. The model used FAHP method to identify the weights of criteria, and the TOPSIS method for the final ranking alternatives.
Nikjo et al. (2015)	WeFA (Weighted Factors Analysis) framework AHP-Extended TOPSIS	Presented a new model for clubs' head coaches and managers by considering experts' votes. This approach is based on the analytical hierarchy method (AHP) which is used to determine the weight of each criterion and the extended TOPSIS method for weighting to decision makers (DM) and ranking of alternatives. A numerical example is given with 10 experts, 3 decision makers, 4 players, and 6 criteria.

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References	Model/System	Application
Ozceylan (2016)	A mathematical model for player selection	In this work, a two-phase approach to the selection of football players was proposed. In the first phase, the attributes of each player at each position were prioritized using the AHP. In the second phase, a 0-1 integer linear programming model was developed using the weights of the player attributes and the best players were determined for inclusion in the team. The proposed solution approach was applied to the Turkish football club to illustrate the applicability and performance of the approach.
Blanco et al. (2018)	A quantitative tool based on PROMETHEE	Constructed a quantitative ranking system to aggregate basketball players using the PROMETHEE methodology. A case study of 191 players who participated in the Spanish ACB basketball league during the 2014-2015 season.
Flegl et al. (2018)	New methodology for personnel selection (AHP-TOPSIS)	Proposed a new methodology for personnel selection based on MCDA and integrate qualitative & quantitative data to select Mexican football team for the 2018 world cup in Russia.
Purwanto et al. (2018)	System for lineup selection	Developed a system to select the starting lineup of football players based on the AHP method.
Ouahli and Cherkaoui (2019)	Team performance model using Fuzzy-AHP	Evaluated 3 performance teams in industrial and safety critical systems based on individual performance, job attributes and team attributes using fuzzy Ahp method (Case study railway company).
Nasiri et al. (2018b)	A bi-objective integer programming model	Proposed an integrated approach that combines multi-criteria decision making analysis (FANP-PROMETHEE II-DEA) and mathematical programming to assist the decision makers in their selection process.

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References	Model/System	Application
Nsolo et al. (2018)	Machine learning algorithms	Compared which attributes and skills best predict the success of individual players in their positions in five top European football leagues and evaluate different machine learning algorithms in terms of their predictive performance.
Pappalardo et al. (2019)	PlayeRank Machine Learning	- Developed a data-driven framework to help professional football scouts evaluate, search, rank, and recommend football players. This tool, called PlayeRank, is based on a machine learning approach. It uses a large dataset of football records consisting of millions of match events from four seasons of 18 well-known football competitions.
Yang et al. (2020)	Deep learning algorithms - MCDM	Argued that when faced with a set of alternatives, multicriteria decision making is one of the most appropriate decision-making tools. Combining deep learning algorithms with multicriteria decision making has proven to be beneficial in Big Data.
Zhao et al. (2021)	Multi-objective optimization - genetic algorithm	Formulated the team composition issue as a multi-objective optimization problem and proposed a variant of the genetic algorithm that can automatically output and recommend a football team with a high win rate by quantifying the players' abilities under a given budget constraint.

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References	Model/System	Application
Wieckowski and Watróbski (2021)	Complex MCDM model based on the COMET method and fuzzy COs	built a complex MCDM model based on the Characteristic Objects Method (COMET) method, which was used to predict the chances of overtaking during pit stops in Formula 1 races. This model is able to reduce the number of Characteristic Objects(COs) pair comparisons needed to be performed by an expert (from 1111 to 111), while maintaining its efficiency.

3.4 Discussion and conclusion

This SLR enabled us to delve deeper into the proposed study area and analyze the literature concerning four research questions. This analysis focused on the following:

- First, we examined the relationship between player performance and football clubs' managerial and financial performance.
- Second, the main criteria and sub-criteria related to football players' positions on the pitch were included in the selection process. In this step, we noticed a lack of publications on this topic. In addition, previous articles did not address all criteria, sub-criteria, and the correlations except for [Tavana et al. \(2013\)](#).
- Third, decision-making methods that could be available to decision makers for solving the player selection problem were identified.
- Finally, studies dealing with the construction of models, case studies, and databases for solving the selection of football players were examined.

The proposed study used the systematic literature protocol and guidelines by [Kitchenham and Charters \(2007\)](#). Data published between 2018 and 2023 were collected from

digital libraries (IEEE, ScienceDirect, Springer, Taylor and Francis and Wiley). Other relevant articles were retrieved from the digital library of the University of Burgundy, although they were not included in the selected period of the SLR, all resources listed in [Tables 3.7 - 3.9](#) were carefully analyzed: Title, Keywords, Abstract, and Text. These findings led us to conclude that of the 66 papers identified by the SLR process, only a few articles addressed our four research questions ([Blanco et al., 2018](#); [Flegl et al., 2018](#); [Nasiri et al., 2018a](#); [Purwanto et al., 2018](#); [Kizielewicz and Dobryakova, 2020](#); [Romero et al., 2021](#)).

We could conclude that player selection for team compositions, recruitment, and transfers using MCDM methods constitutes a relevant and topical research area, especially when combined with machine learning algorithms. Our modeling approach will take into account the subjectivity and emotional intelligence of coaching staff and sporting managers involved in the decision-making process. By aligning this sports optimization process with principles of management and finance, we aim to strike a balance between sporting aspects and principles of human resources, finance, and marketing management.

This study identified innovative approaches to developing a decision support system for player selection issues, considering various conflicting criteria. Its findings offer valuable insights for the research community in this field, facilitating a deeper understanding and design of models and decision support systems that integrate both sporting and managerial-financial aspects.

Selecting football players for a decisive competition is complex because many qualitative and quantitative criteria and sub-criteria must be considered. However, this process tends to be subjectively interpreted, depending on the experience of coaches and managers ([Dadelo et al., 2014](#); [Purwanto et al., 2018](#); [Salles et al., 2019](#)). MCDM approaches may assist decision makers in making more objective decisions. In this context, the current research aims to produce a report on the relationship between managerial-financial and sporting performance, and the application of MCDM and machine learning algorithms in football team formation.

Although this highlighted the combined use of MCDM and machine learning for football player selection and performance prediction, future studies should incorporate more

biometric and psychological data to refine these predictions. In addition, with rapid advancements in technology, the exploration of Artificial Intelligence (AI) techniques will ensure increased transparency in selection decisions. Finally, the proposed methodology deserves to be studied in other sports contexts, paving the way for broader applications and interdisciplinary results.

Chapter 4

Professional football clubs performance and decision-making

4.1 Introduction

In the previous chapters, we have looked at the various facets of governance and management of professional football clubs, covering strategies for human resources, marketing and finance. We have emphasized the importance of aligning sporting performance with overarching leadership and management principles. This is not just about optimizing results on the pitch, but also ensuring that managerial decisions are aligned with the strategic goals of the organization. Furthermore, we emphasize the delicate balance that is required between sporting success and financial stability as well as management efficiency. Football clubs must not only excel on the pitch but also manage the complex financial and operational landscape to remain competitive in the long term.

In this context, the concept of the production function gains importance. The production function, which is extensively studied in economics, illustrates the relationship between inputs and outputs within an organization. In the context of professional football clubs, inputs can include player talent, managerial expertise, facilities and financial resources, while outputs typically manifest themselves in sporting success and financial gains.

The world of professional football is a multi-layered ecosystem where sporting performance and strategic management come together to shape a club's success. In recent years, European football has undergone a remarkable metamorphosis, evolving from a pure sport into a complex financial enterprise. Today's clubs are financial powerhouses that attract shareholders and global corporations.

Decades ago, primary revenue streams emanated from ticket sales and local advertising. However, with the surge in media rights and clubs entering stock markets, broadcast contracts now dominate, and sponsorships have increased. For instance, during the 2022-2023 season, Europe's elite clubs amassed a combined revenue of nearly 10.5 billion euros¹.

The valuation of the top five European leagues has increased exponentially, which serves to illustrate the growing importance of football as a global industry. Significant

¹Source: Deloitte Consulting LLP. www.deloitte.com/uk/en/services/financial-advisory/analysis/deloitte-football-money-league.html. Accessed on May 27, 2024.

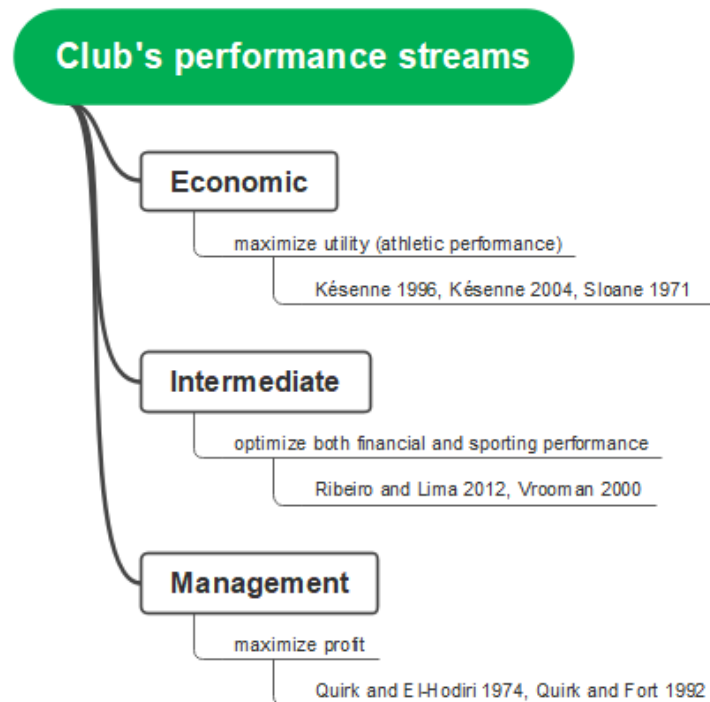


Figure 4.1: Streams of sports clubs performance (By the author)

events, such as the 1995 Bosman ruling, have had a profound impact on the transfer of players, resulting in unprecedented agreements and a notable transformation of the football industry. European clubs evolved from sports entities into industries in their own right. For instance, top clubs, such as Paris Saint-Germain and Real Madrid, have seen their valuations rise, reflecting their success both on and off the pitch.

The literature considers football club performance from three distinct perspectives (Galariotis et al., 2018): economists extend Sloane's² work by assuming that sports managers primarily maximize utility derived from sporting performance (Késenne, 1996, 2004); others believe that clubs, like other businesses, seek profit maximization (Quirk and El-Hodiri, 1974; Quirk and Fort, 1992); while an intermediate position suggests that clubs strive to optimize both financial and sporting performance (Ribeiro and Lima, 2012; Vrooman, 2000) (Figure 4.1).

The reason we focus on European professional football is due to the continued escalation of revenues relative to the total size of the European football market, which reached

²Author referenced in Galariotis et al. (2018).

28.4 billion euros in 2017-2018, with the Big Five contributing 55% of this amount. (Deloitte Sports Business Group, 2019). Professional football clubs are billion-dollar enterprises, with players representing assets worth millions. Consequently, the study of team productivity is vital to clubs, as their revenues depend on the success of their players.

According to UEFA's financial report on the European club football landscape (Widmann and Radovanovic, 2018), Europe's leading clubs generated 21.1 billion euros in revenue and spent 13.5 billion euros on wages, including players, coaches, and administrative staff. This brought the salaries-to-revenue ratio to 63.9%, a pivotal financial metric for football clubs. UEFA's introduction of fair financial rules post-2011 has contributed to stable financial accounts and efficient club investments, albeit necessitating clearer guidance for club managers on resource utilization (Franck, 2014; Rohde and Breuer, 2018).

This chapter aims to delve into the research on sports organizations as production functions, examining both input and output factors. We focus on evaluating club performance and its determinants, particularly within sporting and financial realms. In addition, we explore the intricate relationship between sporting success and financial performance in European professional football clubs (PFCs). Furthermore, we delve into decision-making as a core as a fundamental principle of sports management, particularly in the context of player selection, taking advantage of the emergence of big data.

The subsequent sections of this chapter are structured as follows:

- The production process of professional football clubs.
- Decision-making as the core of the management process.
- Case Study: French Professional Football League 1.
- Discussion, future research directions, and conclusions.

4.2 The production process of PFC

Over the past few decades, the professional football sector has spread around the world, particularly in Europe, where the most financially powerful clubs are located. These clubs

strive not only to offer fans exciting matches but also to maintain close relationships with sponsors and recruit top players. With increasing revenues from television, sponsorship, and transfer fees, clubs are investing heavily in their teams to improve performance on the pitch.

Early research into the management of professional sports clubs focused on optimizing team performance through economic analysis and viewed the professional sports team as a production function to be maximized. In the following sub-section, we examine the production process of professional football clubs to better understand how they optimize their resources for success on and off the pitch.

4.2.1 The concept of production function

The production function approach has a long tradition in the economic analysis of sport (Dawson et al., 2000). It explains the relationship between inputs and output of an organization (Figure 4.2). Rottenberg (1956) proposed the use of the production function concept in analyzing the production process of a team³. He, therefore, defined performance (output) as a function of profit (Dobson and Goddard, 2004). Output is measured by box office receipts. The factors of production, or inputs, are represented first by the team's talent stock (players) and second by a number of other variables, including management (the coach), the place of confrontation, and the quality of the opposing team. In 1974, Scully conducted the first empirical examination of the role of team productivity in American major league sports⁴. He considered the production of an organization through its achievements by using regression analysis. He assumed that teams, like other firms, are involved in a production process whose "output," in the form of sporting success, resulting from the combination of different player and non-player inputs. An organization's performance depends on its athletic success (or winning performance). He assessed the contribution of each player to the team's success and determined how these achievements translated into financial gains. He measured the overall productivity of players relative to their compensation (Carmichael et al., 2000; Dawson and Dobson, 2002).

³ Author referenced in Dobson and Goddard (2004): p245

⁴ Author referenced in Dobson and Goddard (2004): p10

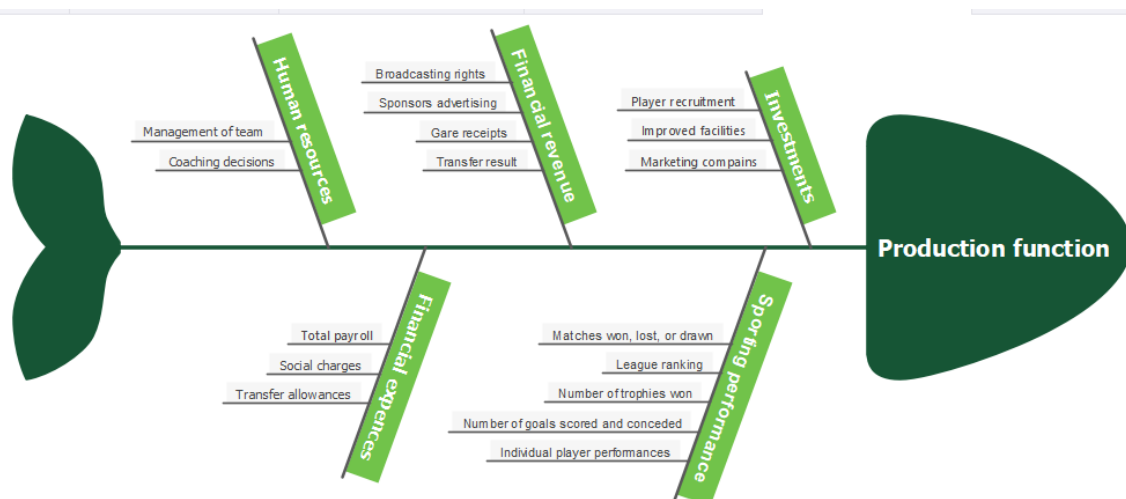


Figure 4.2: Inputs and outputs of a PFC's production function (By the author)

The production function concept has been adopted and extended by a variety of authors and for different collective sports; among others, [Carmichael et al. \(2000\)](#) have also applied the production function to English football clubs. According to them, the success of a team depends on the contributions of the players, the coach, and external variables (such as time, playing conditions, opponents or luck, etc.). The suitability of the players must be studied, as well as the management of the team by the coach, who is responsible for technical and strategic game decisions (player selection, tactics, substitutions) and preparation outside the game (motivation/coaching, fitness and mentality). Performance and its determinants are observed on the football field, at the time of the production process.

This approach aims to identify and empirically assess the success factors of teams, as well as measure the gap between potential and achieved performance, or the efficiency of the team. The ultimate objective is to transform inputs into relevant outputs. The performance of a team is typically evaluated in terms of its athletic performance or winning performance ([Carmichael et al., 2000](#)). This allows for the establishment of a relationship between inputs and their contribution to output, expressed as $Y = F(x)$, where Y represents the collective output (*dependent variable*) and x represents to the inputs (*independent variables*) of the production process.

Nevertheless, the primary role of football decision makers (coaches/managers) may be to make strategic decisions by efficiently converting a set of inputs (player talent, re-

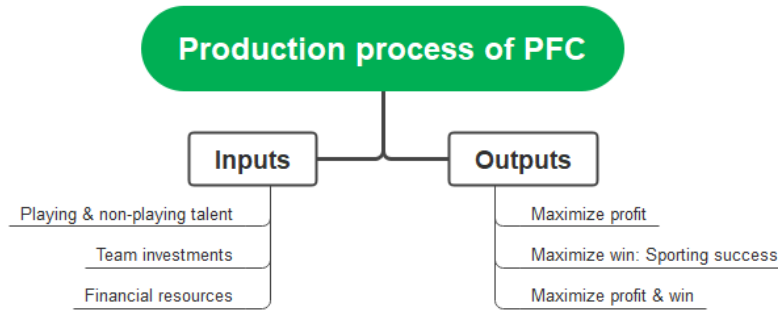


Figure 4.3: Production process of professional football clubs (By author)

sources, investments) into financial and sporting outputs (revenues, wins). Research has traditionally assumed that club managers are either profit maximizers or utility maximizers (maximizing wins). An intermediate position has been suggested by clubs that aim to maximize both profits and wins (Barros, 2006; Galariotis et al., 2018; Rohde and Breuer, 2018) (see Figure 4.3). In addition, the strategic approach may vary depending on the country's culture. Rohde and Breuer (2018) emphasized that North American clubs prioritize profit maximization, while European clubs pursue both financial profit and sporting performance maximization.

Following the findings of Lago et al. (2004)⁵, there exists a virtuous cycle between financial resources and sporting success. This cycle begins with investments in acquiring competent players to build a competitive team and achieve strong athletic performance. Subsequently, the club's revenue increases through various channels such as ticket sales, advertising, TV rights, or merchandising, all of which are essential for sustaining the cycle.

The production process involves the conversion of inputs into product output. Rotenberg⁶ has proposed that professional sports team management could be modeled as a sporting production function, it takes the form:

$$P.Q = f(T, X) \quad (4.1)$$

where: P = average admission fee; Q = number of spectators; T = quantity of playing tal-

⁵ Authors referenced in Dima (2015); Galariotis et al. (2018); Trequattrini et al. (2012)

⁶ Author referenced in Dobson and Goddard (2004); Dawson et al. (2000).

ent available to a team; X = represents all other factor inputs including team management, the stadium, transport and the playing talent of the opposing team. It should be emphasized that one of the other key inputs that Rottenberg specifically names is team management, or more specifically, the coaching staff.

In contrast to the profit-maximizing assumption, another perspective focuses on utility or win maximization. Sloane (1971), as cited in [Dobson and Goddard \(2004\)](#), viewed English football teams as utility maximizers. This perspective considers several key objectives:

- *Playing Success*: This encompasses the primary goal shared by chairmen, directors, managers, players, and fans alike.
- *Attendance or Revenue*: The level of attendance can be seen as a measure of success, reflecting the club's popularity and support base.
- *Profit*: While not the sole objective, financial gain is still significant and may be incorporated as one of several inputs in the utility function.
- *Health of the League*: Recognizing the mutual interdependence among clubs, maintaining the overall well-being and competitiveness of the league becomes an essential aspect.

Formally, the club's objective is to maximize the utility function:

$$U = u(P, A, X, \pi_R - \pi_0 - T) \quad (4.2)$$

Subject to the constraint:

$$\pi_R \geq \pi_0 + T$$

Where: P = playing success; A = average attendance; X = health of the league; π_R = recorded profit; π_0 = minimum acceptable after-tax profit; and T = taxes.

Furthermore, [Késenne \(1996\)](#) extends Sloane's work by suggesting that sports managers primarily prioritize utility maximization of sports performance, further emphasizing the multifaceted objectives of football clubs.

More recently, clubs are supposed to maximize both profits and wins. [Vrooman \(2000\)](#) believes that managers seek to maximize both financial and sporting performance. The same point of view is made by [Dobson and Goddard \(2004\)](#), who claims that when English clubs are financially constrained, they try to maximize revenue and wins first, followed by profit maximization. In the same context, [Barajas et al. \(2005\)](#) emphasized that sports managers look for ways to improve sporting performance while making a minimum profit.

This approach offers some lessons for managing professional sports teams, including player selection and compensation, team preparation, hiring new players, and tactical decisions during a game. Overall, the team is presented by its technical characteristics. Some authors will try to question this approach because it ignores the human dimension of the team [Blossier \(2013\)](#). The competitiveness of the club depends on access to the crucial resources of the players.

Sports teams are managed similarly to other businesses, aiming to achieve sporting success through various inputs. Since then, this approach has been recognized as a standard method in sports production function research [Guzmán and Guzmán \(2021\)](#). Furthermore, individual player performance is integral to team success, highlighting the importance of teamwork. Therefore, the factors that influence efficiency and success include both the club's money and human capital [Guzmán and Guzmán \(2021\)](#). According to [Rohde and Breuer \(2016\)](#), inputs to the production function of professional football teams are efficiency (player and managerial talents), resources and team investment, while the outputs are profit and win maximization.

The study of production functions and management efficiency at the business level is available in the professional team sports industry. It is easy to observe and measure both the contribution of player talent (input) and the product of team performance (output) ([Fig.4.4](#)). It is also easy to identify the coach as the manager who has ultimate responsibility for team performance ([Dawson et al., 2000](#)).

Managing sports organizations has increasingly adopted the perspective of the Resource-Based approach, which emphasizes the significance of sustainable competitive advantages derived from internal resources. This perspective attributes superior organizational perfor-

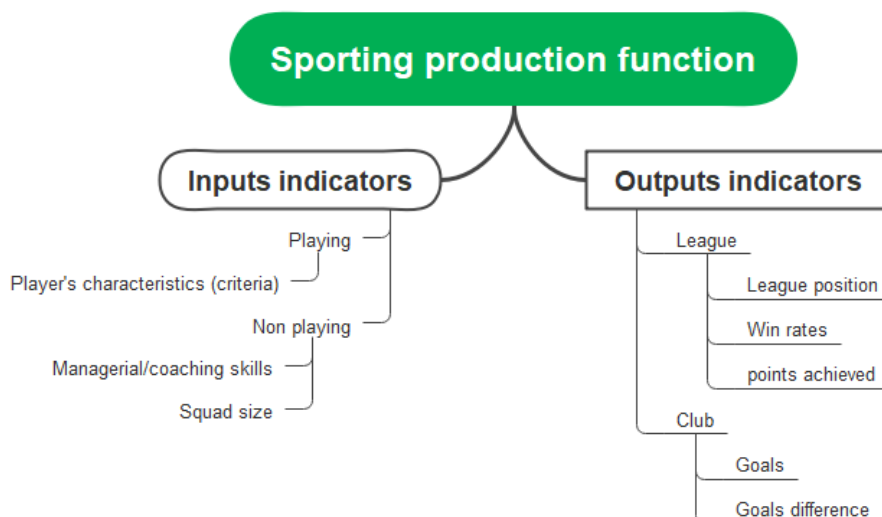


Figure 4.4: Sporting production function (By the author)

mance to the quantity and quality of resources possessed by the company. In the context of sports, athletic resources, particularly human capital, stand out as paramount. These include the skills, experience, and physical attributes of players and coaching staff, forming the core of an organization's competitive advantage. However, measuring performance in sports extends beyond the playing field to encompass various inputs that contribute to organizational success.

4.2.2 Measuring playing an non-playing performance: Inputs

In sports clubs, performance is usually evaluated based on the success of the team. The result of the production process is reflected, on one hand, by the performance of the manager/coach and, on the other hand, by the performance of the teammates, which is influenced by the players' stock talents. However, all football clubs compete under the same rules and use a common technology. Each club employs playing (player performance) and non-playing (managerial/coaching performance) inputs in similar numbers and proportions (Dobson and Goddard, 2004).

Player's performance

To better understand the impact of salary expenditures on athletic success, we explore the existing research examining the win-pay relationship. The players are the foundation of a sports organization; they are the final participants in the production process, namely, in the game. Their contribution is noted on the field to achieve sporting results. Therefore, players are in the best position to benefit from the club's revenues, as their performance is the primary driver of these earnings. Star players, with their exceptional talent and skills, often command higher salaries due to their significant contribution to the team's success. Conversely, support players, who play a crucial role in facilitating the success of star players and maintaining team cohesion, typically receive less remuneration.

It is worth noting that salaries constitute the largest expenditure for professional football clubs, highlighting the significant financial investment in player compensation. This is particularly evident in the 2017/2018 season, as salary expenses outpaced revenue growth. Salaries increased by 13%, surpassing 9 billion euros for the first time ([Deloitte Consulting LLP, 2019](#)).

In the following we present the related literature that explored the relationship between wage expenditures and athletic success (the win-pay relationship) with the aim of identifying a causal link between team performance and team payroll.

[Carmichael et al. \(2011\)](#) posit that wage expenditures are a reliable indicator of players' skills and performance. An interpretation of this evidence is that investing in players' skills and abilities is an effective strategy for achieving success on the field. Teams with greater financial resources are better positioned to maintain or even extend their success by allocating more resources to player development than less successful clubs.

This suggests a causal link between revenue generation and the competitive imbalance resulting from investments in players.

The study by [Ribeiro and Lima \(2012\)](#) examines the correlation between player wage distribution and club efficiency in football. They find that a wider wage spread is typically linked to increased club efficiency. Football is inherently a team sport characterized by high interdependence among players. The majority of a club's revenue is often derived from

on-field success, which underscores the significance of managing personnel and players carefully to maximize business potential.

To elucidate the determinants of athletic performance, [Carmichael et al. \(2000\)](#) focused on various specific play variables including shots on goal, passes, tackles, clearances, dribbling and ball runs, fouls, free kicks awarded, and various goalkeeping aspects, alongside team variables. They aimed to estimate a production function for English Premiership football during the 1997-1998 season. Their findings underscore the importance of key offensive and defensive skills, with playing at home positively correlated with success.

A team's performance depends on its talent pool, and clubs use different approaches to procure and develop players ([Gerrard, 2005](#)). There are two primary methods of changing this stock: either by recruiting new players or by encouraging the development of existing players.

[Scafarto and Dimitropoulos \(2018\)](#) claimed that larger soccer clubs (size) are able to generate more revenue, but clubs that pay higher salaries and have greater leverage are less profitable. It seems that Italian clubs can increase their revenues by recruiting more talented athletes (by paying higher salaries), but cannot convert these higher revenues into profits. [Zambom-Ferraresi et al. \(2018\)](#) suggested that managers should consider hiring players with determinant skills and abilities that influence team success. [Salles et al. \(2019\)](#) emphasized that among any investments made by football clubs, the most important ones are those made for hiring players. Players are thus considered the most valuable resource for the club organization. They are used to operating as a unit under the leadership of the head coach, who is in charge of maintaining the team's unity.

Coaching staff performance

The role of the coaching staff is central to the success of a team and complements the contributions of the players. They play an important role in maximizing the players' potential and promoting team unity. Under the direction of the head coach, the coaching staff is tasked with maintaining team cohesion and ensuring that the players act harmoniously as a unit.

In professional clubs, the coach occupies a strategic and important position. Their tasks include leading the daily training sessions, developing training plans and improving the skills of individual players. They also prepare the team for upcoming matches and are the driving force behind the team's success. As an intermediary between the team and the wider sports organization, coaches are an important link for effective communication and coordination (Blossier, 2013).

Since the coach is dependent on the performance of his teammates, his position is precarious and becomes increasingly uncertain as the sport develops. With this in mind, Audas, Dobson and Goddard (1999)⁷ examine a variety of factors that contribute to the chronic insecurity of the English soccer coach's position. Match results - the most important measure of the coach's performance - are completely transparent, easy to interpret and immediately available to the public. However, the coach's ability to influence results is limited by uncertainty over player fitness, performance and motivation.

According to Dawson and Dobson (2002); Gerrard (2005), the coach influences team performance in two primary ways. Firstly, there's the direct or strategic effect, where the coach converts the given input of player efficiency into the team's output. By selecting tactics and assembling the team, the coach exploits player talents to achieve game results effectively. Secondly, there's the indirect or leadership effect, where coaches impact team efficiency through their ability to recruit, train, and motivate individual players, elevating their performance levels. Thus, the coach's responsibility extends beyond optimizing the use of a fixed quantity of player input to enhancing its quality as well. However, a coach's ability to win as many matches as possible - managerial efficiency - appears to be the primary strategy for maintaining their position within the group.

Overall, teams that change coaches during the season tend to perform less well in the three months following the change (Blossier, 2013). Such changes often introduce volatility in the determinants of short-term performance, driven by immediate concerns such as avoiding relegation. Studies by Audas et al. (1997, 2002) utilizing non-parametric methods on English football data underscore the direct relationship between coach changes and

⁷ Authors referenced in Dobson and Goddard (2004) : p289.

team performance decline. Conversely, [Tena and Forrest \(2007\)](#) provided evidence suggesting an increase in performance following a coach dismissal. However, [Muehlheusser et al. \(2012\)](#) posited that coaching changes in the German football league only lead to improved team performance in homogeneous teams.

Moreover, [Koning \(2003\)](#), in a study of the Dutch Premier League between 1993 and 1998, assessed the influence of coaching changes on team performance using metrics such as average goal difference, goals conceded, and goals scored. Koning also suggested that coach dismissals may serve as a means to appease the press and fans. A new coach, it is believed, can inject motivation into players, potentially leading to improved team performance and, subsequently, increased revenue and better transfer conditions for players.

Building on the research conducted by [Dawson and Dobson \(2002\)](#), which explored the correlation between a coach's performance and their human capital endowment, [Frick and Simmons \(2008\)](#) delved into the impact of hiring a high-quality coach on team performance. Analyzing data from 661 coaches across the major English football leagues from 1992-93 to 1997-98, they concluded that teams hiring better quality coaches tend to accrue higher point totals by reducing technical inefficiencies. Similarly, [Lye \(2013\)](#) supposed that investors seeking specific objectives would opt to invest in hiring new football managers or enhancing player investments to enhance club performance and maximize returns.

The role of the coach goes beyond tactical decisions on match days. While some individuals may simultaneously serve as both coach and manager, particularly in smaller clubs, larger organizations often designate separate individuals for these roles. The coach primarily focuses on the technical aspects of the game and player development, while the manager assumes responsibility for overall team performance and club management.

Manager's performance

Club management has significant influence on the success of a team, making critical decisions that impact individual matches and the overall trajectory of the season. A manager's effectiveness is measured by his ability to effectively allocate human and financial resources and translate them into tangible successes on and off the field ([Dobson and God-](#)

dard, 2004).

In football clubs, the manager holds a multifaceted role encompassing strategic planning, budget management, and player personnel decisions [Muehlheusser et al. \(2012\)](#). While the manager oversees team selection and tactics, distinct from the coach's responsibilities, their ultimate goal is to drive the team's performance and achieve desired outcomes.

Assessing managerial performance involves careful consideration of various factors, including the manager's playing experience and prior affiliations with the club [\(Dawson and Dobson, 2002\)](#). Research by [Audas et al. \(2002\)](#) highlights the impact of managerial changes on team performance, suggesting that such shifts can mitigate relegation threats and improve performance.

4.2.3 Measuring sporting performance: Output

Team sports offer a conducive environment for performance evaluation, given the transparency and comprehensive recording of match results (output), coupled with the availability of extensive data on player and manager attributes (inputs) facilitated by the emergence of Big Data technologies [\(Bai and Bai, 2021; Cacho-Elizondo, 2020; Rein and Memmert, 2016; Yang et al., 2020\)](#). [Carmichael et al. \(2000\)](#) argued that team performance is typically assessed based on the final score, represented as the goal differential: positive for victories, negative for defeats, and zero for draws. Furthermore, the literature examines football club performance through diverse methods such as Data Envelopment Analysis (DEA) and exploring the relationship between financial and sporting aspects.

Subsequently, studies like those conducted by [Boscá et al. \(2009\)](#); [Guzmán and Morrow \(2007\)](#); [Haas \(2003\)](#); [Soleimani-Damaneh et al. \(2011\)](#); [Tiedemann et al. \(2011\)](#) have employed DEA to assess team efficiency and analyze the relationship between inputs (such as salaries, coach wages, and revenue) and outputs (such as points won, ranking, and offensive/defensive performance). These analyses provide insights into the factors influencing a club's efficiency and performance over time.

Furthermore, research delves into the relationship between financial and sporting per-

formance. [Szymanski and Kuypers \(1999\)](#) found a strong correlation between revenues and league performance, indicating that successful teams tend to attract higher revenues. [Carmichael et al. \(2011\)](#); [Pinnuck and Potter \(2006\)](#) explored the impact of on-field success on financial outcomes, highlighting the significance of sporting achievements in driving marketing revenues and overall financial performance. Moreover, studies by [Barajas et al. \(2005\)](#); [Gerrard \(2005\)](#); [Dimitropoulos and Limperopoulos \(2014\)](#); [Rohde and Breuer \(2018\)](#) shed light on various factors influencing a club's financial success, including player contracts, brand value, and revenue sources.

The production process of sports clubs, which includes the measurement of input and output indicators, is essentially based on decision-making. Effective and relevant decisions enable sports clubs to control and regulate their own operations, thereby reducing conflicts of interest between stakeholders. Indeed, judicious resources management and strategic planning are crucial to optimizing a club's sporting and financial performance. In the following section, we explore in detail the importance of decision-making in sports club management.

4.3 Decision-making: the core of sport management process

In professional sport, effective decision-making is the cornerstone of successful management, profoundly influencing competition results and club development. Decisions taken by club board members, coaches and technical staff have major implications, influencing not only on-field performance, but also off-field operations and strategic direction.

The importance of decision-making in sports management cannot be overstated. Every decision, whether it's team composition, player recruitment, tactical strategies, marketing initiatives or investment in facilities, can have an impact on a club's sporting success and financial stability. Mastering the art of strategic decision-making is essential to face the many challenges and opportunities of professional football.

Effective decision-making in sport management encompasses both art and science.

While based on in data-driven analysis and empirical evidence, it also includes elements of intuition, creativity and strategic vision (Sieghartsleitner et al., 2019). Decisions made in the boardroom or on the touchline are guided not only by quantitative measurements and performance indicators but also by an understanding of the game, its stakeholders, and the broader socio-economic landscape.

Moreover, decision-making in sports management is inherently forward-looking, requiring foresight and adaptability in the face of uncertainty and volatility. Whether managing player transfers, negotiating contracts, reacting to injuries or regulatory changes, decision-makers need to remain agile and proactive, anticipating challenges and seizing opportunities to lead their clubs to success.

At its core of sports management, effective decision-making is guided by the principles of ethics, integrity and responsibility. As sports leaders, club boards and coaches must defend the values of fair play, transparency and social impact, ensuring that decisions are made in the interests of all stakeholders, including players, staff, fans and the wider community.

In the next sub-sections, we take a closer look at the different facets of decision-making in football management, including strategic and tactical aspects, as well as financial and human resources considerations.

4.3.1 Strategic decision-making

In the dynamic and competitive landscape of professional sport, strategic decision-making plays an essential role in the direction and success of football clubs. Strategic decisions, characterized by their long-term impact, help clubs to set objectives, allocate resources and handle complex challenges in order to gain a competitive advantage in the football market. It requires a forward-looking approach, based on market knowledge, competitive analysis and an in-depth understanding of the club's specific strengths and weaknesses, to achieve the organization's objectives.

By conducting a market analysis, clubs can identify areas for improvement and growth potential, enabling them to make the right decisions on resource allocation, player selection

and marketing strategies. In addition, strategic partnerships with sponsors, broadcasters and community organizations play a crucial role in improving revenue streams and brand visibility, while effective risk management ensures that clubs are prepared for unexpected challenges.

Moreover, the integration of technological advancements, such as big data, artificial intelligence, and computerized information systems, not only facilitates adaptability and progress for sports clubs but also significantly influences tactical decision-making processes. These innovative technologies serve as strategic imperatives, empowering clubs to maintain agility and competitiveness within the dynamic sports sector.

4.3.2 Tactical decision-making

Tactical decision-making in sport management involves the daily operational decisions made by coaches and managers to optimize team performance during matches and training sessions. These decisions are based on an analysis of the opponent's strengths and weaknesses, players' performance, and playing situations. Coaches must evaluate various tactical formations, player positions and substitution strategies to outsmart the opposition and exploit scoring opportunities.

In addition, tactical decisions go beyond field strategies to involve training methodologies, recovery protocols, and injury management techniques to ensure player readiness and maximum performance. Constant communication and collaboration between coaching staff and players is essential for effective tactical decision-making, allowing for real-time adjustments and strategic adaptations during matches. By leveraging data analysis and performance metrics, clubs can gain insight into player performance trends and opponent behavior. This allows them to make tactical, data-driven decisions that maximize their competitive advantage. Ultimately, tactical decision-making is key to success on the field, as it allows clubs to translate strategic goals into tangible results on match day.

4.3.3 Financial decision-making

Financial decision-making in sport management involves the allocation and management of financial resources to support the strategic and operational objectives of sports organizations. This involves revenue generation, and expenses and investment management aimed at achieving financial sustainability and growth.

Revenue Generation: Implementing strategies to diversify revenue streams is essential, including ticket sales, broadcasting rights, sponsorship deals and merchandise sales. Sports organizations must innovate and explore new revenue opportunities to maximize financial resources and reduce dependence on a single revenue source.

Expenses and investment management: Effective monitoring and control of expenses are crucial to optimize cost-efficiency while maintaining the quality of services and operations. This includes managing player wages and transfer fees, infrastructure investment, scouting, and recruitment. Making strategic decisions regarding capital investments, such as stadium renovations, training facilities, technology upgrades, and player acquisitions, is vital for the long-term success and competitiveness of sports organizations.

Indeed, effective financial decision-making requires collaboration between various stakeholders, including owners, managers, and shareholders.

4.3.4 Human resources decision-making

Human resources decision-making in sport management involves the strategic management of personnel to maximize organizational effectiveness, athlete performance and overall success. This involves various aspects of human resources management, including recruitment, selection, training, development and performance management. Sports organizations need to make the right decisions regarding their human capital in order to build a talented, cohesive team and achieve their goals on and off the field. Effective recruitment and selection processes help sports organizations gain a competitive advantage by building a diverse, high-performance team.

After exploring the production process of professional football clubs and underscoring

the crucial importance of decision-making in sports management, it is now time to delve into a concrete case study. Focused on the French 'Ligue 1', this case study allows us to deepen our understanding of the relationship between on-field success, ensured by effective management of human resources (players and coaches), and its financial repercussion on the club's evolution. By closely examining the variables and data relating to sporting and financial aspects over a decade of the 'Ligue 1', we can identify the correlation between sporting performances and financial outcomes, providing insights into the challenges and opportunities faced by professional football clubs.

4.4 Case Study: French professional football 'ligue 1'

This case study examines the complex relationship between success on the field and financial growth as European football evolves into a financially strong entity. Once dependent on traditional revenue streams, clubs now operate in a landscape dominated by broadcasting contracts, sponsorship and stock market transactions. This study focuses on the French 'Ligue 1' to decipher the reciprocal relationship between success on the field and financial growth over the past decade.

This research attempts to decode whether on-field success translates to financial growth and vice versa. We examine the influence of sports performance on revenue, and conversely, how financial investments impact on-field achievements. Our study's core lies in analyzing decade-long data of French 'Ligue 1' clubs.

Regardless of perspective, the intersection of sporting and financial success is undeniable. Some argue for a strong positive correlation between sports and financial success, whereas others suggest a more nuanced relationship. For instance, [Rohde and Breuer \(2018\)](#) construct a comprehensive financial model to evaluate the process of converting team resources into tangible outcomes. [Gonçalves et al. \(2020\)](#) investigated the intricate relationship between sports and financial performance of Brazilian clubs and found notable differences depending on performance measures and type of revenue source. Similarly, [Di Simone and Zanardi \(2020\)](#) found a strong correlation between the dual objectives of

financial profit and sporting success, underscoring the importance of maintaining balance. As football has grown and adapted, so too has the nature of its financial mechanisms and links to on-field performance.

This study aims to contribute to this ongoing dialogue by offering insights from a decade of data from French 'Ligue 1'.

4.4.0.1 Methods

Our research focuses on examining the relationship between financial and sports performance by conducting a predictive analysis. We will check on the one hand the dependence between (Income) and (Broadcasting rights, Sponsors Advertising, Gate receipts, Rank league, Total payroll), with or without FFP, and on the other hand we will verify the relationship between (Rank league) and (Broadcasting rights, Sponsors Advertising, Gate receipts, Rank league, Total payroll) with or without FFP. This study seeks to shed light on the relationship between financial and sporting performance through a series of predictive analyses. To this end, we have developed four analytical models to establish links between financial and sporting performance.

The analytical models

These relationships are described by the following linear regression models:

Model 1: Excluding financial fair play

$$(1) \text{ Income}_{i(t+1)} = \text{Const} + C1 \times \text{Broadcastingrights}_{it} + C2 \times \text{SponsorsAdvertising}_{it} \\ + C3 \times \text{Gatereceipts}_{it} + C4 \times \text{Rankleague}_{it} + C5 \times \text{Totalpayroll}_{it} + \varepsilon_{it}$$

Model 2: Incorporating financial fair play

$$(2) \text{ Income}_{i(t+1)} = \text{Const} + C1 \times \text{Broadcastingrights}_{it} + C2 \times \text{SponsorsAdvertising}_{it} \\ + C3 \times \text{Gatereceipts}_{it} + C4 \times \text{Rankleague}_{it} + C5 \times \text{FFP}_{it} + C6 \times \text{Totalpayroll}_{it} + \varepsilon_{it}$$

Model 3: Excluding financial fair play

$$(3) \text{ Rankleague}_{i(t+1)} = \text{Const} + C1 \times \text{Broadcastingrights}_{it} + C2 \times \text{SponsorsAdvertising}_{it} \\ + C3 \times \text{Gatereceipts}_{it} + C4 \times \text{Totalpayroll}_{it} + \varepsilon_{it}$$

Model 4: Incorporating financial fair play

$$(4) \text{ Rankleague}_{i(t+1)} = \text{Const} + C1 \times \text{Broadcastingrights}_{it} + C2 \times \text{SponsorsAdvertising}_{it} \\ + C3 \times \text{Gatereceipts}_{it} + C4 \times \text{FFP}_{it} + C5 \times \text{Totalpayroll}_{it} + \varepsilon_{it}$$

Where, for $i = 1..200$ observations and $t = 2011..2020$ seasons:

- $\text{Income}_{i(t+1)}$ = dependent variable to predict in the case of Models 1 and 2
- $\text{Rankleague}_{i(t+1)}$ = dependent variable to predict in the case of Models 3 and 4
- $\text{Broadcastingrights}_{it}$, $\text{SponsorsAdvertising}_{it}$, Gatereceipts_{it} , Rankleague_{it} , Totalpayroll_{it} = independent variables
- $C1, C2, C3, C4, C5$ are the slope coefficients of the independent variables
- Const = Intercept
- ε_{it} = Error

Implementation and tools

Multiple linear regression (MLR) facilitates an understanding of complex relationships in predictive terms. MLR models are popular in machine learning and divide datasets into “test” and “training” (Gu et al., 2019; Pappalardo et al., 2019), they identify model parameters using the test set and then apply the model to the training set. Predictions were made after confirming the satisfactory model training. The Python package scikit-learn, tailored for machine learning, and was used for this purpose (Scikitlearn-developers, 2023). Comprehensive analysis requires tools and libraries from Anaconda and Jupyter notebooks.

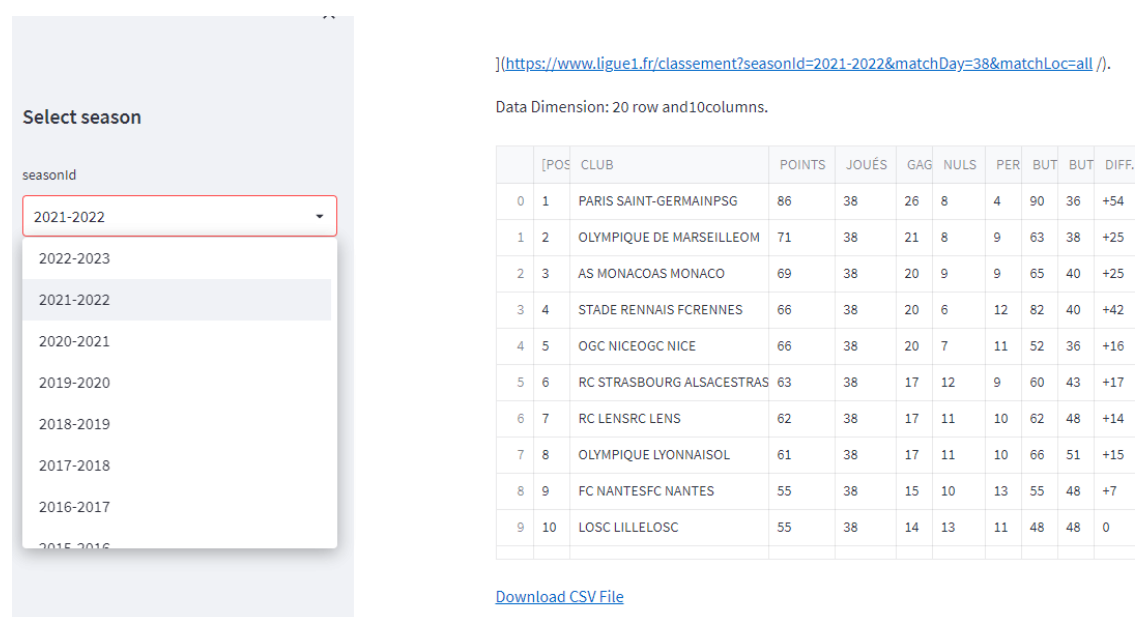


Figure 4.5: A sample of dataset extracted by the Streamlit interface (By the author)

Data collection and variable definitions:

Empirical Data: Our focal point is the French professional football 'Ligue 1' across ten seasons (2011-2021). This choice is motivated by the scarcity of literature on the French League despite accessible financial data from annual DNCG reports and the Professional Football League. The first step was to extract sports data from the official league website [www.Ligue 1.fr](http://www.Ligue1.fr) (last visit in January 2023) using web scraping and the Streamlit Python framework, with the possibility of downloading CSV files (Figure 4.5).

Data Availability: The data supporting the results of this study are available from the official website of 'Ligue 1' and the Direction Nationale du Contrôle de Gestion (DNCG). Data extraction was performed using web scraping tools, including BeautifulSoup and Streamlit Python frameworks. The financial reports from DNCG for the seasons 2011-2021 were accessed from the respective annual reports [DNCG, 2012-2021].

Data Retrieval: Sports data were sourced from the official league website using web scraping tools, such as BeautifulSoup and the Streamlit Python framework. Financial data were derived from the DNCG's annual reports (DNCG, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020). Clubs' financial performance was studied by considering their total operating income and payroll (Figure 4.6). It should be noticed that club rev-

enue comes from three main sources: broadcasting rights, sponsors-advertising, and gate receipts.

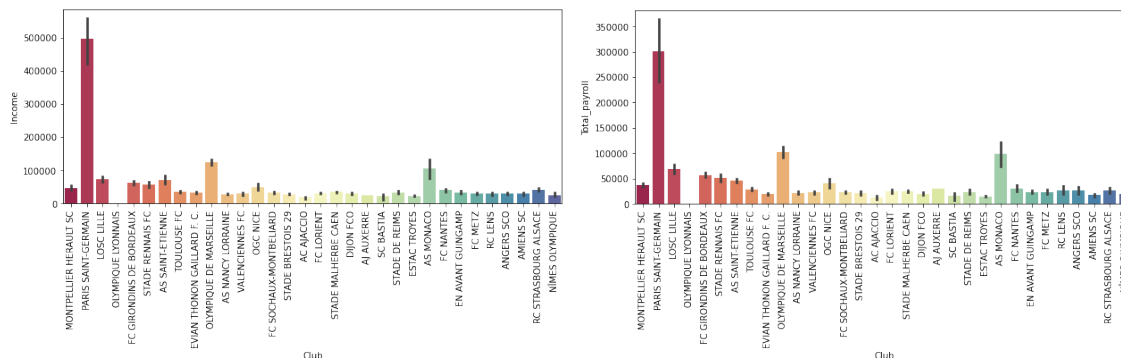


Figure 4.6: Total operating income and total payroll per club

Key Metrics: Club’s financial performance is assessed using total operating income and payroll. The income stems primarily from broadcasting, sponsors, and gate receipts. Financial Fair Play (FFP): This UEFA regulation, pivotal to football governance (Dima, 2015; He et al., 2015), is integrated as a dummy variable for sanctioned clubs. Before analyzing our panel data, we describe the financial and sporting variables (Table 4.1) and normalize our dataset that will be used to study and predict the performance of French League one clubs. Before embarking on panel analysis, it is essential to provide a thorough description of both financial and sporting variables. Following this, our dataset underwent normalization to ensure that our metrics could be analyzed on a standardized scale. This not only enhances the precision of the data but also facilitates a smoother comparison across variables.

Table 4.1: Definitions of variables

Variables	Description
Broadcasting_rights	Revenues derived from broadcasting rights for TV or other media
Sponsors_Advertising	Incomes from commercial sponsors, advertisements, and brand licensing
Gate_receipts	Revenues from the box office, seasonal tickets, and corporate hospitality sales
Income	Total operating income
Total_payroll	Compensation disbursed to players and other staff members
FFP	Financial Fair play: Dummy variable. It is marked as 1 if a club is penalized by the UEFA and 0 otherwise
Rank_League	Denotes the standing of a club in the league during a season’s culmination

Data normalization

Normalization is pivotal for enhancing the precision and consistency of our financial data. Using min–max feature scaling (refer to Equation 5), we can effectively rescale the columns in the dataset to lie within the range of 0 to 1. The formula for this is given by:

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (5)$$

An important observation emerged when analyzing the final league rankings: they had an inverse relationship with most of the study variables. This implies that a club with superior performance has a lower rank value, as reflected by the negative coefficient in the regression model. To rectify this, we normalized the ranking variable using Equation (6).

$$\text{Rank}_{\text{league_norm}} = \frac{n + 1 - p}{n} \quad (6)$$

Where n is the number of clubs that participate in the league and p is the ranking achieved at the end of the season. Figure 4.7 provides a glimpse of the normalized dataset used in our subsequent analyses.

Rank_League	Club	Year	Fair_play_Fin	Broadcasting_rights	Sponsors_Advertising	Gate_receipts	Income	Total_payroll
0	MONTPELLIER HERAULT SC	2011	0	0.179948	0.024168	0.083782	0.083228	0.072439
1	PARIS SAINT-GERMAIN	2011	0	0.232990	0.084766	0.502378	0.337580	0.233201
2	LOSC LILLE	2011	0	0.288595	0.036223	0.126823	0.121629	0.173944
4	FC GIRONDINS DE BORDEAUX	2011	0	0.183660	0.036761	0.118560	0.098844	0.109750
5	STADE RENNAIS FC	2011	0	0.169287	0.035079	0.137088	0.082621	0.085425
...
195	FC LORIENT	2020	0	0.076132	0.009849	0.009195	0.044284	0.063939
196	STADE BRESTOIS 29	2020	0	0.083169	0.015177	0.007689	0.041587	0.050543
197	FC NANTES	2020	0	0.101779	0.021125	0.006658	0.059705	0.090564
198	NÎMES OLYMPIQUE	2020	0	0.092506	0.004628	0.007471	0.037127	0.040765
199	DIJON FCO	2020	0	0.099985	0.016225	0.000733	0.045196	0.045697

190 rows × 9 columns

Figure 4.7: A sample of normalized dataframe

Data analysis:

To unravel the interplay between the variables and predict financial (income) and sports (league rank) outcomes, rigorous statistical analysis was conducted. The initial steps en-

comprised calculating descriptive statistics for each variable, which encapsulated measures of central tendency, spread, and overall data distribution, excluding the NaN values. The results are presented in [Table 4.2](#).

Table 4.2: Descriptive statistics

	Rank_League	Broadcasting_rights	Sponsors_Advertising	Gate_receipts	Income	Total_payroll	Fair_play_Fin
'count'	190.000000	190.000000	190.000000	190.000000	190.000000	190.000000	190.000000
'mean'	0.507105	0.166670	0.056858	0.131669	0.110573	0.106822	0.015789
'std'	0.285059	0.137265	0.133459	0.173549	0.163359	0.136226	0.124990
'min'	0.050000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
'25%'	0.250000	0.090876	0.017448	0.050031	0.045321	0.042876	0.000000
'50%'	0.500000	0.116641	0.024508	0.080156	0.057283	0.061489	0.000000
'75%'	0.750000	0.184815	0.035880	0.139109	0.101004	0.108956	0.000000
'max'	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

To delve further, we employed common statistical measures, namely: correlations and p-values. Although the correlation coefficient probes the association between pairs of variables, the p-value indicates the statistical significance of these relationships. [Figure 4.8](#) shows the correlation metrics.

To ensure robustness before proceeding with model training, the stationarity of the variables was evaluated using the augmented Dickey (ADF) cointegration test. The results (refer to [Table 4.3](#)) confirm the stationarity of our dataset, with a significant p-value (less than 0.05) and ADF test statistic below critical threshold values. An exception is observed in the This stationarity assessment was facilitated by Python packages `statsmodels.tsa.stattools` [The Statsmodels Development Team \(2023\)](#) and `scipy.stats.spearmanr` [SciPy-Developers \(2023\)](#).

[Figure 4.9](#) shows the relationship between the variables, which depicts the link between revenue (dependent variable) and league rank (independent variable); on the right, it maps the association between league rank (dependent variable) and total payroll (independent variable). From these plots, it is evident that clubs that secure higher league ranks generally earn higher revenue. This observation aligns with the findings of [Llorca and Teste \(2016\)](#), who posited a strong and significant correlation between a team's payroll and on-field performance within the French championship. Interestingly, some outliers indicate that clubs with lower payrolls achieve superior league ranks, emphasizing that money is not the sole determinant of sports success.

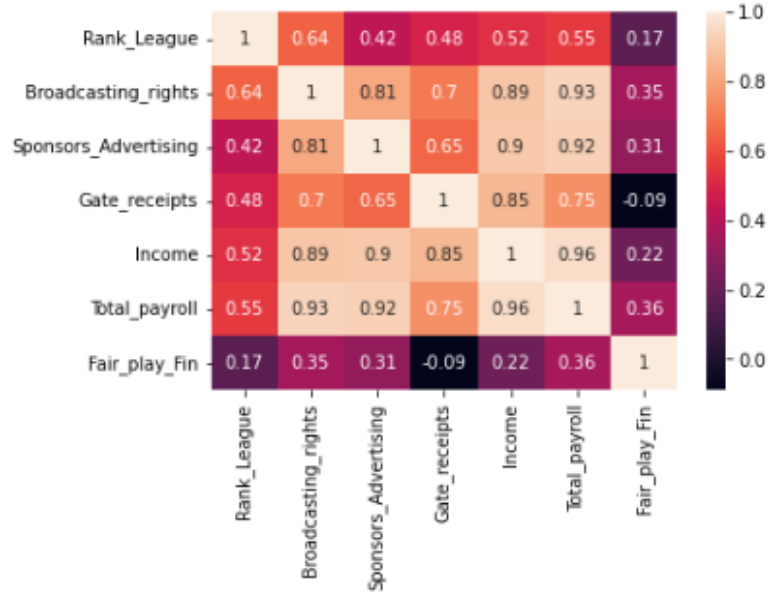


Figure 4.8: Correlation between variables

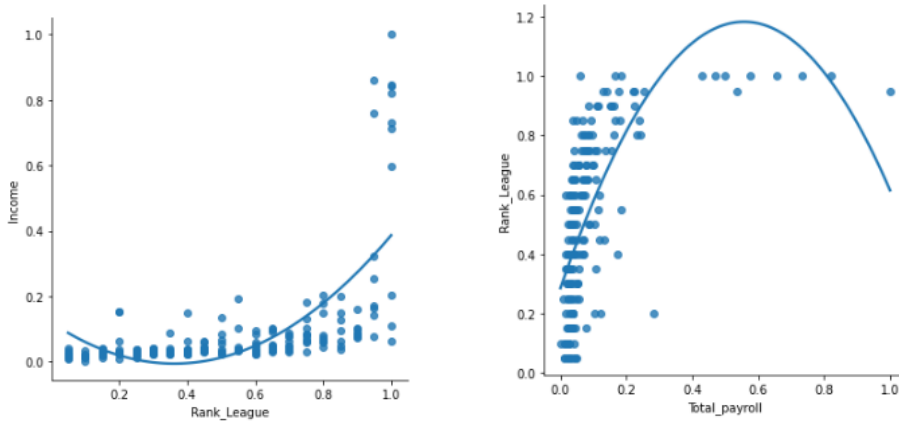


Figure 4.9: Income vs and Rank in the league / Rank in the league vs Total payroll

Models training

Building a machine-learning linear regression model requires a systematic approach to data organization and the application of appropriate algorithms.

Data preparation for training: Initially, the dataset was segregated into two distinct arrays. The *x*-array encompasses the variables that we harness to make predictions (independent variables), whereas the *y*-array contains the data that we aim to predict (dependent variables or targets).

Table 4.3: Data stationarity

Rank_League	ADF statistic: -14.40481 p-value: 0.000000 Critical values: 1% : -3.469 5% : -2.878 10% : -2.576	Sponsors_Advertising	ADF statistic: -13.247577 p-value: 0.000000 Critical values: 1% : -3.465 5% : -2.877 10% : -2.575
Fair_play_Fin	ADF statistic: -0.267322 p-value: 0.930007 Critical values: 1% : -3.469 5% : -2.878 10% : -2.576	Gate_receipts	ADF statistic: -8.591426 p-value: 0.000000 Critical values: 1% : -3.466 5% : -2.877 10% : -2.575
Broadcasting_rights	ADF statistic: -10.59333 p-value: 0.000000 Critical values: 1% : -3.465 5% : -2.877 10% : -2.575	Total_payroll	ADF statistic: -11.557761 p-value: 0.000000 Critical values: 1% : -3.465 5% : -2.877 10% : -2.575

- For Models 1 and 2, the arrays are defined as:

$x = [["Broadcasting rights", "Sponsors Advertising", "Gate receipts", "Rank league", "Total payroll"]]$

$y = [["Income"]]$

- For Models 3 and 4, the arrays are organized as:

$x = [["Broadcasting rights", "Sponsors Advertising", "Gate receipts", "Total payroll"]]$

$y = [["Rank league"]]$

It's noteworthy to mention that for Models 2 and 4, the dummy variable 'FFP' was appended to the x -array.

Addressing multicollinearity and heteroscedasticity: To counter the potential issues of multicollinearity and/or heteroscedasticity among the variables, we employed the generalized least squares (GLS) technique. This method refines the estimation of unknown parameters within our Linear Regression model. The results of this methodology are presented in [Figures 4.10](#) and [4.11](#).

Data split for training and testing: Using the scikit-learn library, we bifurcated our dataset into training and testing datasets. The function `train_test_split` from the `model_selection` module facilitates this division. In our study, 30 percent of the data were used for testing.

GLS Regression Results							GLS Regression Results								
Dep. Variable:	Income	R-squared:	0.969	Dep. Variable:	Income	R-squared:	0.969	Dep. Variable:	Rank_League	R-squared:	0.409	Dep. Variable:	Rank_League	R-squared:	0.413
Model:	GLS	Adj. R-squared:	0.968	Model:	GLS	Adj. R-squared:	0.968	Model:	GLS	Adj. R-squared:	0.396	Model:	GLS	Adj. R-squared:	0.397
Method:	Least Squares	F-statistic:	1158.	Method:	Least Squares	F-statistic:	1158.	Method:	Least Squares	F-statistic:	32.02	Method:	Least Squares	F-statistic:	25.91
Date:	Wed, 24 May 2023	Prob (F-statistic):	5.58e-137	Date:	Wed, 24 May 2023	Prob (F-statistic):	5.58e-137	Date:	Wed, 24 May 2023	Prob (F-statistic):	2.86e-20	Date:	Wed, 24 May 2023	Prob (F-statistic):	9.30e-20
Time:	22:21:35	Log-Likelihood:	405.87	Time:	22:21:35	Log-Likelihood:	405.87	Time:	22:37:06	Log-Likelihood:	83.575	Time:	22:37:06	Log-Likelihood:	84.228
No. Observations:	190	AIC:	-799.7	No. Observations:	190	AIC:	-799.7	No. Observations:	190	AIC:	-157.2	No. Observations:	190	AIC:	-156.5
Df Residuals:	184	BIC:	-780.3	Df Residuals:	184	BIC:	-780.3	Df Residuals:	184	BIC:	-140.9	Df Residuals:	184	BIC:	-137.0
Df Model:	5			Df Model:	5			Df Model:	5			Df Model:	5		
Covariance Type:	nonrobust			Covariance Type:	nonrobust			Covariance Type:	nonrobust			Covariance Type:	nonrobust		
	coef	std err	t	P> t	[0.025	0.975]			coef	std err	t	P> t	[0.025	0.975]	
const	-0.0133	0.005	-2.647	0.009	-0.023	-0.003	const	-0.0133	0.005	-2.648	0.009	-0.023	-0.003	-0.003	
Rank_League	-0.0155	0.011	-1.462	0.145	-0.036	0.005	Rank_League	-0.0155	0.011	-1.460	0.146	-0.036	0.005	0.005	
Broadcasting_rights	0.1165	0.050	2.309	0.022	0.017	0.216	Broadcasting_rights	0.1160	0.051	2.293	0.023	0.016	0.216	0.216	
Sponsors_Advertising	0.2670	0.044	6.025	0.000	0.180	0.354	Sponsors_Advertising	0.2651	0.045	5.869	0.000	0.176	0.354	0.354	
Gate_receipts	0.3170	0.019	16.534	0.000	0.279	0.355	Gate_receipts	0.3139	0.023	13.485	0.000	0.268	0.360	0.360	
Total_payroll	0.5187	0.078	6.685	0.000	0.366	0.672	Total_payroll	0.5256	0.083	6.334	0.000	0.362	0.689	0.689	
Omnibus:	31.098	Durbin-Watson:	1.993	Omnibus:	31.444	Durbin-Watson:	1.993	Omnibus:	37.685	Durbin-Watson:	1.553	Omnibus:	37.685	Durbin-Watson:	1.553
Prob(Omnibus):	0.000	Jarque-Bera (JB):	206.576	Prob(Omnibus):	0.000	Jarque-Bera (JB):	206.576	Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.956	Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.956
Skew:	-0.247	Prob(JB):	1.39e-45	Skew:	-0.256	Prob(JB):	1.39e-45	Skew:	-0.925	Prob(JB):	1.18e-17	Skew:	-0.925	Prob(JB):	1.18e-17
Kurtosis:	8.984	Cond. No.	46.1	Kurtosis:	8.130	Cond. No.	48.4	Kurtosis:	5.534	Cond. No.	19.2	Kurtosis:	5.534	Cond. No.	19.2

Figure 4.10: Summary of model 1 (without FFP) and model 2 (with FFP)

GLS Regression Results							GLS Regression Results								
Dep. Variable:	Rank_League	R-squared:	0.409	Dep. Variable:	Rank_League	R-squared:	0.413	Dep. Variable:	Rank_League	R-squared:	0.413	Dep. Variable:	Rank_League	R-squared:	0.413
Model:	GLS	Adj. R-squared:	0.396	Model:	GLS	Adj. R-squared:	0.396	Model:	GLS	Adj. R-squared:	0.397	Model:	GLS	Adj. R-squared:	0.397
Method:	Least Squares	F-statistic:	32.02	Method:	Least Squares	F-statistic:	32.02	Method:	Least Squares	F-statistic:	25.91	Method:	Least Squares	F-statistic:	25.91
Date:	Wed, 24 May 2023	Prob (F-statistic):	2.86e-20	Date:	Wed, 24 May 2023	Prob (F-statistic):	2.86e-20	Date:	Wed, 24 May 2023	Prob (F-statistic):	9.30e-20	Date:	Wed, 24 May 2023	Prob (F-statistic):	9.30e-20
Time:	22:36:11	Log-Likelihood:	83.575	Time:	22:36:11	Log-Likelihood:	83.575	Time:	22:37:06	Log-Likelihood:	84.228	Time:	22:37:06	Log-Likelihood:	84.228
No. Observations:	190	AIC:	-157.2	No. Observations:	190	AIC:	-157.2	No. Observations:	190	AIC:	-156.5	No. Observations:	190	AIC:	-156.5
Df Residuals:	185	BIC:	-140.9	Df Residuals:	184	BIC:	-140.9	Df Residuals:	184	BIC:	-137.0	Df Residuals:	184	BIC:	-137.0
Df Model:	4			Df Model:	5			Df Model:	5			Df Model:	5		
Covariance Type:	nonrobust			Covariance Type:	nonrobust			Covariance Type:	nonrobust			Covariance Type:	nonrobust		
	coef	std err	t	P> t	[0.025	0.975]			coef	std err	t	P> t	[0.025	0.975]	
const	0.3487	0.033	10.460	0.000	0.283	0.414	const	0.3490	0.033	10.479	0.000	0.283	0.414	0.414	
Broadcasting_rights	0.7739	0.243	3.185	0.002	0.295	1.253	Fair_play_Fin	-0.1590	0.140	-1.136	0.258	-0.455	0.117	0.117	
Sponsors_Advertising	-0.3505	0.213	-1.643	0.102	-0.771	0.070	Broadcasting_rights	0.7591	0.243	3.122	0.002	0.279	1.239	1.239	
Gate_receipts	0.2269	0.104	2.185	0.030	0.022	0.432	Sponsors_Advertising	-0.3726	0.214	-1.740	0.083	-0.795	0.050	0.050	
Total_payroll	0.1897	0.415	0.457	0.648	-0.629	1.009	Gate_receipts	0.1736	0.114	1.524	0.129	-0.051	0.398	0.398	
							Total_payroll	0.3109	0.428	0.726	0.469	-0.534	1.156	1.156	
Omnibus:	38.126	Durbin-Watson:	1.596	Omnibus:	37.685	Durbin-Watson:	1.553	Omnibus:	37.685	Durbin-Watson:	1.553	Omnibus:	37.685	Durbin-Watson:	1.553
Prob(Omnibus):	0.000	Jarque-Bera (JB):	83.301	Prob(Omnibus):	0.000	Jarque-Bera (JB):	83.301	Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.956	Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.956
Skew:	-0.913	Prob(JB):	8.16e-19	Skew:	-0.925	Prob(JB):	8.16e-19	Skew:	-0.925	Prob(JB):	1.18e-17	Skew:	-0.925	Prob(JB):	1.18e-17
Kurtosis:	5.981	Cond. No.	18.7	Kurtosis:	5.534	Cond. No.	19.2	Kurtosis:	5.534	Cond. No.	19.2	Kurtosis:	5.534	Cond. No.	19.2

Figure 4.11: Summary of model 3 (without FFP) and model 4 (with FFP)

Model training and prediction: We commenced the training phase using the prepared data. A simple linear regression algorithm predicted income, yielding an impressive R^2 value of 0.969, indicating that the model explained 96.9 percent of the variance in the dependent variable. When predicting league rank, simple linear regression resulted in an R^2 value of 0.4. Recognizing the need for a more sophisticated algorithm, we transitioned to Support Vector Regression (SVR). After adoption, the R^2 value of the model improved to 0.66, suggesting that the SVR captured the nuances of the dataset more accurately.

To study the regression performance of our model, we analyzed the variation in the actual responses of the dependent variables and predictors of the independent variables. The coefficient of determination R^2 quantifies the proportion of variation in y , that is explained by the dependence on x within a specific regression model. A higher R^2 value indicates a stronger fit, and the model can better explain the variation in the output with different inputs.

4.4.0.2 Results

The models estimated above were used to predict dependent variables (income and rank). The results of our predictive analysis are reported for each model. Figure 4.12 shows the actual versus predicted income and the actual versus predicted ranks in the league.

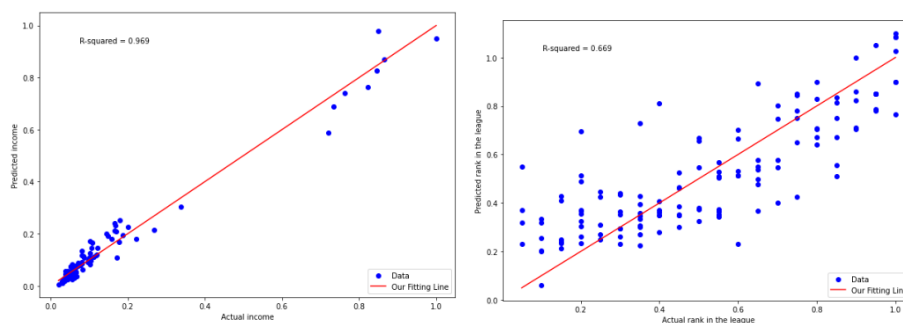


Figure 4.12: Actual vs predicted Income / Actual vs predicted rank in the league

In the case where the prediction involves financial performance (income), Figures 4.13 and 4.14 show views of our data frame in which income was predicted with and without FFP, respectively. However, when we are interested in sporting performance (rank league), the predictions are shown in Figure 4.15 (without FFP) and Figure 4.16 (with FFP).

To test the performance of our models, we applied Mean Squared Error (MSE), which is a performance metric used for regression machine-learning models. The results were, 0.000891; 0.028359, 0.207626, and 0.206257 for Models 1, 2, 3, and 4, respectively.

Discussion

In this study, we examined the relationship between the financial and sporting performance of the French Professional Football League 1 during ten seasons from 2011-2012 to 2020-2021. To achieve these objectives, we predicted a club's income based on broadcasting rights, sponsorship advertising, gate receipts, league rank, and total payroll, considering whether we considered FFP (Models 1 and 2), because we wanted to study the relationship from a managerial perspective. We also examined this relationship from a sports perspective by predicting league rank based on broadcasting rights, sponsorship advertising, gate receipts, total payroll, and FFP (Models 3 and 4). The contributions of these study areas are as follows:

	Club_name	Year	Actual income	Predicted income	Difference
17	STADE MALHERBE CAEN	2011	0.056152	0.054542	0.001610
54	MONTPELLIER HERAULT SC	2013	0.057822	0.053390	0.004432
91	MONTPELLIER HERAULT SC	2015	0.060955	0.043838	0.017116
137	TOULOUSE FC	2017	0.057148	0.056789	0.000359
42	LOSC LILLE	2013	0.105380	0.144341	-0.038961
...
109	EN AVANT GUINGAMP	2016	0.054801	0.048460	0.006341
71	SC BASTIA	2014	0.042028	0.037891	0.004137
124	STADE RENNAIS FC	2017	0.081910	0.092381	-0.010471
50	STADE DE REIMS	2013	0.048205	0.049449	-0.001243
181	PARIS SAINT-GERMAIN	2020	0.864789	0.870318	-0.005529

Figure 4.13: Summary of regression model 1 to predict income without FFP

	Club_name	Year	Actual income	Predicted income	Difference
17	STADE MALHERBE CAEN	2011	0.056152	0.055450	0.000701
54	MONTPELLIER HERAULT SC	2013	0.057822	0.052697	0.005124
91	MONTPELLIER HERAULT SC	2015	0.060955	0.042963	0.017992
137	TOULOUSE FC	2017	0.057148	0.056247	0.000901
42	LOSC LILLE	2013	0.105380	0.145696	-0.040316
...
109	EN AVANT GUINGAMP	2016	0.054801	0.048362	0.006439
71	SC BASTIA	2014	0.042028	0.038349	0.003680
124	STADE RENNAIS FC	2017	0.081910	0.092270	-0.010360
50	STADE DE REIMS	2013	0.048205	0.051028	-0.002823
181	PARIS SAINT-GERMAIN	2020	0.864789	0.877409	-0.012621

Figure 4.14: Summary of regression model 2 to predict income with FFP

(1) A Python program was developed with integrated functions for data collection, data cleaning and normalization, variable stationarity checking, and model training using machine learning regression analysis. All tools in the Anaconda environment and Jupyter notebook necessary for our analysis were used as follows:

- The BeautifulSoup and Streamlit Python frameworks were used to extract sports data from the official Ligue 1 website.

	Club_name	Year	Broadcasting_rights (Actual)	Original rank in the league	Predicted rank	Difference
17	STADE MALHERBE CAEN	2011	0.076023	0.15	0.38	-0.23
54	MONTPELLIER HERAULT SC	2013	0.112805	0.30	0.42	-0.12
91	MONTPELLIER HERAULT SC	2015	0.117028	0.45	0.43	0.02
137	TOULOUSE FC	2017	0.109014	0.15	0.43	-0.28
42	LOSC LILLE	2013	0.183466	0.90	0.56	0.34
...
109	EN AVANT GUINGAMP	2016	0.122747	0.55	0.47	0.08
71	SC BASTIA	2014	0.094152	0.45	0.42	0.03
124	STADE RENNAIS FC	2017	0.161760	0.80	0.51	0.29
50	STADE DE REIMS	2013	0.087853	0.50	0.43	0.07
181	PARIS SAINT-GERMAIN	2020	1.000000	0.95	1.11	-0.16

Figure 4.15: Summary of regression model 3 to predict rank in the league without FFP

	Club_name	Year	Broadcasting_rights(Actual)	Original rank in the league	Predicted rank	Difference
17	STADE MALHERBE CAEN	2011	0.076023	0.15	0.37	-0.22
54	MONTPELLIER HERAULT SC	2013	0.112805	0.30	0.43	-0.13
91	MONTPELLIER HERAULT SC	2015	0.117028	0.45	0.44	0.01
137	TOULOUSE FC	2017	0.109014	0.15	0.43	-0.28
42	LOSC LILLE	2013	0.183466	0.90	0.55	0.35
...
109	EN AVANT GUINGAMP	2016	0.122747	0.55	0.47	0.08
71	SC BASTIA	2014	0.094152	0.45	0.42	0.03
124	STADE RENNAIS FC	2017	0.161760	0.80	0.51	0.29
50	STADE DE REIMS	2013	0.087853	0.50	0.42	0.08
181	PARIS SAINT-GERMAIN	2020	1.000000	0.95	1.05	-0.10

Figure 4.16: Summary of regression model 4 to predict rank in the league with FFP

- Numpy and Pandas libraries manipulate multidimensional structures, such as arrays, matrices, and dataframes, using a large collection of high-level mathematical functions to work with these structures.
- Python packages statsmodels.tsa.stattools and scipy.stats.spearmanr statistically analyzed the data and checked the stationarity of the variables.
- The scikit-learn split package was used to split the data into a test set and training set.
- Generalized least-squares and linear regression models from statsmodels and scikit-learn packages were used to estimate the parameters of Models 1, 2, 3, and 4.

(2) We study the relationship between financial and sports performance from a managerial perspective (Models 1 and 2). It can be concluded that:

(2.1) FFP has no significant impact on revenue in any of our regression models, which can be explained as follows:

- Small number of clubs, only 3 out of 20 clubs,
- The punishment is carried out over a few years (two years),
- The large stock of players available to sanctioned clubs does not necessarily require the hiring of new players.

This result is consistent with [Di Simone and Zanardi \(2020\)](#). They empirically analyze European football companies to test the relationship between sporting results, represented by positions in the league table, and financial performance in a panel framework. They concluded that financial fair play is never significant in any of the regressions for either sports or financial results, confirming the limited effectiveness of the measures. Indeed, it is important to note the effectiveness of the French management control system, which checks the accounts of the clubs and takes necessary sanctions in the case of significant deficits (which can go as far as relegation). By contrast, [Dimitropoulos and Scafarto \(2021\)](#) argued that financial fair play is transforming the business model of Italian clubs from an investment model to one that is more focused on efficiency and gains from player trading.

(2.2) The total payroll remains the most decisive source, which is explained by the impact of recruitment on the attractiveness of sponsor advertising, broadcasting rights, gate receipts, and sports results. Major football players' fame extends beyond the scope of sports. This layering inevitably attracts many brands that want to be alongside popular football players. For Example, the four players with the most sponsors are Mbappé = 16M euro, Neymar = 36M euro, Lionel Messi = 47M euro, and Cristiano Ronaldo = 52M euro⁸.

(2.3) Gate receipt revenue is the second factor that positively influences revenue.

(2.4) Sponsor advertising, broadcasting rights, and gate receipts had positive and significant effects on revenue. According to the financial report of the Direction Nationale du

⁸Source: Sportune. <https://sportune.20minutes.fr/sport-business>. Accessed on March 10, 2023.

Contrôle de Gestion, for the season 2020-2021, [DNCG \(2021\)](#), broadcasting rights, sponsor advertising, and gate receipt revenues represent 43%, 23%, and 8%, respectively (the remainder of the percentage is allocated to other earnings and transfer results).

(2.5) The league ranks are insignificant and have no power to explain the income of the following year, neither for Model 1 nor for Model 2, because the backers are always the same for some clubs (Qatar Sports Investments for PSG and Russian Billionaire Rybolovlev for AS MONACO). Indeed, [Rohde and Breuer \(2018\)](#) developed an empirical model of financial performance and applied it to datasets of the top 30 European football clubs in terms of revenue between 2004 and 2013. The results show that sports success is motivated by player investments, with private and foreign investors representing the majority of these investments.

Our results are consistent with those reported by [\(Eca et al., 2018; Galariotis et al., 2018\)](#). However, [Eca et al. \(2018\)](#) analyzed the relationship between the sporting performance, managerial efficiency, and financial performance of Brazilian sports clubs from 2009 to 2013 with a panel data regression. They concluded that the relationship was positive but not significant. [Galariotis et al. \(2018\)](#) examined a data sample of 12 French soccer clubs that consistently participated in League1 competitions during three seasons: 2010/2011, 2011/2012, and 2012/2013. They find a significant negative relationship between financial performance and sports performance.

(3) Models 1 and 2 had strong explanatory power $R^2 = 0.97$ and a Durbin–Watson test (1.993). The difference between actual and potential revenue is not important. Consequently, our regression model fits the relationship between actual and predicted revenues (Models 1 and 2). The low values of MSE (0.000891; 0.028359) confirm that Multiple Linear Regression and the machine learning algorithms are powerful tools capable of reliably predicting club's revenue. Financial performance is positively related to the total payroll and past revenue from broadcasting rights, sponsorship advertising, and gate receipts.

(4) Examine the relation between sports outcomes and financial performance from an athletic perspective (Models 3 and 4). It can be noticed that:

- The total payroll had no significant impact on the ranking. The history of the last

ranking confirms this exception as clubs, such as Lille, Montpellier, and Monaco, despite not spending the most on recruitment.

- Sponsor advertising has a negative and non-significant effect, which can be explained by the fact that differentiated and discriminatory sponsorship creates animosity within a team, alters cohesion, and negatively affects athletic performance. [Arrondel and Duhautois \(2018\)](#) spoke of individualistic behaviors that can negatively affect team performance when wage dispersion leads to jealousy among players who may even try to hurt their teammates.
- Broadcasting rights positively and significantly impact ranking because of their effect on revenue, which allows the club to recruit players and technical staff of better quality, and improves sports results and ticket revenue.
- League rankings were strongly and positively correlated with broadcasting rights, sponsorship advertising, gate receipts, and previous league rankings. However, when SVR was applied, the overall score was 66%. In France, an analysis of Ligue 1 between 2005 and 2014 revealed comparable results [Llorca and Teste \(2016\)](#). Moreover, [Arrondel and Duhautois \(2018\)](#) show a strong correlation ($R^2 = 0,52263$) between salary expenses and the final ranking for the four 'Ligue 1' seasons between 2012 and 2016.
- The MSE values for Models 3 and 4 were 0.207626 and 0.206257, respectively, confirming that multiple linear regression and machine-learning algorithms are valuable tools for accurately predicting a club's league position.

(5) The financial and sporting predictions resulting from this analysis, as well as our economic interpretations, could be useful for assisting decision-makers (managers, coaches, and technical staff) to make relevant decisions.

Our study embarked on the ambitious task of demystifying the intricate relationship between financial and sporting performance, specifically in the realm of the French Professional Football League 1, which spans a decade. The results of this research illuminate

multiple stakeholders in the football industry, from club managers to sponsors, and even players. The key findings emphasize the role of broadcasting rights, gate receipts, sponsorship deals, and total payroll in predicting the financial and sporting outcomes of clubs. The Python-driven approach we adopted not only facilitated meticulous data processing, analytics, and visualization but also augmented the depth and accuracy of our predictions. Our study substantiates the evolving synergies among sports analytics, finance, and machine learning.

Nevertheless, this study has some limitations. Transfers, which constitute a significant portion of football finances, are beyond the scope of this study. Moreover, the performance intricacies of individual players, arguably the most crucial cogs in football machinery, must be integrated into this model. As we look ahead, our aim is to augment the comprehensiveness of our approach. By considering player performance and transfer activities, and expanding our scope beyond Ligue 1, we aspire to enhance our predictive accuracy and offer profound insights into football analytics.

4.5 Conclusion

The sports industry has experienced a lucrative boom and has become a major factor in the global economy, especially when it comes to football. Professional clubs have become the most gainful sectors, with significant economic impact in the areas of sponsorship, broadcasting and player transfers. Huge financial resources are invested, leading to an exponential increase in the volume of data generated by the sport. This quantity of data, combined with the development of sports technology, has led to the need to make more relevant decisions than ever before ([Raheela et al., 2016](#)).

Previous studies have analyzed the performance of football clubs in several ways, where sporting success is related to managerial change or sacking ([Audas et al., 1997, 2002](#); [Dawson and Dobson, 2002](#); [Frick and Simmons, 2008](#); [Frick et al., 2010](#); [Koning, 2003](#); [Muehlheusser et al., 2012](#); [Tena and Forrest, 2007](#)), evaluation of teams or leagues ([Carmichael et al., 2000](#); [Barros, 2006](#); [Espitia-Escuer and García-Cebrián, 2006](#); [Hamil](#)

et al., 2010), strategic actions (Grundy, 2004; Heij et al., 2006), technical football (Boscá et al., 2009), star players and ownership (Rohde and Breuer, 2017).

However, in our study we are allied with the work of Alaminos et al. (2020); Andreff (2018); Di Simone and Zanardi (2020); Pereira (2018); Rohde and Breuer (2016, 2018); Sakinc et al. (2017); Szymanski and Smith (1997); Szymanski (2010) that treat the efficiency of football clubs as a relationship between financial and sporting performance, since a football club has become a real commercial organization. Therefore, the first studies on the management of professional sports clubs put the team at the center of their analytical models, using economic approaches.

Managers are continuously exploring better approaches to assess organizational performance, aiming to enhance efficiency and effectiveness across their operational units (Mavi et al., 2012). The athletic performance of professional football teams has often been evaluated based on their results competition, namely the league positions. In addition, evaluating and selecting football players that meet clubs' managers and decision makers is a difficult process from managerial and economic point of view.

The success of a team may be defined not only by its own results, but also depends on the way of managers should organize and manage a football club. Several parameters must, indeed, be taken into account during the decision-making analysis. Managerial and economic process is viewed as an investment activity in club organization where footballers represent a major asset. Tell now, this strategic process subscribed in a conventional approach that doesn't refer to deep scientific method; it is made most of time in a subjective and uncertain way (Dadelo et al., 2014; Purwanto et al., 2018; Salles et al., 2019).

In the next chapter, we will examine the theoretical foundations of the integration of MCDM and ML in sports decision-making. This integration aims to provide a more objective and data-driven approach that can help managers and decision makers in sport organizations make more informed and effective decisions.

Chapter 5

Theoretical foundations for integrating multi-criteria decision making and machine learning in sport Decision making

5.1 Introduction

Decision-making processes require innovative approaches to improve accuracy and relevance, particularly in complex scenarios. This chapter examines the theoretical foundations for integrating two approaches: multi-criteria decision methods (MCDM) and machine learning (ML). Our goal is to explore the various techniques of multi-criteria decision support and machine learning, as well as their integration, laying the foundations for understanding their synergy and application in sports decision-making contexts. The fusion of ML and MCDM is therefore of great importance to our analysis in the field of sport decision-making.

ML's ability to discern models and predict outcomes complements MCDM's structured approach to handling multiple and conflicting criteria, enriching the decision-making process. This union enhances accuracy and fosters a robust decision support system, facilitating data-driven decision-making in the dynamic field of sport. As sports decision makers face the challenges of player selection, team composition, recruitment, and transfers, the integration of ML and MCDM offers a strategic advantage.

Each technique, ML and MCDM, has distinct strengths; their combination leverages their complementary characteristics, promoting data-driven decision-making, and offering a decision-making framework adapted to the complex world of sport. ML, characterized by decoding complex models, enables understanding relationships within data sets. In our modeling, the ML concept will be used to weigh player physical, technical, tactical, and behavioral criteria, exploiting its ability to extract meaningful information from large datasets. Meanwhile, MCDM structures multi-criteria decision problems, providing a rigorous method for evaluating players based on their weighted criteria.

This integration seeks to help decision makers gain an understanding of the decision-making process by providing data-driven analysis. Furthermore, by combining the objectivity of data-driven assessments with the experience and subjectivity of decision makers, this integration provides a balanced approach to player evaluation in the sporting context.

The integration extends to overcoming the uncertainties associated with decision-making

in sports. Thoughtful theoretical considerations are required for integrating ML predictions, determining their weight in relation to other decision criteria, and incorporating them into the sports decision-making process. Afterward, MCDM introduces structured decision criteria that form a solid basis for evaluating and managing uncertainty specific to sports.

This chapter is structured around three main sections. First, it discusses the theoretical basis of decision-making in sports, examining the underlying principles and methodologies involved in decision-making processes. Next, it explores machine learning concepts for sports decision-making. Finally, the chapter examines works in the literature that have applied machine learning and MCDM in sports management.

5.2 Theoretical foundations of sports decision-making

A managerial problem arises when there is a disparity between the current situation and the desired state (Huber, 1980). Managers are consistently confronted with such challenges that demand action. Each managerial action typically stems from a decision. According to Lévine and Pomerol (1990)¹, a decision is an action taken to overcome a difficulty or respond to environmental changes, thereby addressing individual or organizational issues. Similarly, Mintzberg (1979) defines a decision as a commitment to action, signifying an explicit intention to act. It represents a choice made by individuals or work groups in response to a situation, delineating a course of action based on expectations.

Furthermore, Roy and Bouyssou (1993) consider decision-making as the exercise of free choice among various actions at a given moment, often resulting from interactions among multiple actors. Decision-making, therefore, involves identifying managerial problems, establishing preferences, evaluating alternatives, and determining the optimal course of action (Schoemaker and Russo, 2016). Tzeng and Huang (2011) describe decision-making as a process encompassing the definition of decision goals, gathering pertinent information, generating an array of alternatives, evaluating their advantages and disadvantages, selecting the optimal alternative, and monitoring outcomes to ensure goal achievement.

¹Authors referenced in Agrebi (2018): p7.

This iterative process of problem formulation, information gathering, drawing conclusions and learning from experience underlines the importance of adopting an organized approach to solving a decision-making problem.

5.2.1 Introduction to decision-making theory

Decision-making theory, an interdisciplinary field, has evolved from contributions spanning economics, mathematics, psychology, and management science, among others, highlighting its fundamentally interdisciplinary nature. This interdisciplinary nature is rooted in the recognition of three main approaches to decision-making: *normative*, *descriptive*, and *prescriptive* (Shanteau, 2001).

The *normative* approach, focusing on rationality and theoretically ideal decisions, describes the decision-making process in a framework where decision makers have access to all necessary information to make perfectly rational decisions. However, in reality, individuals do not always make perfectly rational decisions, leading us to explore the *descriptive* approach. The descriptive approach seeks to describe how decision makers actually make decisions in their everyday lives, shedding light on the gaps between theory and practice.

Concurrently, the *prescriptive* approach concentrates on improving decision-making processes by integrating both normative and descriptive elements. It offers recommendations on how decision makers should make decisions while acknowledging the constraints and limitations of the real-world context in which these decisions are made.

Before delving further into decision-making theory, it's important to clarify the distinctions between three fundamental concepts: *decision making*, *choice making*, and *problem solving*.

It is also crucial to distinguish between the concepts of problem-solving, decision-making, and choice-making, as emphasized in the book "Managerial Decision Making" by Huber (1980). This distinction clarifies the different stages of the decision-making process and prevents confusion between these fundamental concepts.

- *Decision making*: this process involves a series of activities aimed at addressing a problem. It begins with identifying the problem, followed by generating various

alternative solutions to the problem. Then, decision makers evaluate these alternatives based on certain criteria or preferences. Finally, they select the most suitable alternative from the available options.

- *Choice making*: unlike decision making, choice making specifically refers to the act of evaluating and selecting among the alternative solutions that have been generated during the decision-making process. It focuses solely on the final step of decision making, where a decision maker chooses one option from the alternatives presented.
- *Problem solving*: it involves the entire process of dealing with a problem, from identification to implementation and beyond. It includes not only the activities involved in decision-making, such as generating alternatives and selecting a solution, but also the subsequent steps of implementing the chosen solution, maintaining it, monitoring its effectiveness, and reviewing the overall solution program. In essence, problem solving is a broader concept that incorporates decision making as one of its components.

It should be noted that, this work falls within the problem-solving stream, as it addresses the complex challenges inherent in the decision-making process for football player selection. Beyond decision-making, our aim is to construct and implement a decision support system that incorporates the entire decision-making process and ensures its effectiveness through collaboration with all stakeholders involved in the player selection process.

5.2.1.1 Problem-solving process

Problem-solving serves as the foundation for the decision-making process. As depicted in [Figure 5.1](#), problem-solving involves identifying, defining, and diagnosing the problem and its causes. This initial phase allows decision makers to accurately identify and investigate the issues at hand, laying the foundations for the subsequent decision-making steps. Problem-solving also encompasses generating alternative solutions, selecting the optimal solution, implementing it, and monitoring its effectiveness. It is an iterative process that forms the context within which decisions are made ([Huber, 1980](#)).

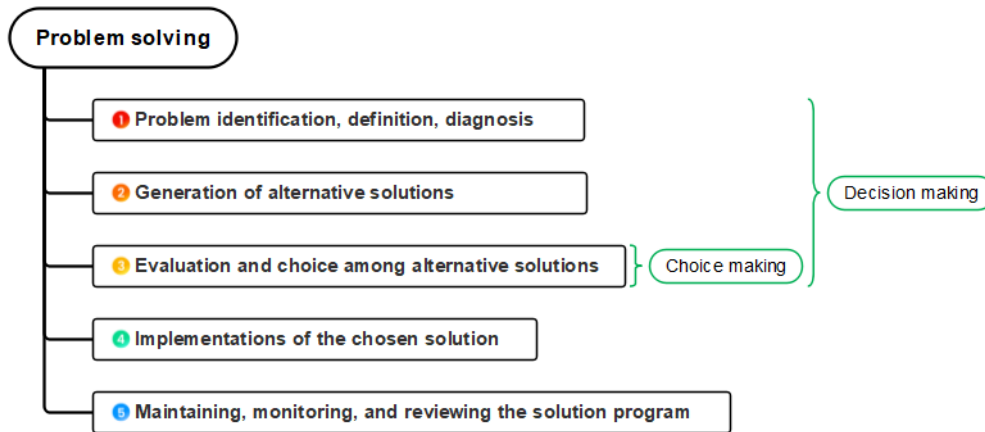


Figure 5.1: Illustration of the problem-solving process

1. Exploring the nature of the problem: In this initial phase, decision makers delve into identifying, defining, and diagnosing the problem and underlying causes. It's imperative for decision makers to gain a thorough understanding of the problems to effectively address them. This phase involves defining the organization's goals, collecting data and then identifying and classifying the problems.

This phase is managed by sports decision makers who possess a strategic vision regarding the club's needs in terms of human resource management and financial and managerial aspects. Drawing on their expertise, these decision makers analyze the club's current status and future objectives. They assess the team's strengths and weaknesses, considering both on-field performance and off-field management. In addition, they evaluate the financial resources available for player acquisition, wages, and other operational expenses. This strategic approach ensures that player selection, recruitment, and transfer decisions align with the club's overall objectives and long-term sustainability.

Our approach involves collecting both sporting and financial data on player performance. Leveraging Big Data and real-time data sources allows us to access up-to-date information. Once this data is collected, including technical, tactical, physical, and behavioral criteria of players, as well as their positions (goalkeeper, defender, midfielder, forward), we proceed to the next step.

2. Generating alternatives solutions: During this phase, the focus is on identifying actions or alternatives that could minimize the gap between the current situation and the desired situation.

In the context of our work, this phase entails identifying a pool of players who serve as potential alternatives to address the player selection challenge. These candidates possess the capacity to narrow the disparity between the current scenario and the desired objective. This situation may relate to the immediate needs of a matchday lineup, where the coach must select a line-up that can make a difference on the field. Alternatively, it may relate to recruitment or transfer decisions, which can significantly impact both the team's performance and the club's financial stability.

This phase is a collaborative effort involving sports decision makers who contribute their insights and expertise. They propose candidate players based on various factors such as their position within the club, their profile (whether they are star players or support players), their salary demands, and other pertinent considerations.

3. Choosing among alternatives solutions: During this phase, solutions are evaluated and selected from the pool of available alternatives, leading to final decisions. In this stage, we begin by assigning weights to the criteria or attributes of each player, allowing for a comparison of their performances. Sports decision makers then analyze the proposed solutions, considering factors such as player skills, tactical fit, financial implications, and alignment with the club's objectives.

By evaluating each alternative according to established criteria, decision makers can identify the most promising combinations that best meet their sporting and financial requirements. These choices are made taking into account the interests of the club and the needs of its stakeholders.

Ultimately, this phase ends with the strategic selection of players for alignment considerations, recruitment strategies or transfer decisions, ensuring that the solutions chosen correspond to the overall objectives of the club and contribute to its long-term success.

4. Implementing the selected solution: During this stage, the implementation phase involves planning and adapting the problem solving process to effectively address the identified challenges. In our work, we have developed and implemented a Decision Support System that integrates Machine Learning and Multi-Criteria Decision Making techniques.

This DSS is designed to assist decision makers in player selection, recruitment, and transfer decisions. By leveraging advanced algorithms, it analyzes player data, evaluates performance based on predefined criteria, and provides tailored recommendations to meet the club's specific needs and objectives. Through this implementation, decision makers are empowered to make relevant and strategic decisions that optimize player management and contribute to the overall success of the club.

5. Controlling the solution program: In the monitoring phase, it is crucial to evaluate the effectiveness of the implemented solution. This step is about tracking and reviewing the decisions made during implementation to ensure that they are achieving the desired results. In our work, this involves continuously evaluating the performance of the decision support system (DSS) implemented for player selection, recruitment and transfer decisions. By comparing the results generated by our model with historical data and matches already played, as well as analyzing feedback from decision makers and stakeholders, we can refine the DSS and make the necessary adjustments to improve its efficiency and effectiveness over time.

In addition, we plan to explore the opportunities presented by advances in artificial intelligence and big data to obtain updated sports and financial data from teams in order to expand our database and further improve our decision-making process in the future.

5.2.1.2 Decision-making approaches in sports

Following that, decision-making is indispensable in everyday life, with individuals making countless decisions on a daily basis. In organizations, decisions are omnipresent, guiding all management functions, including planning, organizing, coordinating and controlling. Moreover, the literature proposes several approaches to decision-making, including:

Multi-criteria decision-making: This approach evaluates multiple criteria or objectives to make a decision. It's well suited for complex problems with multiple conflicting criteria, such as a player's skill abilities, experience, and fitness, to make a decision about which players to select (Blanco et al., 2018).

In the field of sports decision-making, particularly in player selection, MCDM can be applied to evaluate several criteria or attributes of players, such as skill level, experience, physical fitness, and team ability. Decision makers can take advantages of MCDM techniques to compare the attributes of different players and make effective decisions about who to include in the team lineup, recruit or transfer.

Group decision-making: In this approach, a group of actors (decision makers), such as coaches, managers, and scouts, work together to make a decision about which players to select. This can be useful because decision makers may have different perspectives and expertise, which can lead to more relevant decision-making (Yue, 2011).

Given the collaborative nature of sports teams and organizations, group decision-making is highly relevant in the context of player selection. Coaches, managers, scouts, and other stakeholders often collaborate to evaluate players and make decisions about team composition. Group decision-making allows for the integration of diverse perspectives, expertise, and insights, leading to more comprehensive and well-informed decisions. For instance, a selection committee comprised of coaches, scouts, and team administrators may convene to collectively assess players' performance and suitability for the team.

Decision-making under uncertainty: This approach deals with decision-making in situations where future events are uncertain, and stochastic models are used to incorporate uncertainty in the decision process. This approach can be supported by the Bayesian decision theory (Ze-Jun and Xin-Yu, 2021).

Decision-making in sport is inherently fraught with uncertainty, e.g. player injuries, fluctuating performances and unpredictable match outcomes. Decision-making under uncertainty uses probabilistic models and risk assessment techniques to make appropriate decisions under uncertain conditions. When selecting players, decision makers may use

probabilistic models to assess the likelihood of a player's performance and potential risks associated with injury or other factors. For example, a team manager may analyze historical data and injury trends to assess the risk of selecting a player with a history of injuries.

Decision-making is thus the core of management activities in an organization. The selection of human resources is a serious factor for the successful growth of a team, whether in football, or any other collective sport. It is crucial to investigate how to pick the best footballer based on the team's interests (Salles et al., 2019).

In our context, The most important aspect of football management is making decisions about which players to select, for the starting lineup, recruitment and transfer, that will lead their team to athletic success, and thus financial performance. These strategic decisions can benefit players on and off the field and also affect their value on the transfer market (Zambom-Ferraresi et al., 2018). According to Qader et al. (2017), player selection is a critical procedure for clubs capable of producing great sports and financial returns but also being vulnerable to big risks if the implanted expectations are not satisfied.

The management of professional sports clubs is based on success-oriented decision-making strategies. Similar to other organizations, sports clubs have unique characteristics related to their activities and environment. As a relatively new field of research, sport management, in conjunction with decision making methods and machine learning techniques, offers the opportunity to understand the performance and effectiveness of professional sport organizations. Before we delve further into the discussion, it is important to define the key principles and concepts of decision making in sport that will guide us throughout our modeling work.

5.2.2 Key principles and concepts of sports decision-making

In sports decision-making, particularly in the context of player selection, multi-criteria decision making plays a crucial role. To ensure clarity, this study provides definitions and distinctions for key concepts associated with MCDM:

Alternatives: these are the potential solutions or actions for the decision problem. In the context of player selection, alternatives could include different players available for

team composition, recruitment or transfer. Represented as $A = \{a_1, a_2, \dots, a_m\}$, where A is the finite set of alternatives and m is the number of alternatives. Alternatives are screened, prioritized, and eventually ranked.

Criteria: also known as attributes, criteria are evaluated for each alternative to find the solution. In player selection, criteria could include physical, technical, tactical, behavioral and financial aspects. They measure quantitative performance, allowing comparison based on decision makers' needs. Represented as $C = \{c_1, c_2, \dots, c_n\}$, where C is the set of criteria and n is the number of criteria. Each $c_j(a)$ represents an alternative's performance on criterion c_j .

Weights: these represent the importance of criteria in decision-making. The interpretation of weights varies between MCDM techniques, serving as trade-offs or strength of evidence. In player selection, weights could reflect the relative importance of different criteria, depending on the player's profile (star or water carrier) and position. Represented as $W = \{w_1, w_2, \dots, w_n\}$, where W is the finite set of weights. In the decision-making process, weights could reflect the relative importance of different criteria based on the team's strategic objectives and the specific requirements of each position. For example, a team prioritizing attacking play might assign higher weights to criteria related to offensive skills (such as finishing and long shots), while a team focusing on defensive solidity might prioritize criteria related to defensive skills (such as tackling, interceptions, and positioning).

Performance Matrix: Denoted as M , it is built for $A \times C$, where $c_j(a)$ represents the performance in row a and column j . It allows for systematic evaluation of alternatives across criteria.

$$M_{m,n} = \begin{pmatrix} & w_1 & w_2 & w_3 & \cdots & w_n \\ & c_1 & c_2 & c_3 & \cdots & c_n \\ a_1 & a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_2 & a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ a_m & a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} \end{pmatrix}$$

Where:

- $M_{m,n}$ is the performance matrix.
- w_j represents the weight assigned to the j -th criterion.
- c_j represents the j -th criterion.
- a_i represents the i -th player.
- a_{ij} represents the performance of the i -th player on the j -th criterion.

In conjunction with our modeling, the performance matrix could quantify each player's performance on different criteria, facilitating comparison and decision-making. Moreover, the performance matrix can be dynamic, evolving over time as players' performances change or new criteria are introduced, reflecting the dynamic nature of sports decision-making environments.

Decision Maker (DM): the individual or group aiming to satisfy certain objectives or values through the decision. DMs provide acceptable choices or rankings of alternatives, experiencing and resolving the decision problem. In the context of player selection, decision makers could include the team's head coach, assistant coaches, scouting staff, medical staff, and management team. These decision makers would collaborate to assess the performance of potential recruits, analyze their suitability for the team based on predefined criteria, and make relevant decisions about player recruitment and team composition.

Decision makers are tasked with evaluating player performance, identifying talent, and making strategic choices to achieve desired outcomes, such as team success and financial stability. They collaborate closely to analyze data, assess player suitability, and make relevant decisions that align with the club's objectives and values. In the player selection process, decision makers rely on their expertise, experience, and knowledge of the game to evaluate potential recruits and determine their fit within the team. They consider various factors, including technical skills, tactical, physical attributes, and behavioral characteristics, to make well-rounded assessments of player suitability.

Moreover, decision makers have to deal with uncertainty in dynamic and unpredictable environments where factors such as player injuries, fluctuating performance levels, and

unpredictable game outcomes occur. They are also faced with competing objectives, such as balancing short-term success with the club's long-term sustainability, optimizing player performance while managing financial resources, and addressing individual player needs within the team context.

After defining the key concepts related to the decision-making process, we will present a variety of multi-criteria decision-making methods. We will include their classification, strengths, and weaknesses to understand their applicability in the context of sport management.

5.2.3 Review of MCDM approaches

Multi-Criteria Decision Making (MCDM) methods serve as fundamental tools for rationalizing decision-making processes in various fields. While MCDM techniques find widespread application in domains such as healthcare, software engineering, and environmental management, their utilization in sports management, particularly in football, is relatively less common.

MCDM approaches are particularly valuable in evaluating both criteria and alternatives, allowing decision makers to make optimized choices tailored to their specific objectives and constraints. In the context of sports decision-making, MCDM methods play a crucial role in assessing various criteria relating to player selection, team composition, strategy formulation, and resource allocation. These criteria may include player performance metrics, financial considerations, strategic objectives, and other relevant factors. By evaluating criteria, decision makers can gain insights into the relative importance of different factors and their impact on the overall decision outcome.

MCDM methods encompass a diverse range of techniques, each with its own theoretical foundations and practical applications. According to [Ishizaka and Nemery \(2013\)](#), MCDM methods are classified into three major categories: full aggregation approach, out-ranking approach, and goal or reference level approach. These categories provide a framework for understanding different decision-making paradigms and methodologies.

- **Full aggregation approach (or American school):** This approach assumes com-

pensable scores, meaning that a bad score for one criterion can be compensated for by a good score on another. It involves evaluating a score for each criterion and synthesizing them into a global score. The Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) are examples of full aggregation approaches.

- **Outranking approach (or French school):** This approach assumes that a bad score may not be compensated for by a good score, allowing for incomparability between alternatives. Outranking methods aim to determine the best alternative by ranking the alternatives based on their outranking relationships. Examples of outranking methods include Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) and Elimination Et Choix Traduisant la Réalité (ELECTRE).
- **Goal or reference level approach:** This approach defines a goal on each criterion and identifies the closest options to the ideal reference level or goal. Goal methods establish a set of objectives that the alternatives must meet, while reference level methods establish reference levels or standards that the alternatives must meet or exceed. Examples of goal and reference level methods include the Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS).

Multi-Criteria Decision Making (MCDM) approaches are instrumental in sports decision-making, particularly in scenarios involving player selection, team composition, and strategic planning. These approaches enable decision makers to evaluate multiple criteria simultaneously, considering various factors that impact the outcome of decisions. In sports management, where complex trade-offs and competing objectives are common, MCDM provides a structured approach to analyzing and optimizing decisions.

Furthermore, MCDM methods enable decision makers to evaluate alternative courses of action or options available in sports management. Whether it's selecting players for a team, allocating resources, or making investment decisions such as players recruitment and transfers, MCDM techniques provide a structured approach to compare and prioritize alternatives based on their performance across multiple criteria. Consequently, the examination of MCDM approaches in sport management encompasses the evaluation of criteria and al-

ternatives, underlining the importance of decision-making processes in achieving desired outcomes.

Within the framework of these approaches, there are various methods for addressing decision-making problems. In the following subsections, we will classify these methods into two categories: those for evaluating criteria and those for evaluating alternatives. [Table 5.1](#) summarizes the strengths and weaknesses of some classical MCDM methods.

Table 5.1: Strengths and Weaknesses of some MCDM methods

Method	Strengths	Weaknesses
AHP	<ul style="list-style-type: none"> • Structured and hierarchical decision-making process • Ensures consistency in decision-making • Transparency by allowing decision makers to understand how decisions are made 	<ul style="list-style-type: none"> • Complex to implement for large and complex decision-making problems • Relies on expert judgment, which can lead to errors or biases in the decision-making process
ANP	<ul style="list-style-type: none"> • Ability to handle complex interdependent relationships between criteria and alternatives • Transparency and ability to handle large and complex decision-making problems 	<ul style="list-style-type: none"> • Subjectivity and difficulty in determining the relationships between criteria • Computational complexity of the analysis

Continued on next page

Method	Strengths	Weaknesses
Entropy	<ul style="list-style-type: none"> • Objectivity; employs mathematical calculations to determine criterion weights, making it objective and less prone to human biases • Adaptability; It can be applied to various types of data and decision problems • Ease of use; once the process is understood, the Entropy method is relatively straightforward to implement and interpret 	<ul style="list-style-type: none"> • Sensitivity to data; Entropy method results may vary depending on input data, rendering them less reliable if data is not properly collected or representative. • Complexity of calculations; For large-scale problems with numerous criteria, the calculations associated with the Entropy method can become complex and require significant computational resources.
CRITIC	<ul style="list-style-type: none"> • Objectivity; it provides an objective approach to weighting criteria, reducing the influence of subjective biases • Incorporation of intercriteria relationships • Flexibility; it handles qualitative and quantitative criteria • Transparency; it provides clear and interpretable results, allowing decision makers to understand how each criterion contributes to the overall decision 	<ul style="list-style-type: none"> • Relies on data describing the relationships between criteria • complexity in calculating pairwise correlations between criteria

Continued on next page

Method	Strengths	Weaknesses
PROMETHEE	<ul style="list-style-type: none"> • Flexibility and can be applied to a wide range of decision-making problems 	<ul style="list-style-type: none"> • Complex and requires a good understanding of the decision-making criteria and the data used to evaluate the alternatives
ELECTRE	<ul style="list-style-type: none"> • Provides a ranking of alternatives based on their relative performances, making it easy to identify the best option 	<ul style="list-style-type: none"> • Makes assumptions about the criteria and the alternatives, which can impact the validity of the results
TOPSIS	<ul style="list-style-type: none"> • Simple and intuitive • Incorporates both objective and subjective factors • Considers both the strengths and weaknesses of alternatives • Consideration of large number of criteria 	<ul style="list-style-type: none"> • Sensitivity to weights • Difficulty in determining weights • Assumes that the criteria are independent • Lack of transparency in weight assignment

5.2.3.1 Methods for criteria weighting

In MCDM, assigning appropriate weights to criteria is a crucial step that significantly influences the decision-making process. The weighting process involves determining the relative importance of each criterion in achieving the decision objectives. Several methods can be employed for criterion weighting, and the choice of method often depends on the nature of the decision problem and the preferences of decision makers. The following are common approaches to criterion weighting in MCDM:

5.2.3.1.1 AHP method: The Analytic Hierarchy Process, introduced by Saaty in 1977 and further developed in 1980, is a widely used method in decision-making processes where the decision maker cannot perform a utility function (Saaty, 1980). This method leverages human-like reasoning, particularly hierarchical decomposition, judgment, and synthesis. AHP can handle qualitative and quantitative criteria. It structures the decision problem into hierarchical levels, including objectives, criteria, sub-criteria, and alternatives, allowing decision makers to focus on smaller decision sets.

A key aspect of AHP is the reliance on pairwise comparisons, where decision makers assess the relative importance of criteria or alternatives. These comparisons form the basis for deriving quantitative scores and weights from qualitative judgments. Eigenvalues are utilized to convert the resulting tables of pairwise comparisons into weights and scores. While AHP excels in providing a structured decision-making frameworks, it may encounter instability issues when dealing with a large number criteria and alternatives.

5.2.3.1.2 ANP method: The Analytic Network Process (ANP) extends the capabilities of AHP by considering interdependent relationships between criteria and subcriteria in decision-making problems. Building upon the principles of AHP, ANP allows for the consideration of both direct and indirect relationships between elements. ANP employs a network structure to represent these relationships, with nodes representing criteria or alternatives and directed arcs indicating the strength of relationships.

In ANP, decision problems are modeled as networks, where nodes represent criteria or alternatives, and arcs denote relationships. ANP utilizes pairwise comparisons and super-matrix techniques to calculate the relative importance of each node in the network. Its ability to handle complex interdependencies, transparency, and scalability make it suitable for large and intricate decision-making problems (Saaty, 1996).

Despite its strengths, ANP also presents challenges such as subjectivity in determining relationships between criteria and the computational complexity of analysis. Both AHP and ANP rely heavily on expert judgment, which can sometimes be difficult to obtain. Expertise in the domain of the decision problem is crucial for providing accurate assessments

and pairwise comparisons. However, acquiring this expertise may pose challenges, particularly in specialized areas of sports management where knowledgeable experts are limited or inaccessible.

5.2.3.1.3 Entropy method: The entropy method is a widely utilized technique in MCDM that focuses on the objective determination of criteria weights. It employs concepts from information theory to evaluate the relative importance of criteria in decision-making processes (Dong and Yang, 2021). The method is particularly effective when dealing with decision matrices involving multiple criteria, providing decision makers with quantitative approach to assigning weights to various criteria.

Key steps of the entropy method:

Step 1- Normalize the decision matrix: Standardizing the elements of the decision matrix is essential to make values comparable between criteria. Given a decision matrix X representing alternatives and criteria, normalize each element x_{ij} using the formula:

$$\bar{X}_{ij} = \frac{X_{ij} - X_j^{\text{worst}}}{X_j^{\text{best}} - X_j^{\text{worst}}} \quad (5.1)$$

where X_j^{best} is the best value for criterion j , and X_j^{worst} is the worst value for criterion j .

Step 2- Compute entropy: Entropy measures the dispersion of criterion values in the normalized matrix. For each criterion j , calculate the entropy using the normalized decision matrix \bar{X}_{ij} :

$$E_j = - \sum_{i=1}^m \bar{X}_{ij} \cdot \log(\bar{X}_{ij}) \quad (5.2)$$

Step 3- Compute the weight vector: Determine the weight vector using the computed entropy values:

$$w_j = \frac{1 - E_j}{n - \sum_{j=1}^n E_j} \quad (5.3)$$

The weight vector w_j obtained through the entropy method represents the relative importance of each criterion in the decision-making process.

5.2.3.1.4 CRITIC method: The Criteria Importance Through Intercriteria Correlation method is a well-established technique in the field of MCDM. It was proposed by Diakoulaki et al. (1995). The aim of the CRITIC method is to determine the objective weights of the criteria. These weights include contrast intensity and conflicts inherent in the structure of the decision problem. The association of weights in multiple criteria problems is a critical step in the decision-making process. In situations where extracting subjective preferences is difficult or undesirable, the CRITIC method provides an alternative approach. The CRITIC method analyzes inter-criteria correlations to objectively determine the importance of each criterion and considers the indirect influence of each criterion on others.

The steps of the CRITIC method are as follows:

Step 1- Define the decision matrix: Let X be the decision matrix representing alternatives and criteria. The element x_{ij} in the matrix corresponds to the performance of alternative i on criterion j .

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}$$

Step 2- Normalize the decision matrix: In this step, each element of the decision matrix is normalized using the formula:

$$\bar{X}_{ij} = \frac{X_{ij} - X_j^{\text{worst}}}{X_j^{\text{best}} - X_j^{\text{worst}}} \quad (5.4)$$

where X_j^{best} is the best value for criterion j , and X_j^{worst} is the worst value for criterion j .

Step 3- Calculate the standard deviation σ_j for each criterion:

For each criterion j , calculate the standard deviation using the normalized decision matrix \bar{X}_{ij} :

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (\bar{X}_{ij} - \bar{X}_j)^2}{m}} \quad (5.5)$$

Step 4- Determine the symmetric matrix (R) of $n \times n$ with element r_{jk} , which is the linear correlation coefficient between the vector x_j and x_k : Construct the symmetric matrix R with elements r_{jk} for all j and k .

Step 5- Calculate the measure of conflict created by criterion j with respect to the decision situation defined by the rest of criteria:

$$\sum_{k=1}^m (1 - r_{jk}) \quad (5.6)$$

Step 6- Determine the quantity of the information in relation to each criterion:

$$c_j = \sigma_j \sum_{k=1}^m (1 - r_{jk}) \quad (5.7)$$

Step 7- Determine the objective weights:

$$w_j = \frac{c_j}{\sum_{k=1}^m c_i} \quad (5.8)$$

The objective weight w_j represents the importance of criterion j in the decision-making process.

We have detailed the Entropy and CRITIC methods because they will be used in our modeling, due to their objectivity in weighting criteria. These two methods do not rely on expert judgments, making them particularly suitable for our data-driven approach and our goal of providing objective and reliable evaluations in player selection problem.

5.2.3.2 Methods for alternatives evaluation

In sports management, making informed decisions about available alternatives is vital for achieving the strategic objectives of teams and organizations. Whether it pertains to player selection or investment planning for player recruitment and transfer, accurately evaluating different options is crucial for gaining a competitive advantage, both on the field and financially. This section explores various methods used to evaluate alternatives in the context of sports management. It emphasizes their significance in the decision-making process and their practical application in real-world scenarios.

5.2.3.2.1 PROMETHEE method: Preference Ranking Organization Method for Enrichment Evaluations, introduced by [Mareschal et al. \(1984\)](#), is a method for evaluating and ranking alternatives based on their relative dominance over each other, rather than absolute values. It employs a combination of weighted criteria and outranking relationships to rank alternatives. PROMETHEE provides decision makers with a ranking of actions based on degrees of preference, allowing them to make relevant decisions in complex decision-making scenarios.

5.2.3.2.2 ELECTRE method: ELimination Et Choix Traduisant la REalité, first introduced by [Roy \(1968\)](#), deals with outranking relations by using pairwise comparisons among alternatives under each criterion separately. This method allows decision makers to assess the dominance of one alternative over another based on a set of criteria. If one alternative excels in certain criteria and equals or performs slightly worse in others compared to another alternative, it is considered to outrank the latter. ELECTRE enables decision makers to identify dominated alternatives and make choices that align with their strategic objectives.

5.2.3.2.3 TOPSIS method: Technique for Order of Preference by Similarity to Ideal Solution was proposed by [Hwang and Yoon \(1981\)](#) To identify the optimal alternative, the compromise solution involves selecting an option that minimizes the Euclidean distance from the ideal solution while maximizing the distance from the negative ideal solution.

TOPSIS works by first defining a set of criteria, then transforming the data into a normalized form and finding the similarity between each alternative and an ideal solution. The ideal solution is the alternative that has the best scores for the desirable criteria and worst scores for the undesirable criteria. The ranking of alternatives is based on the shortest Euclidean distance between each alternative and the ideal solution.

TOPSIS enables sporting decision makers to evaluate and rank a set of alternatives (individual players) based on their proximity to an ideal solution. This method considers various performance attributes essential for success on the field, providing decision makers with a structured and quantitative approach to identifying and prioritizing players who exhibit a balanced combination of attributes.

One notable advantage of TOPSIS is its adaptability to dynamic sporting environments, allowing decision makers to continuously reassess and update player rankings based on evolving performance data. Additionally, the simplicity of the TOPSIS algorithm makes it computationally efficient, offering a practical solution for decision makers in complex scenarios.

The TOPSIS method involves several key steps:

TOPSIS algorithm

Let m be the number of alternatives (professional football players), and let n be the number of criteria (technical, tactical, physical and behavioral attributes).

Step 1- Normalize the decision matrix: For each alternative i and each criterion j , normalize the decision matrix X by dividing each element x_{ij} by the square root of the sum of squares in the column:

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (5.9)$$

Step 2- Determine weighted normalized decision matrix: Assign weights w_j to each criterion based on their importance. The sum of weights should be 1.

$$V_{ij} = w_j \times R_{ij} \quad (5.10)$$

In the context of our study, these weights are derived systematically, using advanced techniques such as the random forest algorithm, or multi-criteria methods that calculate weight in an objective way like entropy or CRITIC. This approach ensures that criteria are appropriately weighted, reflecting their importance in the decision-making process. However, it is important to note that employing various weight calculation techniques aims to address the significant drawbacks associated with the TOPSIS method, such as sensitivity to weights and challenges in determining appropriate weights.

Step 3- Determine positive (A+) and negative (A-) Ideal Solutions:

- For the positive ideal solution A^+ , select the maximum value for each criterion.
- For the negative ideal solution A^- , select the minimum value for each criterion.

Step 4- Calculate separation measures: Calculate the separation measures for each alternative i from the positive and negative ideal solutions:

$$S_i^+ = \sqrt{\sum_{j=1}^n (V_{ij} - V_{ij}^+)^2} \quad (5.11)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (V_{ij} - V_{ij}^-)^2} \quad (5.12)$$

Step 5- Calculate proximity to positive (C+):

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-} \quad (5.13)$$

Step 6- Rank the alternatives: Rank the alternatives based on the values of C_i^+ . A smaller C_i^+ value indicates a higher rank.

In this section, we've outlined the TOPSIS method because it will serve as a foundation in our modeling, specifically for classifying players based on their football perfor-

mance while leveraging criteria weights derived from other methods. TOPSIS provides a systematic approach to evaluating alternatives by assessing their proximity to ideal solutions, which suits our need to comprehensively evaluate football players across various performance criteria.

Moreover, TOPSIS' flexibility to handle a large number of criteria aligns perfectly with our dataset, where we have a wide range of factors to consider, ranging from tactical, tactical, physical to behavioral attributes. This adaptability ensures that our player evaluation process remains responsive to the evolving dynamics of sports data and player performance. It should be noted that our choice of TOPSIS does not diminish the importance of other multi-criteria decision-making methods; on the contrary, it complements them by offering a structured approach tailored to our specific needs and objectives.

At the end of our exploration of multi-criteria decision-making approaches, we turn to the examination of machine learning concepts. This shift marks an evolution in our methodology, as we delve into the computational intelligence to improve our comprehension of player evaluation and decision-making processes in sports management.

5.3 Overview of machine learning concepts

Machine learning is a scientific discipline that emerged in the early 1980s, revolutionizing the field of artificial intelligence. Instead of relying on explicit programming, machine learning allows computers to learn from examples and experiments, improving autonomously over time ([Kubat, 2017](#)).

Essentially, ML eliminates the need for explicit programming by enabling systems to learn and evolve from experience. ML relies on algorithms to discern patterns, predict outcomes and continuously improve, offering decision makers a powerful tool for managing complex scenarios.

ML is based on fundamental principles that determine its dynamic and adaptive nature. It allows algorithms to independently gather information from data, enabling them to evolve and improve over time. This adaptability enables models to handle changing en-

vironments and respond to different patterns. Generalization, another important principle, enables models to transfer knowledge from specific cases to new scenarios. Evaluation measures, such as accuracy, assess the effectiveness of models on new data, underlining the iterative nature of improvement.

Having outlined the basics of machine learning, we'll now explore the different types of ML algorithms, delve into the essential steps of ML modeling, and take a closer look at the Random Forest algorithm.

5.3.1 Types of machine learning algorithms

Machine learning encompasses a variety of algorithmic approaches designed to handle different tasks (Figure 5.2). The main types of ML algorithms are:

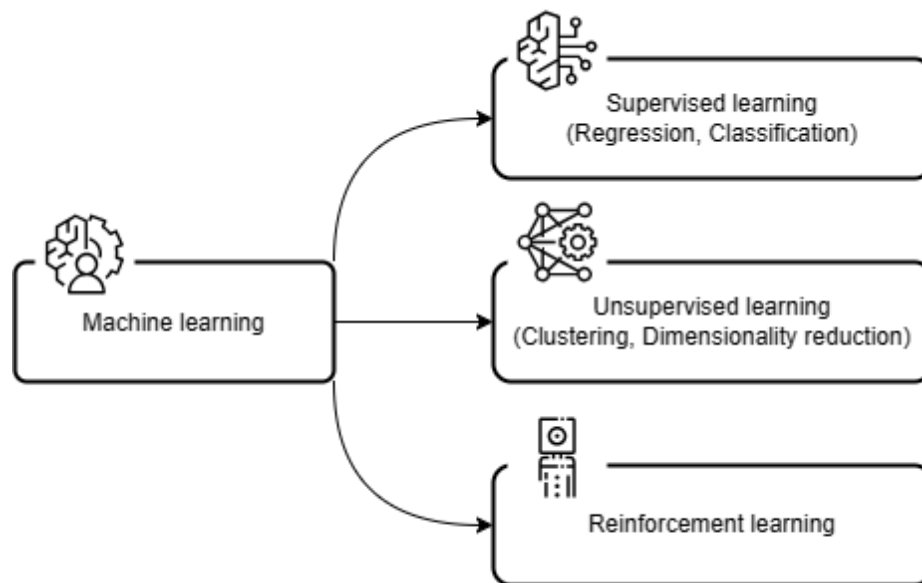


Figure 5.2: Types of machine learning

Reinforcement learning: operates in an interactive framework in which an agent navigates an environment and makes decisions to obtain cumulative rewards. In this dynamic process, the agent receives feedback in the form of rewards or punishments depending on his or her actions. In successive iterations, the agent refines its decision-making strategies and learns to optimize its actions over time (Kubat, 2017). Reinforcement learning proves

beneficial in scenarios that require sequential decision making, where the agent adapts its strategies based on evolving circumstances. This kind of learning is commonly used in gaming, where agents learn to play games by trial and error, gradually improving their performance through experience.

Unsupervised learning: works with unlabelled data where the algorithm must independently recognize patterns or structures without predefined results outcomes. In this paradigm, the model navigates through the data landscape without explicit guidance, which is particularly useful when the nature of the desired outcomes is unknown or undefined. The machine uses algorithms to uncover the underlying structures in the data, with clustering and dimensionality reduction among the main tasks. Clustering groups similar data points based on inherent patterns, making it easier to identify meaningful segments. Dimensionality reduction, on the other hand, simplifies the data while retaining key features, helping to streamline computational processes ([Kubat, 2017](#)).

Supervised learning: Supervised learning is a fundamental paradigm in machine learning, characterized by algorithms trained on labeled datasets, where input data are associated with corresponding output labels. This approach is essential when there is a clear understanding of the correct result and the relationship between input and output, especially in the case of labeled datasets and algorithms.

In our study, the dataset adheres to this paradigm, as players' criteria serve as input data labeled based on past data experiences, essentially constituting historical data. During supervised learning, the model's objective is to map input features to the correct output by reducing the discrepancy between expected and actual outputs. The machine is provided with the last calculated data, known as 'target data,' which includes both the input data (players' criteria) and the corresponding result (wage). The trained models are stored in the machine to facilitate predictions.

Supervised learning encompasses two categories: classification and regression. Classification involves training machines to recognize specific data formats, determining a unique class, whether discrete or Boolean. On the other hand, regression deals with identifying labeled data, such as players' attributes, and calculating results based on predictions. In

our specific context, we utilize regression, where the machine learns from historical data, providing results with continuous values and relying on independent variables.

Supervised learning can be beneficial in improving decision-making processes related to player evaluation and team management. Our study, which focuses on predicting the salaries of football players based on their attributes, fits in perfectly with the principles of supervised learning.

In this sports application, the input data consists of the players' criteria, which represent a variety of information that contributes to the players' overall performance and value. These criteria, ranging from technical and tactical skills to physical and behavioral abilities, make up the labeled input data. The labeling process is based on past data experience and uses historical information to effectively understand and categorize player attributes.

In this scenario, the target or outcome is the wage of football players. Using supervised learning regression, the model learns from historical data and aims to predict the real-valued outcome, which in this case is the salary estimate. This structured approach ensures that the prediction process is rooted in historical context, enabling sports decision makers to make relevant, data-driven decisions.

5.3.2 Steps in machine learning modeling

Machine learning algorithms learn patterns from data and use this acquired knowledge to make predictions. The process begins by clearly understanding our prediction goals, whether it be classification or regression, and identifying the target variable—the key factor we aim to predict. The subsequent steps in this process typically include (Figure 5.3):

Collect data: The algorithm begins by incorporating a dataset that comprises input features and corresponding output labels (in the case of supervised learning) or unlabeled data (in unsupervised learning). The quality and relevance of the data play a crucial role in the algorithm's ability to learn meaningful patterns.

Prepare data: Following data collection, the next step involves preparing the dataset

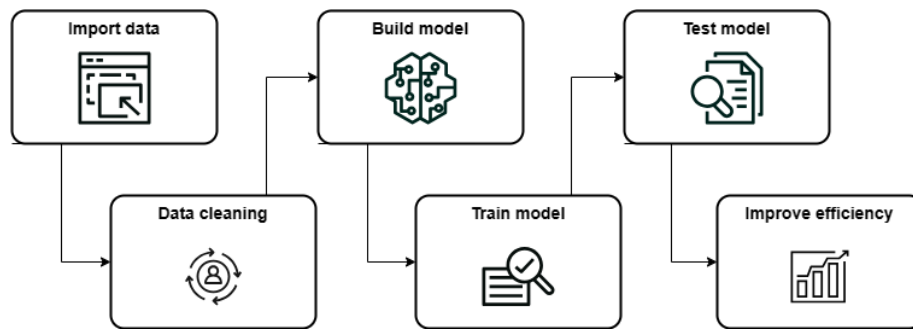


Figure 5.3: Machine learning pipeline

for analysis. This includes addressing any missing values, handling outliers, and ensuring the uniformity of the data.

Choose a model: Once the dataset has been prepared, the next critical step is to select a suitable machine learning model. The choice of a model depends on the problem’s characteristics, the data type, and the desired outcomes. The selection process involves consideration of factors such as model complexity, ease of interpretation, and specific problem requirements. A careful choice at this step provides the basis for effective learning and prediction. In our specific case of predicting player salaries and capturing attribute weights, we opted for the Random Forest model, which will be detailed in the next subsection.

Train the Model: Following the selection of the appropriate machine learning model, the next step is to train the model using the prepared dataset. During training, the model learns patterns and relationships present in the data, allowing it to make predictions on new, unseen instances. This process involves adjusting the model’s parameters to enhance its performance. The trained model captures the underlying patterns in the dataset, forming the basis for making accurate predictions in real-world applications.

Test the Model: After training, the model needs to be evaluated to assess its performance with new, unseen data. This is achieved by using a separate testing dataset that the model hasn’t seen during training. The testing process involves applying the trained model to this dataset and comparing its predictions with the actual results. Evaluating the model

on an independent set helps to assess its capacity to generalize and make precise predictions beyond the training data, providing information about its actual performance.

Evaluate the Model: After testing the model on unseen data, the next crucial step is to assess its overall performance and reliability. Evaluation involves using predefined metrics to measure how well the model predicts outcomes compared to the true values. The chosen metrics depend on the specific goals of the project. A thorough evaluation provides a clear understanding of the model's capabilities and limitations, and helps to guide potential improvements or adjustments for optimum performance in practical applications.

After exploring the fundamental steps of the machine learning pipeline, we now examine in detail a specific and powerful algorithm: Random Forest. In particular, Random Forest is not a black box like other algorithms, because it allows us to capture the weighting values necessary for our study, which allows us to prioritize the attributes of players in our predictive modeling.

5.3.3 Random forest algorithm

Renowned for its robustness and versatility, the Random Forest algorithm is distinguished by its unique composition. It is meticulously designed, incorporating several decision trees that collaborate harmoniously to make collective and accurate predictions.

In the field of machine learning, a decision tree serves as a fundamental and interpretable model mainly used in supervised learning scenarios. These hierarchical structures resemble organizational charts, where each internal node signifies a decision based on a specific feature, leading to subsequent nodes or sheets representing results. This model is suitable for classification and regression tasks. In classification, decision tree label input is based on learned decision rules, while in regression, it predicts a continuous target variable.

However, a decision tree is not without weaknesses. Overfitting is a common challenge, influenced by factors such as the selected maximum depth and asymmetry of the data for highly variable characteristics. In addition, the decision tree exhibits model instability, as even a small disturbance of the drive dataset can significantly alter the structure of a tree.

Sensitivity to unbalanced data is another problem, as the identification of branch divisions depends on the number of labels for each class.

To address these challenges, comprehensive methods have been proposed to improve the accuracy of decision trees. These methods are an integral part of more sophisticated algorithms, such as Random Forest, which leverage the collective wisdom of multiple decision trees to overcome individual gaps and provide robust predictions. The random forest algorithm is renowned for its unbiased nature and stability. It handles both categorical and numerical problems, ensuring smooth operation even in the presence of missing data. Despite its advantages, the algorithm comes with the trade-off of high complexity in both structure and process, given its ensemble of multiple decision trees. The training phase may also require a considerable amount of time due to this complexity.

Fundamental Principles

The random forest is based on the principle of creating a set of decision tree models. Each tree is built from a random subset of the available training data and features. This diversification reduces over-fitting and improves the generalizability of the model.

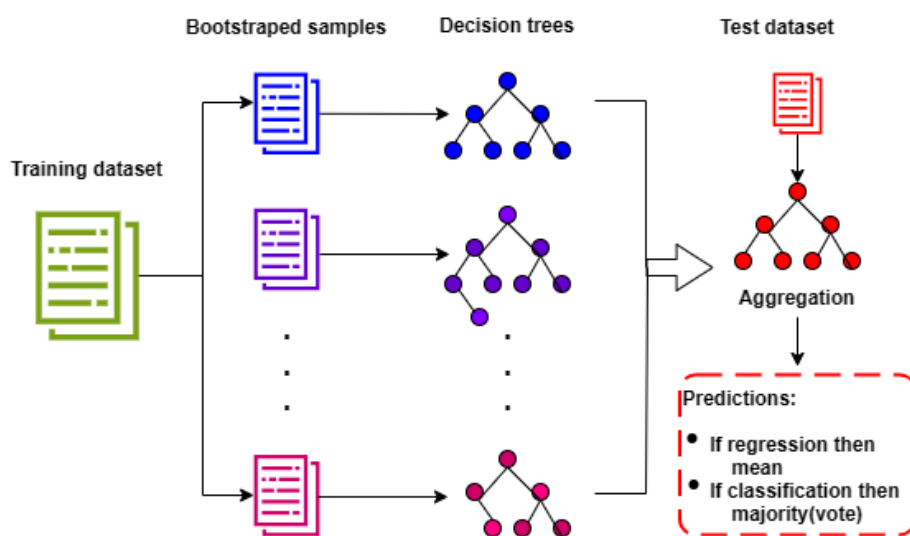


Figure 5.4: Random forest fundamental Principles (By the author)

Construction Process

The algorithm begins by creating multiple independent decision trees. Each tree is trained on a different random sample of data, selected with replacement (bootstrap). During the construction of each tree, at each node, a random subset of features is considered for decision-making, adding an additional random component.

Prediction and Aggregation

Once the trees are constructed, the Random Forest makes predictions by aggregating the results from each tree. In classification, a majority vote determines the predicted class, while in regression, the average of predictions is considered. This aggregation approach enhances the stability and accuracy of the model.

Advantages and Applications

The Random Forest offers several advantages, such as resistance to overfitting, ability to handle large and complex datasets, and relevance for various tasks like classification and regression. It finds wide applications in domains like finance, medicine, and pattern recognition.

A notable advantage of the Random Forest algorithm for predicting the salaries of football players lies in its ability to systematically assign importance to different attributes. Unlike some other machine learning algorithms, such as neural networks, logistic regression and linear regression, which are often perceived as 'black boxes', Random Forest provides transparency in the decision-making process. This transparency is manifested in the form of attribute weighting assessments.

In the context of predicting player salaries, Random Forest systematically evaluates the contribution of each attribute, such as technical, tactical, physical and behavioral attributes, in determining the final prediction. The algorithm assigns weights to these attributes, giving a clear indication of their influence on the salary prediction. This feature not only improves interpretability, but also provides valuable insights for decision makers

and stakeholders in the football management. The interpretability of Random Forest is particularly beneficial when dealing with complex decision scenarios, as it allows decision makers and practitioners to understand the factors that influence the model's predictions. This is in contrast to 'black box' models, where the internal workings are less transparent, making it difficult to understand the reasons behind certain predictions. Thus, Random Forest's systematic assignment of weighting contributes to the utility and applicability of the model in the context of predicting salaries for football players.

Key Parameters

Some key parameters profoundly influence the performance of the Random Forest model. These include the number of trees in the forest, the maximum depth of individual trees, and the number of features considered at each split. Thoughtful adjustment of these parameters is crucial for optimizing results.

Additionally, model validation with the coefficient of determination (R^2) is employed to assess the performance of the Random Forest model. With replacement, a crucial advantage in our sporting dataset, labeled, and historical data contribute to the robustness of the model. This approach involves randomly sampling instances from the dataset for training each tree in the ensemble, allowing each instance to be included multiple times or not at all. The crucial aspect of replacement ensures that the training process exposes each tree to a diverse set of instances, capturing various patterns and dependencies in the data. Essentially, with replacement, no single tree sees the exact same subset of data, promoting diversity in the learning process. This diversity enhances the model's ability to generalize and make precise predictions on new data, as it learns from a wide range of data.

5.4 Application of ML and MCDM in sports decision-making

The convergence of technology and sports in recent years has brought about significant transformations. ML and MCDM have emerged as indispensable tools, reshaping sports performance, team management, and strategic decision-making. This section delves into

the applications of ML and MCDM in the sports industry, highlighting their contributions to data understanding, precision analysis, and relevant decision-making.

[Bai and Bai \(2021\)](#) explore the challenges and opportunities presented by the integration of information technology in sports, focusing on the analysis of sports big data. The paper covers the background of sports big data, its management aspects, including acquisition and labeling, and methods such as statistical analysis and sports social network analysis. Additionally, the authors discuss applications like evaluation and prediction, and address key research issues, including predicting athletes' performance and ensuring privacy protection in sports big data.

In the field of football, human evaluators play a central role in assessing player performance. [Pappalardo et al. \(2017\)](#) sheds light on this complex process, where humans regularly evaluate the performance of individuals, influencing outcomes in a variety of fields, from science and education to sport. However, the metrics underlying this human evaluation process often remain elusive. This study looks at a massive dataset capturing player evaluations by human judges, using ML to design an artificial judge that faithfully reproduces human evaluation.

A standout application is presented by [Pappalardo et al. \(2019\)](#) through the introduction of PlayeRank, a data-driven framework designed for the evaluation of football player performance. Leveraging extensive match data, PlayeRank excels in conscious role evaluation, surpassing existing algorithms. Pappalardo's study demonstrates its superiority through comparisons and evaluations by professional recruiters, revealing intriguing performance models. With versatile applications in player search and performance evaluation, PlayeRank proves to be a streamlined and efficient tool for football analysis.

In the pursuit of team success, the performance of individual players stands as a critical factor, prompting significant research into player performance valuation. [Nsolo et al. \(2018\)](#) contribute to this discourse by conducting a comprehensive analysis across five European top football leagues. Their research examines and contrasts the attributes and skills that most accurately predict players' success across different positions. Additionally, the research evaluates the effectiveness of various machine learning algorithms in predicting

player success.

Nsolo et al.'s findings shed light on distinguishing features of top-tier players, uncovering nuances that contribute to success. Notably, the research reveals that prediction performance is higher for forwards compared to other positions. This insight prompts consideration for more advanced metrics in predicting the success of defensive players. The integration of such nuanced analyses into player performance valuation adds depth to the understanding of individual contributions within a team context.

Gu et al. (2019) contribute to the field with a data-driven expert system for the National Hockey League (NHL), aiming to predict game outcomes, enhance recruiting, and optimize salary decisions. Using player and team data from various sources, the system uses principal component analysis, non-parametric statistics, a support vector machine, and ensemble learning. Results indicate superior predictive accuracy, exceeding 90% on the testing set, outperforming the SVM reference. The user-friendly system demonstrates potential applications in refining NHL team strategies and decisions, catering to stakeholders' interests in league competitiveness.

The complex and financially significant world of top player transfers in major European football leagues is characterized by substantial transactions. Beyond the immediate transfer periods, the ability to obtain a robust economic evaluation of players throughout the year is of significant value. It is similarly important to comprehend the relationship between a player's market value and their performance. These aspects are contingent on a number of variables related to the player in question, which can be obtained from a variety of public sources on the Internet.

In this context, He et al. (2015) concentrate on modeling the market value and performance of players in the Spanish football league. Their work showcases the utilization of extensive public data sources to provide insights into the intricate relationship between economic valuation and on-field performance. This study contributes to the broader understanding of the dynamics surrounding player valuation and performance in the European football landscape.

Historically, tactical analysis in elite soccer relied on observational data, lacking vital

contextual details. Recent advancements in technology provide a wealth of data, including technical skills, physiological performance, and team formations. However, the sheer volume of this information poses a challenge without clear methodological guidelines. In their work [Rein and Memmert \(2016\)](#), the authors propose leveraging big data and machine learning to address these challenges. They discuss the organizational hurdles related to data governance and technology access, presenting a potential technological stack for elite soccer research. This approach not only aids in developing a theoretical model for tactical decision-making but also offers a guideline for other sports science domains grappling with the surge in data.

In addition to the aforementioned studies, [Cacho-Elizondo \(2020\)](#) explores the proven impact of big data on internal processes and decision-making within football clubs. The article evaluates its relevance not only to business and strategy, but also to the technical management of players and teams. Cacho-Elizondo's conceptual framework proposes a comprehensive analysis of the applications and consequences of Big Data technologies in football. The focus is on their extraordinary potential to disrupt the sports industry, particularly influencing the entire strategic decision-making process. The exploratory study concludes with several key findings, including the surge of data analysis in sports beyond traditional correlations, the development of new technological devices generating meaningful real-time information, and the increasing implementation of scientific methods in decision-making processes, directly contributing to achieving satisfactory results.

Table 5.2: Summary of studies on ML and MCDM in sports

References	Study's goal	Methods used	Results
Bai and Bai (2021)	Explore challenges and opportunities of integrating information technology in sports.	Sports big data management, statistical analysis	Addresses challenges and opportunities in sports big data, emphasizing its role in evaluation and prediction.

Continued on next page

Table 5.2 Summary of studies on ML and MCDM in sports

References	Study's goal	Methods used	Results
Pappalardo et al. (2017)	Investigate human evaluation of football player performance.	Machine learning	Reveals biases in human evaluation through the creation of an artificial judge, unveiling a noticeability heuristic.
Pappalardo et al. (2019)	Introduce PlayeRank, a data-driven framework for football player performance evaluation.	Data-driven framework	Introduces PlayeRank, showcasing its superiority in conscious role evaluation and efficient football analysis.
Nsolo et al. (2018)	Conduct a comprehensive analysis across five European top football leagues.	Machine learning algorithms for success prediction.	Identifies distinguishing features of top-tier players, with a focus on forwards and considerations for advanced metrics.
Gu et al. (2019)	Develop a data-driven expert system for the National Hockey League (NHL).	Nonparametric statistics, support vector machine (SVM), and ensemble learning.	Develops a data-driven expert system for the NHL with superior predictive accuracy, offering potential applications for team strategies.

Continued on next page

Table 5.2 Summary of studies on ML and MCDM in sports

References	Study's goal	Methods used	Results
He et al. (2015)	Model the market value and performance of players in La Liga, the Spanish football league.	Models the market value using extensive public data sources.	Models the intricate relationship between economic valuation and on-field performance in La Liga.
Rein and Memmert (2016)	Propose leveraging big data and machine learning for tactical analysis in elite football.	Big data and machine learning	Proposes leveraging big data and machine learning for tactical analysis in elite soccer, providing a potential technological stack.
Cacho-Elizondo (2020)	Explore the impact of Big Data on internal processes and decision-making within football teams.	Big Data's impact on internal football team processes	Explores Big Data's impact on internal football team processes, highlighting the surge of data analysis, development of new technological devices, and increasing implementation of scientific methods.

5.5 Conclusion

In conclusion, the application of ML and MCDM in sports has ushered in a new era of data-driven insights, transforming how we perceive and analyze athlete performance, team dynamics, and strategic decision-making. While these studies collectively showcase the broad applications of ML and MCDM in sports, it is noteworthy to mention that our specific research problem, focusing on the selection of football players for recruitment or in-match scenarios through a combination of ML and MCDM, has not been extensively addressed in the existing literature. This highlights a potential avenue for future research to explore and contribute to the evolving landscape of sports analytics. Overall, these advancements underscore the ongoing revolution in sports sciences, emphasizing the continual integration of technology for more informed decision-making in the realm of sports.

Chapter 6

A Decision support system for football player selection based on ML and MCDM techniques

6.1 Introduction

In an era of data explosion and technological advances, the world of football is going through an exciting period of change. With the growing amount of data available from big data and artificial intelligence, coaches, managers, and analysts are more empowered than ever to make data-driven decisions. Traditional team training and recruitment, enriched by decades of experience, are now complemented by the power of data analysis. In this context, the idea of an integrated model has emerged—a model that combines the predictive robustness of machine learning with the structured process of multi-criteria decision-making. The combination of these two methods promises a comprehensive approach to player selection that respects the expertise of human judgment, reflecting subjective aspects, while leveraging the information provided by the data referring the objective criteria.

In this chapter, we explore the complexity of an integrated model by defining its input parameters and prioritizing a wide range of criteria (attributes) essential for effective player selection. We evaluate the alternatives (players) and compare the model results with real-world data, which allows us to draw comprehensive conclusions.

Our main goal is to demonstrate how the fusion of machine learning and multi-criteria decision-making has the potential to significantly improve the player selection process in football. By providing decision makers with a decision support system that complements their dose of subjectivity, our research aims to increase the effectiveness of player selection strategies in sports.

Throughout this chapter, we will use Paris Saint-Germain (PSG) as a case study to illustrate the functionality of our integrated model, which combines machine learning and multi-criteria decision making. The importance of PSG in football and the availability of financial data make it an ideal example of our approach. By detailing each step of the process, from data collection to applying weighting and evaluating alternatives, we aim to provide a concrete demonstration of our approach and its effectiveness in player selection strategies. This case study will offer valuable insights into the practical application of our research, contributing to the advancement of sports analysis and decision-making

processes.

It is important to note that our decision support system is not limited to a single club or a single season. In fact, our DSS is designed to manage several professional clubs and cover several seasons, guaranteeing continuous evaluation and improvement of player performance, as well as openness to the player market. This helps decision-makers in the recruitment or transfer process.

In this chapter, we will first model the football player selection system by identifying the selection problem and weighting criteria by player position, based on methods such as the Random Forest algorithm and MCDM techniques. We will then apply the TOPSIS method to rank players based on these weighted criteria. Following this, we will evaluate the system by conducting a comparative analysis with real-match data and providing detailed interpretations of the results.

6.2 Modeling the football player selection system

The process of selecting football players is a complex task that goes far beyond the mere selection of athletes for a team. Rather, it is a detailed search for players whose skills, technical, tactical, physical and behavioral attributes are best suited to contribute to the overall success of the team and the club.

Sports decision makers and recruiters face a variety of challenges in the selection process. One of these challenges is the limited availability of reliable player performance data, which is often a major obstacle. While performance data is available in abundance, its quality and reliability can fluctuate significantly, making it difficult for sports decision makers to make relevant decisions.

In addition, the multiplicity of criteria to consider when selecting players makes the process even more complex. As a result, sports decision makers have to juggle a variety of factors when selecting players, which underlines the importance of AI-based tools and multi-criteria methods to support them in this complex decision-making process.

The importance of a decision support system in the selection of football players is cru-

cial for several reasons. Firstly, such a system offers the advantage of objectivity. Unlike traditional selection methods, which can be influenced by subjective biases or personal preferences, a decision support system uses predefined criteria and objective data to evaluate players. This ensures a more equitable and transparent evaluation of each player and makes it possible to select the most suitable candidates regardless of any bias.

It is important to realize that the decision support system is not meant to replace human expertise, but to complement it. Managers and recruiters have a deep understanding of the specific needs of their team as well as the specifics of the game that may not be easily quantifiable. The decision support system reinforces their expertise by providing them with a more objective analysis that allows them to make more appropriate decisions.

Figures 6.1 and 6.2 respectively summarize the hierarchical model used for football player selection and the modeling of the decision-making process, delineating the key steps of the decision-making process, including the problem identification phase, the criteria weighting phase and the player evaluation phase, which will be examined in the following sub-sections.

Furthermore, to illustrate the PSG case study, we collected data for thirty-three players and their thirty-five performance criteria for the 2021-2022 season. The decision matrix, as shown in Appendix A, represents the raw state of the data before it is processed for each playing position: goalkeeper, defender, midfielder and forward. Using PSG as an example, we demonstrate how our decision support system can analyze and compare player performance, leading to adjustments in recruitment strategies and optimized management decisions within professional clubs. The multi-club and multi-season capability of our system allows for adaptation to various contexts and needs, thus providing a tool to improve player selection processes in the football industry.

To demonstrate the functionality of our model, we have chosen to explain the calculation steps of the entropy, CRITIC and TOPSIS methods specifically for the goalkeeper position. This decision was driven by several factors. First, there are only a limited number of criteria at the goalkeeper position, which makes it easier to visualize and understand our approach. Positions such as defender, midfielder and striker, on the other hand, have a

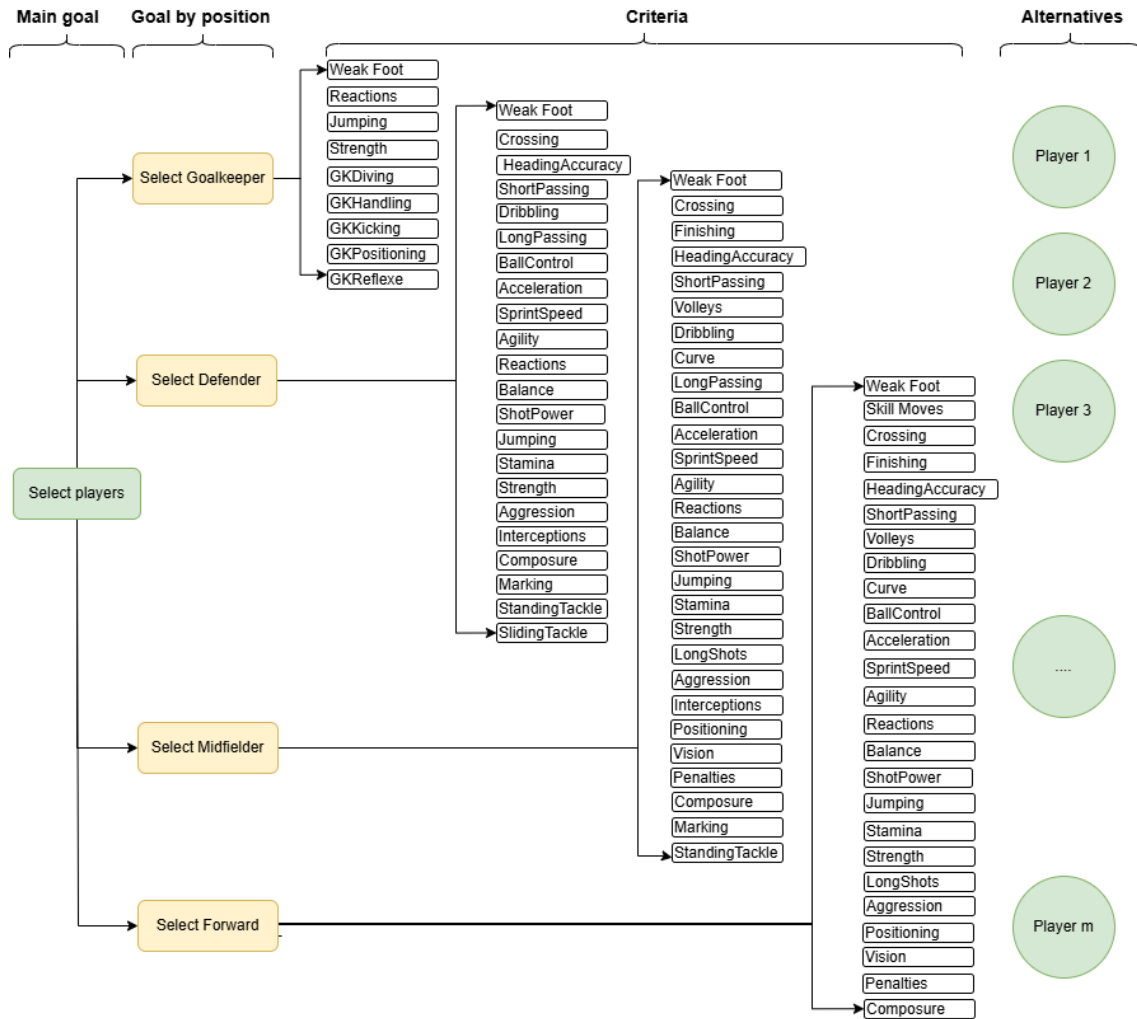


Figure 6.1: Hierarchical decision-making model for football player selection

larger number of criteria, making it difficult to present them comprehensively in the body of the text. Nevertheless, to ensure a thorough presentation of our model, we have planned to include detailed analyzes for these positions in [Appendix B](#). This appendix contains the interfaces used to apply the player selection methods to the different positions. For readers interested in the technical and algorithmic aspects of our model, [Appendix D](#) contains the full source code used to implement our decision support tool.

6.2.1 Identification of the football player selection problem

This phase focuses on the input parameters of our model. Our database, obtained from Kaggle and covering the 2016 to 2022 seasons, includes detailed profiles of over 20,000

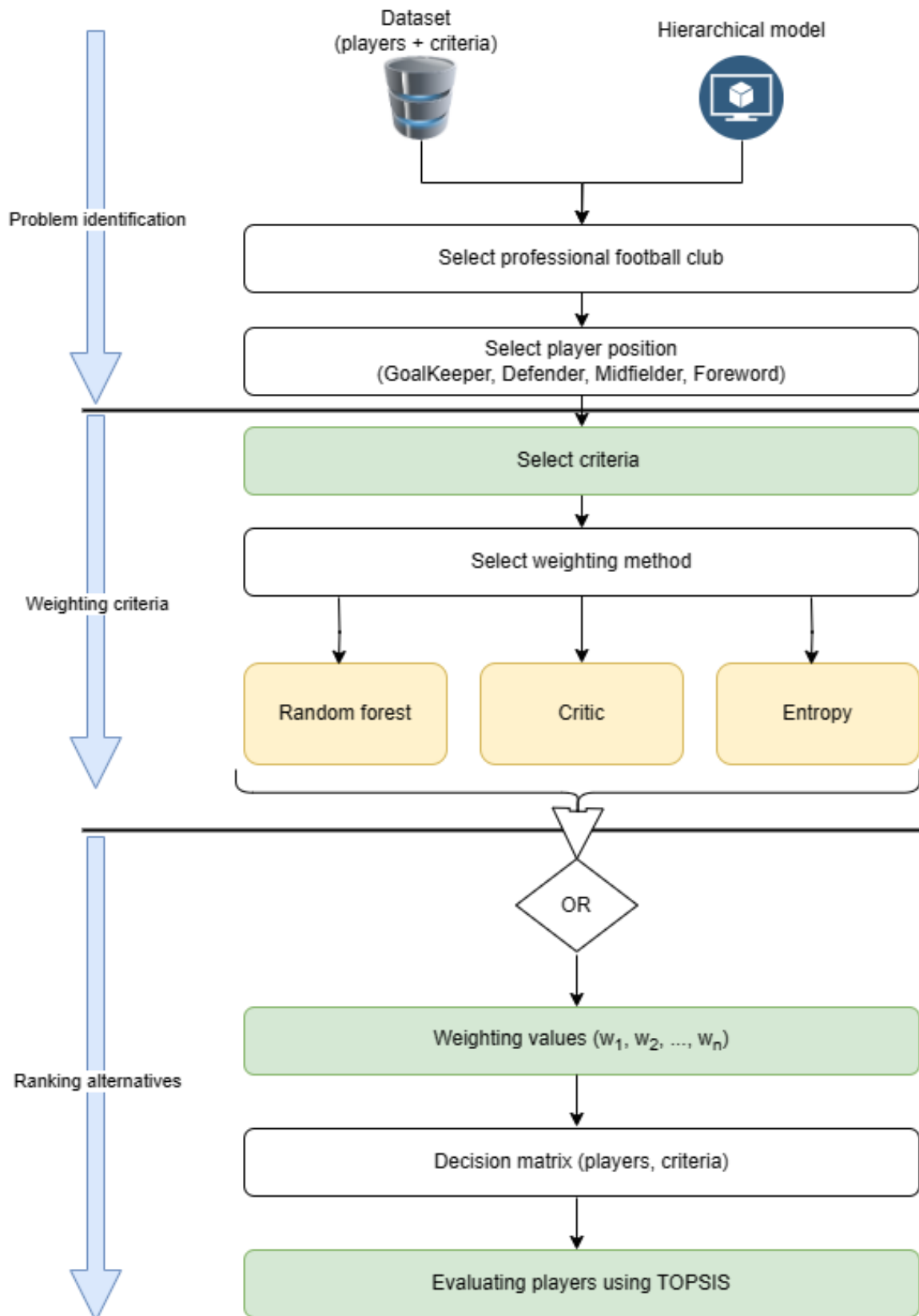


Figure 6.2: Decision process modeling

players and 500 professional football clubs. Each player is characterized by a variety of criteria, including technical, physical, tactical, and behavioral skills, as well as information such as age, wage, club, and position on the field.

The process of selecting a player for a match, recruitment, or transfer takes place within the organization of a club, which is why the first parameter to consider in our model is the selection of the professional club. By focusing on a specific club, we narrow down our universe and customize the analysis to the unique needs and strategies of that club.

In football, different positions, such as goalkeeper, defender, midfielder or forward, require different tasks and responsibilities. The attributes of a forward player differ from those of a midfielder or goalkeeper. Therefore, specifying a player's position ensures that our analysis accounts for the specific tasks and expectations of that position.

To ensure the effectiveness of our model, we considered the attributes that best align with the unique role of each player position (Figure 5.2). The criteria selection process for all player functions was based on the mean attribute values for each criterion. Attributes with a mean value exceeding the threshold of fifty percent were chosen as suitable criteria, while those below this threshold were excluded.

Our development environment is central to implementing our decision support system. The Python ecosystem provides tools and libraries that facilitate various aspects of our project. For data manipulation and analysis, we rely on 'pandas', a powerful library that simplifies the process of data manipulation and transformation. For machine learning tasks, 'scikit-learn' is indispensable as it provides a wide range of algorithms and utilities for model creation and evaluation. In addition, 'pyDecision' supports multi-criteria decision processes and provides methods for implementing techniques such as entropy, CRITIC and TOPSIS. To create interactive web applications to visualize and interact with our data and models, we use 'Streamlit' to develop and deploy data applications.

6.2.2 Weighting criteria by player position

In football, the importance of each player's characteristics often varies according to his position on the pitch. For example, the attributes of a goalkeeper are very different from those

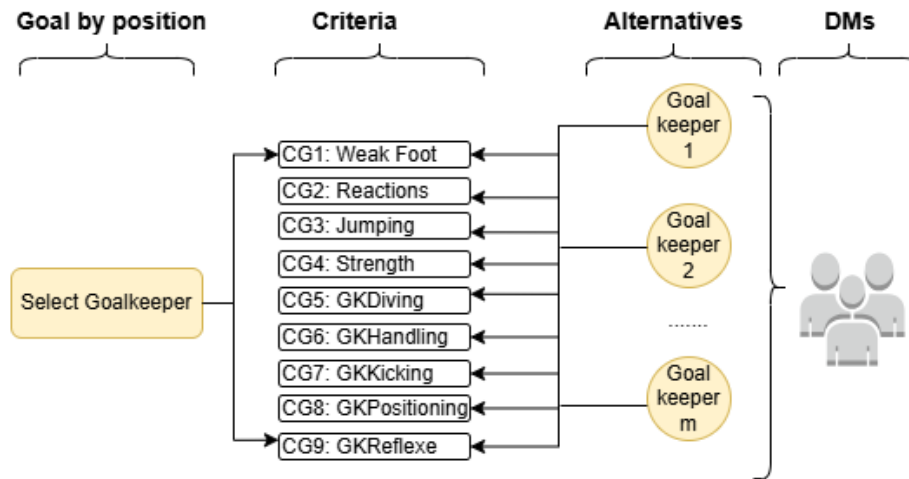


Figure 6.3: Hierarchical model for goalkeeper selection

of a defender or a midfielder. It is therefore essential to define and evaluate the relevant criteria for each player position to ensure the accuracy and efficiency of our decision-making model.

To methodically evaluate potential football talent and ensure that the right player is selected for the right position, we start by defining and analyzing the relevant criteria for each position. Our database includes a wide range of attributes - around thirty-five. However, for targeted decision-making, it's essential to organize the criteria for each position.

To provide a more visual representation of the organization of these criteria, [Figures 6.3 to 6.6](#) are illustrated. These figures break down the criteria chosen for each player position: goalkeepers, defenders, midfielders and forwards, providing an intuitive overview of the anatomy of player selection for each role.

The next step in the selection process is to understand the importance and weighting of each criterion. Assigning the right weighting to each attribute ensures that player selection is data-driven and contextually relevant.

We used three different methods to weight player criteria. The first method, derived from artificial intelligence, is the Random Forest algorithm. This algorithm, renowned for its data-driven analysis, offers an objective perspective by evaluating each attribute according to its impact and importance in predicting player performance. The other two tech-

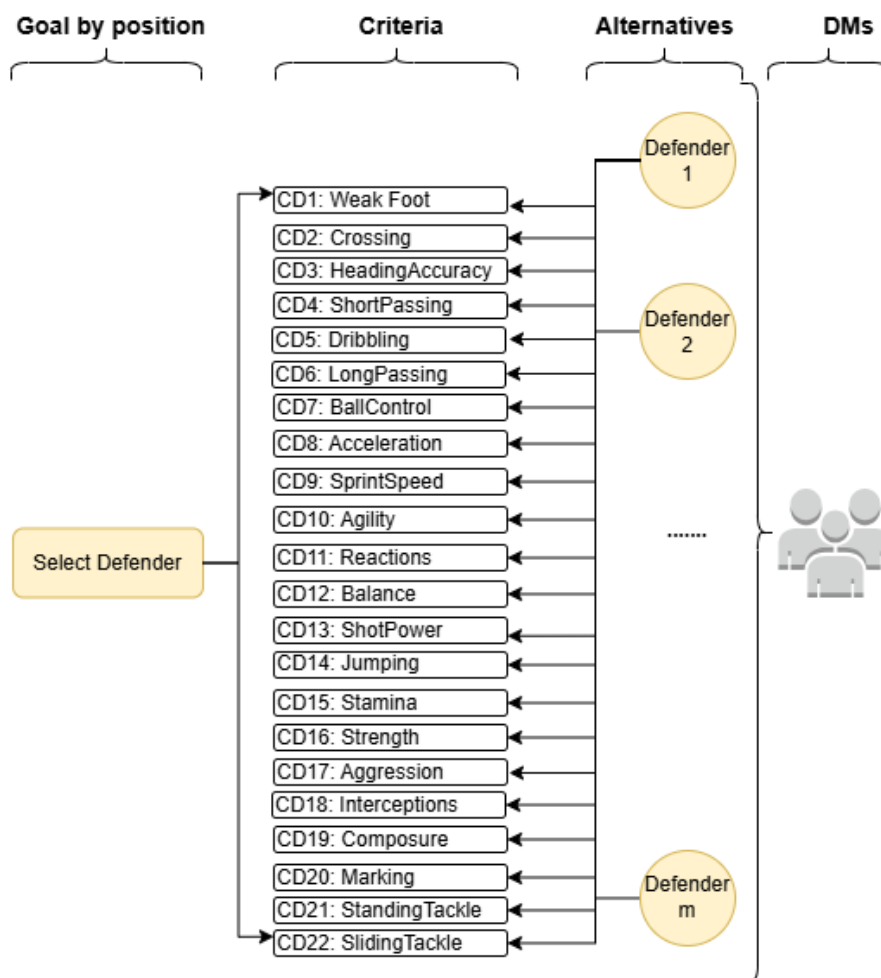


Figure 6.4: Hierarchical model for defender selection

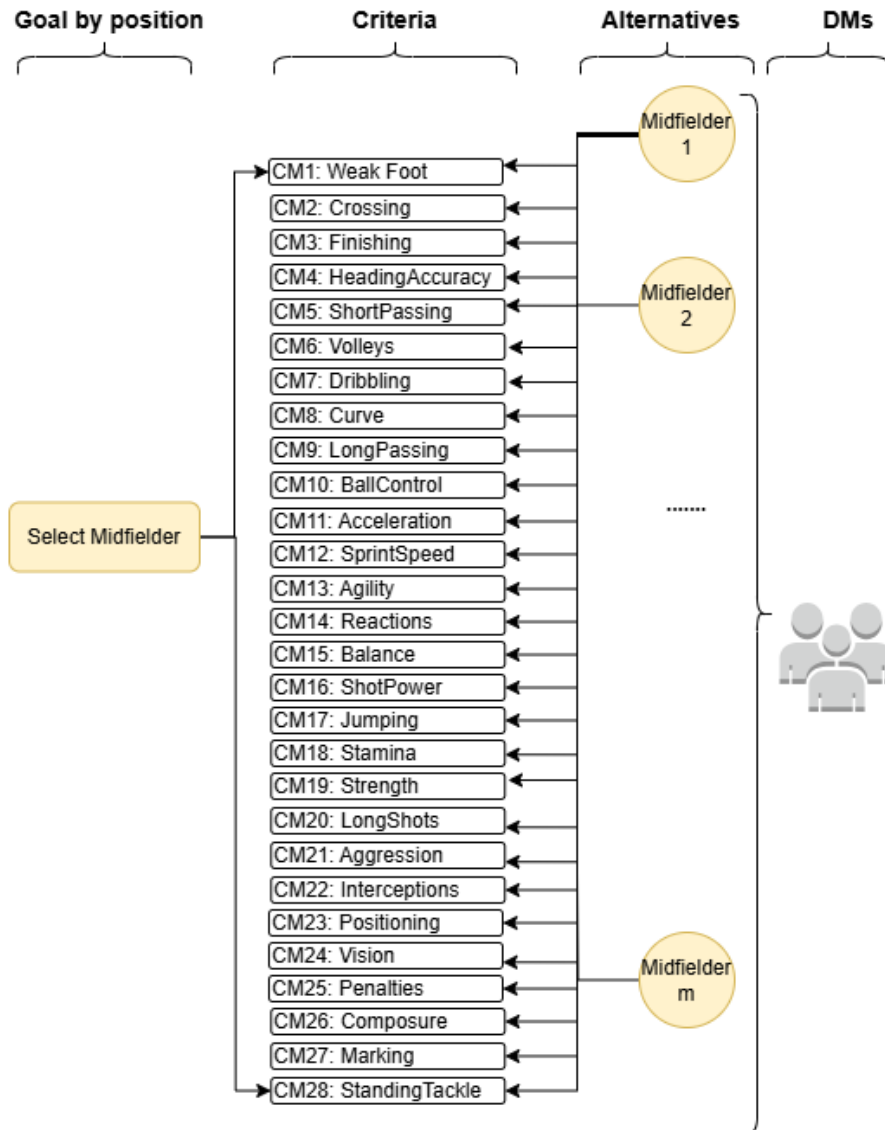


Figure 6.5: Hierarchical model for midfielder selection

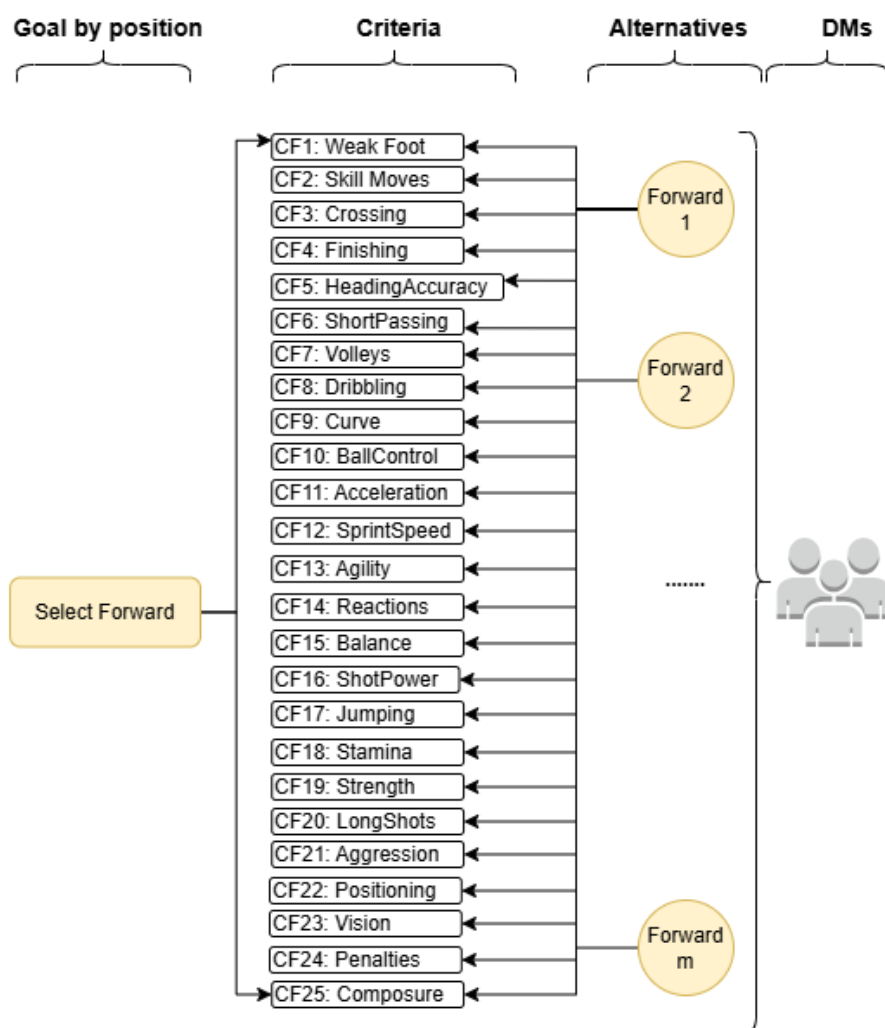


Figure 6.6: Hierarchical model for forward selection

niques, Entropy and CRITIC, are derived from multi-criteria decision-making approaches.

The idea behind using these three methods is to offer decision makers a diversity of analyses and perspectives, rather than relying on a single evaluation method. The Entropy and CRITIC techniques enable criteria to be weighted, taking into account variations and correlations between the different attributes of the players. Entropy measures the uncertainty and dispersion of criteria values (Dong and Yang, 2021), while CRITIC assesses the importance of criteria in terms of the amount of information and conflict they bring to the decision-making process (Diakoulaki et al., 1995).

6.2.2.1 Random forest algorithm

Machine learning, in particular the random forest algorithm, is a powerful tool for deciphering complex patterns and relationships in large datasets. To determine the weights of different player attributes, we relied on the random forest approach. Traditionally, the random forest is renowned for its robustness to over-fitting and its ability to handle large datasets efficiently. It works by constructing a multitude of decision trees during training, and produces either the class mode (classification) or the average prediction (regression) of the individual trees.

Criteria weighting by random forest regression:

It is essential to note that in our approach, we used random forest regression to weight the player criteria. Unlike classification, where the result is a class label, regression predicts continuous numerical values. In our case, we sought to predict player "wage" as a continuous variable, allowing us to capture the relationship between attributes and player salaries.

In our machine learning model, the target variable was the "wage" of football players. Players' salaries at professional clubs are largely determined by their skills, potential and performance. Consequently, the attributes that most influence the prediction of a player's wage are particularly relevant to the assessment of his skills and value.

Using the importance (weight) of each attribute to predict salaries offers a quantifiable means of assessing the relevance of each attribute. Data on player salaries essentially reflect

decisions made by club management and market dynamics.

By using attribute importance to predict salaries, we can obtain an objective, data-driven assessment, that identifies the most significant attributes in determining player value. This approach enables decision makers to better understand which attributes contribute most to a player's performance and financial potential, facilitating more optimized selection decisions.

Therefore, we indirectly capture expert judgments about the importance of attributes by predicting these wages. The random forest model adjusts the weights according to the data. If the data changes over time or new data is added, the model can be retrained and the weights updated. This dynamic adjustment ensures that the importance scores are always up-to-date and relevant. Thanks to this flexibility and scalability, the random forest algorithm is well suited for applications where the underlying data changes. It provides a robust and adaptable solution for the continuous improvement of the model.

Model training:

By training a random forest model using player attributes as independent variables and their respective wages as the dependent variable (as shown in equations (1), (2), (3), and (4) for forward, defender, midfielder, and goalkeeper positions, respectively), we were able to retrieve weights assigned by the model to each attribute. These weights, obtained through the learning process of the random forest algorithm, are used as coefficients in the wage equations specific to each position.

The model intrinsically captures non-linear interactions and relationships, allowing us

to understand the importance of attributes in determining player salaries.

$$\begin{aligned}
 (1) \quad \text{Wage}_{\text{forward}} = & w_1 \times \text{Weak Foot} + w_2 \times \text{Skill Moves} + w_3 \times \text{Crossing} + w_4 \times \text{Finishing} \\
 & + w_5 \times \text{HeadingAccuracy} + w_6 \times \text{ShortPassing} + w_7 \times \text{Volleys} \\
 & + w_8 \times \text{Dribbling} + w_9 \times \text{Curve} + w_{10} \times \text{BallControl} + w_{11} \times \text{Acceleration} \\
 & + w_{12} \times \text{Agility} + w_{13} \times \text{Reactions} + w_{14} \times \text{Balance} + w_{15} \times \text{ShotPower} \\
 & + w_{16} \times \text{Jumping} + w_{17} \times \text{Stamina} + w_{18} \times \text{Strength} + w_{19} \times \text{LongShots} \\
 & + w_{20} \times \text{Aggression} + w_{21} \times \text{Positioning} + w_{22} \times \text{Composure} + w_{23} \times \text{Vision} \\
 & + w_{24} \times \text{Penalties} + w_{25} \times \text{SprintSpeed}
 \end{aligned}$$

$$\begin{aligned}
 (2) \quad \text{Wage}_{\text{defender}} = & w_1 \times \text{Weak Foot} + w_2 \times \text{Crossing} + w_3 \times \text{HeadingAccuracy} \\
 & + w_4 \times \text{ShortPassing} + w_5 \times \text{Dribbling} + w_6 \times \text{LongPassing} \\
 & + w_7 \times \text{BallControl} + w_8 \times \text{Acceleration} + w_9 \times \text{SprintSpeed} \\
 & + w_{10} \times \text{Agility} + w_{11} \times \text{Reactions} + w_{12} \times \text{Balance} \\
 & + w_{13} \times \text{ShotPower} + w_{14} \times \text{Jumping} + w_{15} \times \text{Stamina} \\
 & + w_{16} \times \text{Strength} + w_{17} \times \text{Aggression} + w_{18} \times \text{Interceptions} \\
 & + w_{19} \times \text{Composure} + w_{20} \times \text{Marking} + w_{21} \times \text{StandingTackle} \\
 & + w_{22} \times \text{SlidingTackle}
 \end{aligned}$$

$$\begin{aligned}
(3) \quad \text{Wage}_{\text{midfielder}} = & w_1 \times \text{Weak Foot} + w_2 \times \text{Crossing} + w_3 \times \text{Finishing} + \\
& w_4 \times \text{HeadingAccuracy} + w_5 \times \text{ShortPassing} + w_6 \times \text{Volleys} \\
& + w_7 \times \text{Dribbling} + w_8 \times \text{Curve} + w_9 \times \text{LongPassing} + w_{10} \times \text{BallControl} \\
& + w_{11} \times \text{Acceleration} + w_{12} \times \text{SprintSpeed} + w_{13} \times \text{Agility} + \\
& w_{14} \times \text{Reactions} + w_{15} \times \text{Balance} + w_{16} \times \text{ShotPower} + w_{17} \times \text{Jumping} \\
& + w_{18} \times \text{Stamina} + w_{19} \times \text{Strength} + w_{20} \times \text{LongShots} + w_{21} \times \text{Aggression} \\
& + w_{22} \times \text{Interceptions} + w_{23} \times \text{Positioning} + w_{24} \times \text{Vision} \\
& + w_{25} \times \text{Penalties} + w_{26} \times \text{Composure} + w_{27} \times \text{Marking} + \\
& w_{28} \times \text{StandingTackle}
\end{aligned}$$

$$\begin{aligned}
(4) \quad \text{Wage}_{\text{goalkeeper}} = & w_1 \times \text{Weak Foot} + w_2 \times \text{Reactions} + w_3 \times \text{Jumping} + w_4 \times \text{Strength} + \\
& w_5 \times \text{GK Diving} + w_6 \times \text{GK Handling} + w_7 \times \text{GK Kicking} + \\
& w_8 \times \text{GK Positioning} + w_9 \times \text{GK Reflexes}
\end{aligned}$$

We began by loading the necessary data, which included the criteria. These criteria are selected based on the player's position, with specific attributes tailored to different positions. The next step involves splitting the data into training and testing sets. We used a training set to train our random forest model. We selected attributes as independent variables (X), and 'Wage' as the dependent variable (y).

The model was then trained to understand the relationships between these attributes and players' wages. The random forest model is then applied to predict player wages based on the selected attributes. The model generates weights for each attribute, indicating their contribution to the prediction. The weights assigned by the random forest model offer insights into the attributes that play a more significant role in determining player wages. This step enables us to fully understand the relevance of each attribute in the decision-making process.

The benefit of using random forest in this application lies in its ability to take into

account non-linear relationships and potential interactions between attributes, which can be very complex in the field of sports analysis. A player's wage is not necessarily a linear association of his attributes but may involve complex interactions that the random forest is able to capture.

6.2.2.2 MCDM methods for objective weighting

Multi-criteria decision making methods such as Entropy and CRITIC enable objective comparison of the attributes of different players, unlike traditional methods such as AHP and ANP, which rely on expert judgment to assign weights. In addition, these methods make it possible to assign a relative weight to each criterion according to its importance. They also facilitate the structuring of decision-makers' opinions on player characteristics, contributing to more transparent and rational decision-making. Before recruiting a player, multi-criteria analysis enables us to assess his performance potential in terms of various attributes, thus optimizing the recruitment process. Finally, after a season, this approach can be used to retrospectively assess player performance, helping to identify areas for improvement in subsequent seasons.

Weighting with multi-criteria approaches begins with the construction of the decision matrix, followed by the normalization of this matrix. Normalization is essential to make the criteria comparable, particularly when the criteria have different units or scales. This step ensures that each criterion contributes equally to the overall evaluation by adjusting the values to a common scale. Using the decision matrix for the goalkeeper position [Table 6.1](#), we illustrate the detailed steps of our modeling process.

Table 6.1: Decision matrix for goalkeeper position

	Player	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	G. Donnarumma	3	85	72	72	91	83	79	85	90
P2	K. Navas	3	85	74	75	89	84	75	87	89
P3	Sergio Rico	3	72	63	53	77	74	77	74	80
P4	A. Letellier	2	67	57	72	68	67	62	67	72

Entropy method

The entropy weighting method provides a significant advantage by eliminating the influence of human factors on indicator weights, thereby increasing the objectivity of comprehensive evaluation results. Utilizing the normalized matrix, we calculate the entropy value, which quantifies the dispersion of criterion values in the normalized matrix. Subsequently, we determine the weight vector using the computed entropy values.

Step 1: Normalizing the decision matrix

The first step in the entropy method involves normalizing the decision matrix, which enables the comparison of criteria with different scales or units. [Table 6.2](#) presents the normalized decision matrix for goalkeeper position used in this step.

Table 6.2: Goalkeeper normalized decision matrix

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	0,273	0,275	0,271	0,265	0,280	0,269	0,270	0,272	0,272
P2	0,273	0,275	0,278	0,276	0,274	0,273	0,256	0,278	0,269
P3	0,273	0,233	0,237	0,195	0,237	0,240	0,263	0,236	0,242
P4	0,182	0,217	0,214	0,265	0,209	0,218	0,212	0,214	0,218

Step 2: Computing entropy for four alternatives or players

In this step, the entropy values for the alternatives or players are computed using the formula: $e_j = -h * \sum r_{ij} * \ln r_{ij}$, where $h = 1/\ln(4)$. This formula quantifies the dispersion of criterion values within the decision matrix. [Table 6.3](#) displays the computed entropy values for each criterion.

Step 3: Computing the entropy weight vector

After computing the entropy values for each criterion, the next step involves determining the entropy weight vector. This vector represents the relative importance of each criterion

Table 6.3: Entropy values for goalkeeper position

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	-0,354	-0,355	-0,354	-0,352	-0,356	-0,353	-0,353	-0,354	-0,354
P2	-0,354	-0,355	-0,356	-0,355	-0,355	-0,354	-0,349	-0,356	-0,353
P3	-0,354	-0,339	-0,341	-0,319	-0,341	-0,343	-0,351	-0,341	-0,343
P4	-0,310	-0,331	-0,330	-0,352	-0,327	-0,332	-0,329	-0,330	-0,332
$\sum r_{ij} * \ln r_{ij}$	-1,373	-1,381	-1,381	-1,378	-1,380	-1,382	-1,382	-1,381	-1,382
e_j	0,990	0,996	0,996	0,994	0,995	0,997	0,997	0,996	0,997

in the decision-making process, considering their entropy values. Table 6.4 illustrates the weight vector obtained from the calculated entropy values.

Table 6.4: Entropy weights for goalkeeper position

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	-0,354	-0,355	-0,354	-0,352	-0,356	-0,353	-0,353	-0,354	-0,354
P2	-0,354	-0,355	-0,356	-0,355	-0,355	-0,354	-0,349	-0,356	-0,353
P3	-0,354	-0,339	-0,341	-0,319	-0,341	-0,343	-0,351	-0,341	-0,343
P4	-0,310	-0,331	-0,330	-0,352	-0,327	-0,332	-0,329	-0,330	-0,332
$\sum r_{ij} * \ln r_{ij}$	-1,373	-1,381	-1,381	-1,378	-1,380	-1,382	-1,382	-1,381	-1,382
e_j	0,990	0,996	0,996	0,994	0,995	0,997	0,997	0,996	0,997
$1 - e_j$	0,010	0,004	0,004	0,006	0,005	0,003	0,003	0,004	0,003
W_j	0,230	0,093	0,094	0,151	0,117	0,073	0,075	0,096	0,070

CRITIC method

The CRITIC method evaluates the importance of attributes based on the inherent characteristics of the data. It assesses the conflict (difference in evaluation scores) between criteria to determine weights.

Step 1: Normalizing the decision matrix

The first step in the CRITIC method is to normalize the decision matrix. Table 6.5 presents the normalized decision matrix for the goalkeeper position using the CRITIC method.

Table 6.5: Goalkeeper normalized decision matrix using CRITIC method

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	1,000	1,000	0,882	0,864	1,000	0,941	1,000	0,900	1,000
P2	1,000	1,000	1,000	1,000	0,913	1,000	0,765	1,000	0,944
P3	1,000	0,278	0,353	0,000	0,391	0,412	0,882	0,350	0,444
P4	0,000	0,000	0,000	0,864	0,000	0,000	0,000	0,000	0,000

Step 2: Calculating standard deviation σ_j for each criteria

The second step in the weighting process involves calculating the standard deviation σ_j for each criterion. Standard deviation measures the amount of variation or dispersion of a set of values. In the context of our decision matrix, it helps to determine the variability of each criterion across all players being evaluated. The standard deviation σ_j is calculated for each criterion based on the values observed for all players (Table 6.6).

Table 6.6: The standard deviation σ_j for each criteria

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	1,000	1,000	0,882	0,864	1,000	0,941	1,000	0,900	1,000
P2	1,000	1,000	1,000	1,000	0,913	1,000	0,765	1,000	0,944
P3	1,000	0,278	0,353	0,000	0,391	0,412	0,882	0,350	0,444
P4	0,000	0,000	0,000	0,864	0,000	0,000	0,000	0,000	0,000
σ_j	0,500	0,510	0,467	0,459	0,469	0,473	0,452	0,471	0,470

Step 3: Determining the symmetric matrix $n \times n$

In this step, we calculate the symmetric matrix of size $n \times n$, where each element r_{jk} represents the linear correlation coefficient between the vectors x_j and x_k . This matrix helps us understand the degree of correlation between the different criteria. Table 6.7 presents the symmetric matrix for the goalkeeper position. Each value r_{jk} indicates the correlation between two criteria. A value that is close to 1 indicates a strong positive correlation, while a value that is close to -1 indicates a strong negative correlation.

Table 6.7: The symmetric matrix $n * n$

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
CG1	1,000	0,744	0,798	-0,264	0,819	0,829	0,977	0,795	0,847
CG2	0,744	1,000	0,991	0,442	0,989	0,989	0,727	0,993	0,984
CG3	0,798	0,991	1,000	0,370	0,983	0,997	0,758	1,000	0,985
CG4	-0,264	0,442	0,370	1,000	0,318	0,320	-0,284	0,375	0,277
CG5	0,819	0,989	0,983	0,318	1,000	0,992	0,817	0,986	0,998
CG6	0,829	0,989	0,997	0,320	0,992	1,000	0,799	0,998	0,995
CG7	0,977	0,727	0,758	-0,284	0,817	0,799	1,000	0,759	0,838
CG8	0,795	0,993	1,000	0,375	0,986	0,998	0,759	1,000	0,987
CG9	0,847	0,984	0,985	0,277	0,998	0,995	0,838	0,987	1,000

Step 4: Calculating the measure of the conflict created by criterion j with respect of the decision situation defined by the rest of criteria $\sum(1 - r_{jk})$

The sum of the conflicts created by criterion j with respect to the other criteria is calculated as $\sum(1 - r_{jk})$ (Table 6.8). This measure helps to identify the degree of conflict or redundancy among the criteria, providing insights into their relative importance and interaction.

Step 5: Determining the quantity of the information in relation to each criterion $c_j = \sigma_j * \sum(1 - r_{jk})$

The quantity of information for each criterion (c_j) is calculated as the product of the standard deviation (σ_j) and the sum of the conflicts created by criterion j with respect to the other criteria ($\sum(1 - r_{jk})$) (Table 6.8).

Step 6: Determining the objective weights

Objective weights are determined based on the calculated quantities of information for each criterion. These weights are a measure of the relative importance of each criterion in the decision process. Table 6.8 displays the objective weights assigned to each criterion.

Integrating the capabilities of both methods ensures in-depth analysis of the entire data set, and adaptability to different scenarios and data inputs. This adaptability extends to the weight determination process, where users of the decision support system can select the appropriate method according to their preferences and specific needs. This flexibility

Table 6.8: CRITIC weights for goalkeeper position

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
CG1	0,000	0,256	0,202	1,264	0,181	0,171	0,023	0,205	0,153
CG2	0,256	0,000	0,009	0,558	0,011	0,011	0,273	0,007	0,016
CG3	0,202	0,009	0,000	0,630	0,017	0,003	0,242	0,000	0,015
CG4	1,264	0,558	0,630	0,000	0,682	0,680	1,284	0,625	0,723
CG5	0,181	0,011	0,017	0,682	0,000	0,008	0,183	0,014	0,002
CG6	0,171	0,011	0,003	0,680	0,008	0,000	0,201	0,002	0,005
CG7	0,023	0,273	0,242	1,284	0,183	0,201	0,000	0,241	0,162
CG8	0,205	0,007	0,000	0,625	0,014	0,002	0,241	0,000	0,013
CG9	0,153	0,016	0,015	0,723	0,002	0,005	0,162	0,013	0,000
$\sum(1 - r_{jk})$	2,454	1,140	1,118	6,445	1,096	1,081	2,609	1,108	1,089
C_j	1,227	0,581	0,522	2,959	0,514	0,511	1,178	0,522	0,512
W_j	0,144	0,068	0,061	0,347	0,060	0,060	0,138	0,061	0,060

enhances the applicability of the model in various scenarios and directly influences the following subsection, which deals with the ranking of football players based on the TOPSIS method.

6.2.3 Football player ranking based on TOPSIS method

The selection of an appropriate MCDM method is critical to the design of an effective decision support system. Although TOPSIS is chosen for its specific advantages in our application, it is essential to acknowledge that various MCDM methods offer different strengths. The following are some considerations that contribute to the selection of TOPSIS.

- Multi-criteria decision making encompasses a variety of methods, including well-known approaches such as Analytic Hierarchy Process, Analytic Network Process and Simple Additive Weighting. While each method has its own approach to handling multiple criteria and prioritizing weightings, our decision support system benefits from the computational efficiency of TOPSIS.
- Unlike other methods, such as AHP, which can require multiple iterations to calculate priority values and weights, TOPSIS features a streamlined decision-making process. This efficiency is particularly valuable in real-time applications as it ensures a fast

and effective decision-making mechanism within our system.

- The nature of the decision problem influences the choice of MCDM method. TOPSIS handles complex, multidimensional decision matrices. In the context of sport and football player selection, this often involves evaluating players on the basis of multiple performance parameters, such as physical attributes and technical skills. Methods such as TOPSIS are particularly well suited to this context, as they can manage a large number of criteria and alternatives, and effectively prioritize these complex, multi-dimensional criteria, providing an objective and transparent ranking of players. This ensures that the decision-making process is aligned with the team's strategic objectives.
- The computational complexity of MCDM methods is a practical consideration, especially in systems where real-time decision making or quick iterations are necessary.

The choice of TOPSIS in our decision support system is essentially based on its focus on the characteristics of football player selection and the specific advantages it offers in handling complex weighted criteria. The large number of criteria, ranging from twenty-five for forwards, twenty-two for defenders, and twenty-eight for midfielders to nine for goalkeepers, underlines the need for an efficient method capable of handling this complexity. On the other hand, TOPSIS is justified as a customized solution to the complexities of the decision problem, not as a way to disprove the efficacy of other approaches.

In the subsequent phase of our decision support system, we employ TOPSIS to evaluate player alternatives in distinct positions: Defender, Goalkeeper, Forward, and Midfielder. The weights crucial for this evaluation are derived from the random forest algorithm, which assigns specific importance values to each attribute through extensive training on player attributes and wages.

The first step involves normalizing player attribute data using these position-specific weights to ensure a fair comparison across diverse criteria. Following normalization, we constructed decision matrices for each position, capturing the complex relationships between attributes. As TOPSIS cannot determine the weighting for criteria, it takes them

from the previous weighting criteria methods, which are Random forest, CRITIC, or Entropy. The TOPSIS algorithm is then applied to calculate both the positive and negative ideal solutions and determine the proximity of each player to these solutions.

The final rankings were established based on these properties, providing an assessment of player suitability for each position. To exemplify the efficacy of our approach, let us consider a scenario in which a globally renowned football club is recruiting new players to strengthen its team. In this hypothetical situation, the club operates within a budget constraint and seeks to make relevant decisions to maximize the quality of the players recruited based on their specific positions.

To manage this decision-making process, we constructed a decision matrix in which each row represents a potential player and the columns correspond to various attributes relevant to each position. For instance, attributes like finishing, acceleration, and agility are crucial for forwards, whereas defenders might be assessed based on attributes such as interceptions, standing tackles, and strength.

After obtaining the position-specific weights using our random forest model, we employed the TOPSIS method on the decision matrix. This allowed us to rank and prioritize players for each position, considering both their individual attributes and the importance assigned by the random forest algorithm. The club and decision-makers can then make decisions based on these rankings, ensuring judicious allocation of the budget while meeting the unique demands of each on-field position.

Step 1: Calculating normalized matrix \bar{X}_{ij}

The first step of the TOPSIS method involves normalizing the initial decision matrix. The normalized decision matrix, denoted as \bar{X}_{ij} , is obtained by dividing each element of the initial matrix by the square root of the sum of the squares of all elements in the same column (Table 6.9).

Table 6.9: Normalized decision matrix \bar{X}_{ij} based on TOPSIS

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	0,097	0,004	0,004	0,004	0,003	0,003	0,004	0,003	0,003
P2	0,097	0,004	0,004	0,004	0,003	0,004	0,003	0,004	0,003
P3	0,097	0,003	0,004	0,003	0,003	0,003	0,004	0,003	0,003
P4	0,065	0,003	0,003	0,004	0,003	0,003	0,003	0,003	0,003

Step 2: Calculating weighted normalized matrix $V_{ij} = \bar{X}_{ij} * w_j$

In this step, we multiply each element of the normalized decision matrix \bar{X}_{ij} by its corresponding weight w_j . The weights are determined using the entropy method described earlier (alternatively, we can also apply CRITIC or Random Forest weights in this phase). This results in the weighted normalized matrix V_{ij} , which adjusts the normalized values based on the relative importance of each criterion (Table 6.10).

Table 6.10: Prioritize normalized matrix with entropy weights

W_j	0,2302	0,0933	0,0944	0,1515	0,1169	0,0728	0,0748	0,0963	0,0699
	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	0,0223	0,0003	0,0004	0,0006	0,0004	0,0003	0,0003	0,0003	0,0002
P2	0,0223	0,0003	0,0004	0,0006	0,0004	0,0003	0,0003	0,0003	0,0002
P3	0,0223	0,0003	0,0003	0,0004	0,0003	0,0002	0,0003	0,0003	0,0002
P4	0,0148	0,0003	0,0003	0,0006	0,0003	0,0002	0,0002	0,0003	0,0002

Step 3: Calculating the ideal best and ideal worst value V_i^+, V_i^-

In this step, we determine the ideal best and ideal worst values for each criterion, assuming that we are maximizing the criteria. In the context of football player selection, maximizing performance criteria is crucial as it ensures that we are identifying the best possible players based on their highest performance metrics. The ideal best value V_i^+ represents the highest possible value for each criterion, indicating the best performance observed, while the ideal worst value V_i^- represents the lowest possible value, indicating the least desirable performance.

The ideal best and ideal worst values are calculated as follows:

$$V_i^+ = \max(V_{ij}) \quad \text{for all criteria}$$

$$V_i^- = \min(V_{ij}) \quad \text{for all criteria}$$

Table 6.11 shows the ideal best and ideal worst values for each criterion based on the weighted normalized matrix V_{ij} .

Table 6.11: The ideal best and ideal worst value

	CG1	CG2	CG3	CG4	CG5	CG6	CG7	CG8	CG9
P1	0,0223	0,0003	0,0004	0,0006	0,0004	0,0003	0,0003	0,0003	0,0002
P2	0,0223	0,0003	0,0004	0,0006	0,0004	0,0003	0,0003	0,0003	0,0002
P3	0,0223	0,0003	0,0003	0,0004	0,0003	0,0002	0,0003	0,0003	0,0002
P4	0,0148	0,0003	0,0003	0,0006	0,0003	0,0002	0,0002	0,0003	0,0002
V_i^+	0,0223	0,0003	0,0004	0,0006	0,0004	0,0003	0,0003	0,0003	0,0002
V_i^-	0,0148	0,0003	0,0003	0,0004	0,0003	0,0002	0,0002	0,0003	0,0002

Step4: Calculating the euclidean distance from the ideal best S_i^+

Table 6.12 displays the results of calculating the Euclidean distance from the best ideal for each player. This indicates the player's proximity to the best ideal.

Step5: Calculating the euclidean distance from the ideal worst S_i^-

displays the results of calculating the Euclidean distance from the worst ideal for each player. This indicates the player's proximity to the worst ideal. Table 6.12

Step6: Calculating Performance score $P_i = \frac{S_i^+}{S_i^+ + S_i^-}$

The performance score calculated for the player from the S_i^+ and S_i^- values, using the specific formula of the TOPSIS method. This score indicates the relative efficiency of the player compared to the best and worst ideals (Table 6.12).

We used the same steps with CRITIC weights, and the final results are presented in the

Table 6.12: Performance score for each player using entropy weights

	Si+	Si-	Pi
P1	2,7669E-05	0,00742811	0,99628889
P2	1,6546E-05	0,00742864	0,99777776
P3	0,00021268	0,00742472	0,97215275
P4	0,00742679	0,00015308	0,02019574



Figure 6.7: Ranking of players based on performance scores using entropy weights

Table 6.13.

Table 6.13: Performance score for each player using CRITIC weights

	Si+	Si-	Pi
P1	5,6069E-05	0,00465773	0,98810538
P2	2,6024E-05	0,00466179	0,99444856
P3	0,00041346	0,00464303	0,91823196
P4	0,00464499	0,00035069	0,07019859

The steps involved in the previous sections, namely RF, CRITIC, entropy, and TOPSIS, are part of the development of our Decision Support System for football player selection. This DSS aims to offer a comprehensive framework for assessing and selecting football players based on various criteria and methodologies.

[Appendix B](#) showcases the user interfaces that can assist decision-makers in the decision making process.

6.3 Evaluation of the football player selection system

The steps involved in the previous sections, namely RF, CRITIC, entropy, and TOPSIS, are part of the development of our Decision Support System for football player selection. This DSS aims to provide a comprehensive framework for evaluating and selecting football players based on various criteria and techniques. This section discusses the interactive validation and comparison of the model results. Integrating an interactive showcase adds a dynamic dimension to the evaluation process, allowing decision makers to explore and assess the outcomes in a user-friendly manner. To facilitate this interactive experience, we employed a user interface that visualizes and compares the model's player selections. The showcase provides insights into the decision-making process and allows for direct comparison with real-world player data. This approach not only enhances transparency, but also enables decision-makers to validate the model's efficacy more intuitively.

6.3.1 Comparative analysis with real match data

In order to rigorously assess the performance of our DSS in player selection, we employ the *Jaccard index*. The Jaccard index is a metric commonly used in set theory and data analysis to measure the similarity between two sets. In our context, these sets represent the players selected by our model and the players actually chosen by decision makers in real match scenarios.

The rationale behind using the Jaccard index is rooted in its ability to quantify the intersection and union of sets, providing a comprehensive measure of how well the selections made by our model align with the actual choices made during real matches. This approach allows us to systematically compare the overlap between the predicted and real selections, offering insights into the reliability and accuracy of our decision support system.

As we progress to compile and analyze the results, the Jaccard index evaluates the concordance between players identified by our DSS and those ultimately chosen in real-world football matches. This comparative analysis seeks to determine the percentage of similarity between the predictions of our model and the decisions made by professionals

in the field.

The Jaccard index, or Jaccard similarity coefficient, quantifies the similarity between two sets by measuring the ratio of the intersection of the sets to the union of the sets. (Fletcher and Islam, 2018). When applied to the context of comparing the players selected in real matches y_{true} with the players predicted by our model y_{predict} , the Jaccard Index can be expressed as follows:

$$J(y_{\text{true}}, y_{\text{predict}}) = \frac{|y_{\text{true}} \cap y_{\text{predict}}|}{|y_{\text{true}} \cup y_{\text{predict}}|} \quad (6.1)$$

Where:

- y_{true} represents the set of players selected in real matches.
- y_{predict} represents the set of players predicted by our model.
- $|y_{\text{true}} \cap y_{\text{predict}}|$ is the size of the intersection of the two sets (common players).
- $|y_{\text{true}} \cup y_{\text{predict}}|$ is the size of the union of the two sets (all unique players selected).

The Jaccard index returns a value between 0 and 1, where 0 represents no similarity (no common elements between the sets) and 1 represents complete similarity (the sets are identical). In the context of our comparative analysis with real game data, the Jaccard index can be applied to evaluate the similarity between the players selected by our approach and the players selected by the decision makers in real games. This index provides a quantitative measure of the overlap between the two groups of selected players and provides insight into the accuracy and effectiveness of our model in predicting real player selections.

$$y_{\text{true}} = \left\{ \begin{array}{l} \text{K. Navas, A. Diallo, Marquinhos, T. Kehrer, A. Hakimi,} \\ \text{P. Kimpembe, M. Verratti, I. Gueye, G. Wijnaldum, L. Paredes, Ander Herrera,} \\ \text{J. Draxler, Neymar Jr, K. Mbappé, A. DiMaria, L. Messi} \end{array} \right\}$$

$$y_{\text{predict}} = \left\{ \begin{array}{l} \text{K. Navas, Marquinhos, Sergio Ramos, P. Kimpembe, A. Hakimi, A. Diallo,} \\ \text{G. Wijnaldum, L. Paredes, M. Verratti, Ander Herrera, J. Draxler, I. Gueye,} \\ \text{K. Mbappé, L. Messi, A. DiMaria, Neymar Jr} \end{array} \right\}$$

- $|y_{\text{true}} \cap y_{\text{predict}}| = 15$
- $|y_{\text{true}} \cup y_{\text{predict}}| = 16$
- $J(y_{\text{true}}, y_{\text{predict}}) = \frac{15}{16} = 0.94$ represented on the y-axis
- C presents the comparison between y_{true} and y_{predict} represented on the x-axis

6.3.2 Interpretation of results

In this section, we will compare our results with the actual decisions made in the analyzed football matches in the 2021-2022 season. It should be noted that there is no work in the current literature that combines machine learning algorithms with multi-criteria methods for football player selection. This approach aims to fill this gap by providing a new perspective for optimizing the performance of football teams.

We have applied three different models to select football players (Random Forest/TOPSIS, Entropy/TOPSIS and CRITIC/TOPSIS) and compared the results with the coaches' actual decisions in fourteen specific PSG matches ([Appendix C](#)). All players of the club are available to the coach, in our case thirty-three. The Jaccard index measures the similarity between the selections of each method and the actual selections in the matches ([Figure 6.8](#)). The interpretation of the Jaccard index presented here is of key importance in understanding the degree of similarity between the results generated by our models and the actual choices made by sports decision makers. The [Table 6.14](#) provided shows Jaccard index values for different PSG matches using three different methods: Random Forest/TOPSIS, Entropy/TOPSIS and CRITIC/TOPSIS. Each method compares the similarity between predictions and actual results for different PSG matches:

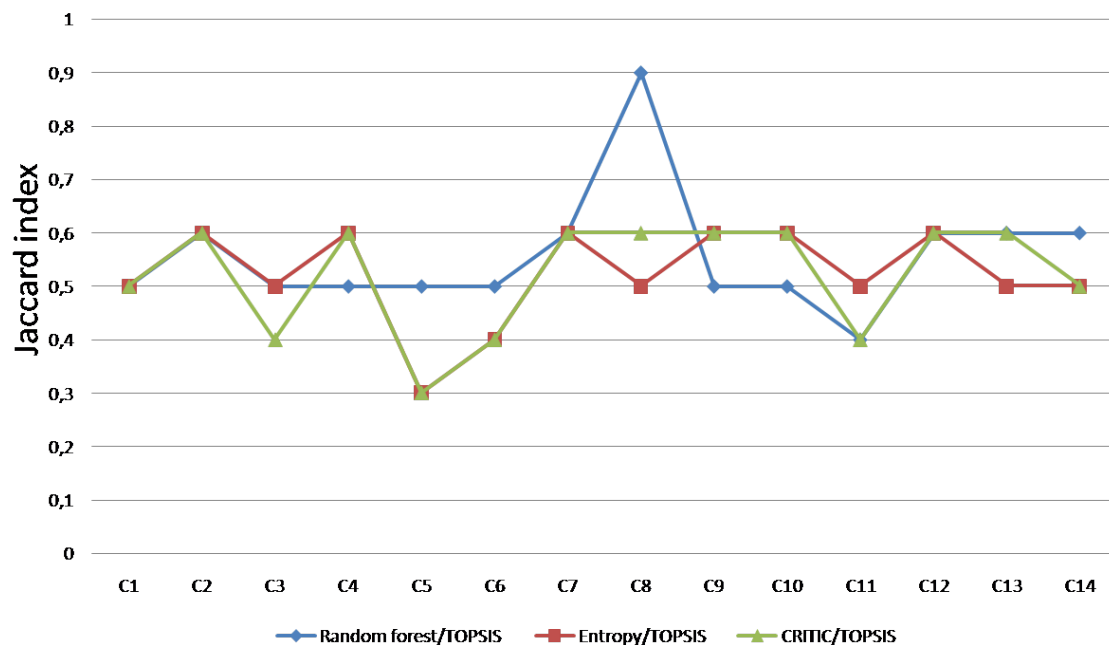


Figure 6.8: The degree of similarity between the model’s player selection and the decision-makers’ player selection

Table 6.14: Jaccard index for different matches

	PSG vs.													
	Metz		RC lens		Real		Reims		OM		Manches.		Rennes	
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
Random forest/TOPSIS	0,5	0,6	0,5	0,5	0,5	0,4	0,6	0,9	0,5	0,5	0,4	0,6	0,6	0,6
Entropy/TOPSIS	0,5	0,6	0,5	0,6	0,3	0,4	0,6	0,5	0,6	0,6	0,5	0,6	0,5	0,5
CRITIC/TOPSIS	0,5	0,6	0,4	0,6	0,3	0,3	0,6	0,6	0,6	0,6	0,4	0,6	0,6	0,5

- Random Forest/TOPSIS: This method shows moderate similarity for most matches, with particularly high similarity for the PSG vs. Reims match (0.9).
- Entropy/TOPSIS: This method also shows moderate similarity, with values around 0.5-0.6, except for PSG vs. Real (0.3, 0.4).
- CRITIC/TOPSIS: This method shows similar results to Entropy/TOPSIS, with moderate similarity for most matches but lower similarity for PSG vs. Real (0.3, 0.3).

The Random Forest/TOPSIS model introduces player salaries as a dependent variable in the weighting of the criteria. The salaries are not evenly distributed among the players; the stars have significantly higher salaries than the water carriers. This implicitly introduces an element of subjectivity, as the salaries are set by football experts and reflect the market value of the players.

By including the salary variable in the Random Forest model, we can account for the club's financial investment in each player. In this way, team compositions, recruitment, and transfer decisions are aligned with the club's economic expectations and performance. Players with high salaries often represent large investments and therefore require special attention from sporting decision-makers both on and off the pitch. However, a high salary is not always synonymous with outstanding sporting performance.

The PSG vs. Reims match showed the highest similarity (0.9) using the Random Forest/TOPSIS method, indicating that the prediction and actual results were very similar for this match. The actual selection was within one player of that proposed by the model. This formation presented an ideal balance between the stars and the support players who play in defense and midfield to support the forwards (stars). Overall, various comparisons show that support players are the benchmark and the key criteria on which model choices are based. Historically, "flops" have mainly involved stars (forwards).

The Entropy-TOPSIS and CRITIC-TOPSIS models have a Jaccard index between 0.5 and 0.6 for most comparisons, i.e. an average degree of concordance between the selection made by the model and the choices made during actual matches. This value is justified by the fact that these models evaluate and weight player criteria according to the correlation

between these criteria in an objective manner. The idea is to minimize flops. These models can be useful for reflecting player performance and match results, i.e. sporting value.

To further improve the performance of our approach and close the remaining gap between actual selections and those predicted by our models, it is essential to include the knowledge of experts in the field. To do this, we must not only rely on big data and AI, but also integrate the expertise and know-how of various specialists. In some clubs, several specialists are interested in developing players' skills for the same position. Each brings a unique perspective that can significantly refine player selection, taking into account factors such as emotional intelligence and working relationships.

For example, for the role of forward, there may be experts focusing on shooting accuracy, off-the-ball movement and pressing techniques. Similarly, goalkeepers may benefit from specialist coaching in shot-stopping, distribution and penalty-area command. By leveraging the knowledge of these intra-positional specialists, our model can adjust recommendations to better reflect the complex, multi-faceted nature of player performance and preparation.

The facts proved the coach right when Real Madrid and Borussia Dortmund met in the UEFA Champions League on June 1, 2024. If we had only referred to AI and algorithms, Lunin would have been the goalkeeper (as Courtois had suffered several injuries). However, the coach preferred to put Courtois in goal thanks to his expertise and memory. This decision proved the relevance of a model based on an ideal balance between the subjective and the objective. By integrating the coach's human perspective, the choice of Courtois was more in tune with the team's needs and dynamics for this crucial meeting. It demonstrated the importance of balancing objective data and human intuition in decision-making.

By combining machine learning and multi-criteria analysis with human expertise, in particular intra-position specialists, we can significantly reduce the gap between algorithmic recommendations and actual decisions. This approach ensures that player selection is not only data-driven but also aligned with the sporting and extra-sporting needs of professional clubs. In our model, we have sought to optimize the balance between the subjective and the objective, as subjectivity reflects human relations within the workplace and the

company, in this case, the sports club. This subjective element is essential as it represents the counterweight to AI, namely emotional intelligence. Indeed, understanding emotions, motivations and interpersonal dynamics enables more empathetic and humane team management.

For these reasons, clubs are increasingly turning to psychological trainers to reinforce their technical and medical staff. Productivity and performance don't just reflect a player's technical and physical qualities. Many stars have failed in their careers due to their psychological fragility (Ronaldinho, Adriano, etc.).

What's more, a star with a high salary is not always a guarantee of undeniable sporting performance, as we saw in the case of Neymar and Messi at PSG. PSG sacrificed its all-time top scorer, Cavani, to keep Neymar (a star). On the other hand, objectivity, embodied by the use of AI and multi-criteria analysis, guarantees decisions based on measurable facts and reduces bias in performance evaluation, but does not always produce good results because it is not reinforced by the consideration of psychological and behavioral references.

The French championship, 'Ligue 1', is dominated by PSG. Regardless of the formation, PSG is likely to win the championship. For this reason, there is no significant difference in terms of financial return between the stars and the water carriers, even if the salary differentials are considerable. Indeed, with the arrival of Luis Enrique in 2023, this gap has narrowed considerably. The coach has based his selections on fundamental objective criteria, relegating the stars' salary criterion to second place.

At PSG, the choice of coaches was often not based on criteria of competence and consistency, which are fundamental principles of human resources management. Outside sport, coaches were often guided by considerations imposed on them. These considerations included marketing, decisions on the transfer market (MERCATO), and managing ego conflicts between players.

In order to integrate these different expert opinions, a central database must be created in which technical, tactical, physical and psychological assessments are recorded. This data can then be integrated into algorithms to improve the granularity and accuracy of the selection process. In addition, continuous feedback mechanisms need to be put in place to

refine the model according to actual performance and expert judgment. With this in mind and to extend these results, we carried out the same simulations for formations without attackers (stars). The results showed a high Jaccard index of over 80%.

By combining machine learning and multi-criteria analysis with human expertise, especially from positional specialists, we can significantly reduce the discrepancy between the algorithmic recommendations and the actual decisions. This approach ensures that player selection is not only data-driven but also aligned with the sporting and non-sporting needs of professional clubs.

Artificial intelligence and multi-criteria decision-making models are playing an increasingly important role in various fields, including sports, to improve decision-making. However, despite their advances, they cannot completely replace coaches and sports decision-makers for several key reasons.

Firstly, human and emotional complexity remains an area where AI has significant limitations. Human coaches possess an emotional intelligence that enables them to understand and react to players' emotions, manage conflicts and motivate teams in an empathetic way. Interpersonal relationships and team dynamics require a deep understanding of human interaction that is difficult for AI to replicate.

What's more, the experience and intuition of human coaches are irreplaceable. During matches, coaches make instant decisions based on their experience and intuition, adapting to unforeseen situations with great flexibility. This ability to adapt is essential in situations where circumstances can change unpredictably.

Non-sporting factors are another area where human skills are crucial. Managing the Mercato, marketing and player transfer decisions requires an understanding of commercial and social aspects that an AI cannot fully capture. Coaches also need to manage players' personalities and egos, which is crucial for maintaining harmony and cohesion within the team. On the technical side, AI models and multi-criteria decision support systems are often limited by the available data. Intangible aspects such as motivation or psychological pressure are difficult to quantify and integrate into algorithms. In addition, algorithms can inherit biases from historical data, leading to suboptimal decisions.

Finally, ethical considerations and trust also play a decisive role. Players generally have more trust and respect for an experienced human coach than for an algorithm. Human decision-making allows ethical and moral considerations to be taken into account, which is crucial in elite sport. While AI and MCDM models can provide valuable support to coaches and sport decision makers, they cannot replace the richness of human experience, emotional intelligence and understanding of interpersonal dynamics. Human skills remain essential for reliable and effective decision-making in the sporting arena.

6.4 Conclusion

A professional football club is not just a sports club, but a multi-layered organization in which principles from various disciplines such as marketing, human resources management, economics and finance overlap. These principles are inextricably linked to the player, who is the main product of this organization. Therefore, the selection and management of players is crucial to the success of the club on and off the pitch.

The idea to develop a decision support tool that combines multi-criteria decision making methods and machine learning algorithms is to help sports decision makers in the selection of football players for composition, recruitment and transfer of teams.

Our goal with this tool is not to replace coaches, but rather to find an optimal balance between the interests of owners and the interests of club managers. By providing data-driven insights and analysis, we want to empower coaches and managers to make relevant decisions that align with both the strategic objectives of the owners and the needs of the club on and off the field.

The decision support system integrates three different methods for weighting criteria: Random Forest, CRITIC and Entropy to prioritize players' attributes. We also use the TOPSIS method to rank players according to their performance.

To evaluate the effectiveness of our system, we also included the Jaccard index to compare the selections suggested by the model with those made by sports decision makers during real matches. This comparison allows us to measure the consistency and accuracy

of our recommendations in relation to the decisions made on the pitch.

However, it is important to recognize that our DSS aims to complement human expertise by providing objective, data-driven analysis to assist sports decision makers in player selection. By integrating artificial intelligence with human judgment and emotional intelligence, our tool provides a balanced approach to strategic player management. Through the PSG case study, we have demonstrated the practical application of our system and showed that it has the potential to optimize decision-making process and contribute to the sustainable success of football organizations.

As football continues to evolve as a global industry, the importance of informed decision-making in player selection cannot be overstated. By harnessing technological innovation while respecting the fundamental role of human judgment, clubs can navigate the complexities of modern football optimize their decision-making processes.

Chapter 7

Conclusions and future directions

This chapter presents a synthesis of the research (section 7.1) and highlights its main contributions to the advancement of knowledge (section 7.2). In addition, it outlines the limitations of the study and proposes recommendations for future research (section 7.3).

7.1 Research Summary

The research presented in this thesis is situated within the context of managing professional football clubs, where achieving a balance between human and financial factors is crucial for the long-term viability of sports organizations. An effective player selection strategy for line-ups, recruiting, and transferring must be based on selecting the right players for their respective positions and roles. This strategy should consider human resources management concepts, particularly player salaries and attributes that require simultaneous analysis and evaluation.

Traditional methods of player selection, often subjective and uncertain, have historically guided decision-making processes within football clubs. These strategic decisions can significantly impact the financial, economic, and sporting performance of the team. As football evolves into a more data-driven sport, it becomes increasingly recognized that these traditional approaches need to be complemented by scientific methods based on artificial intelligence and multi-criteria decision-making techniques to optimize player selection and enhance team performance.

Our approach focuses on modeling these processes by integrating ML and MCDM methods to weigh a large number of criteria and rank players according to their performance. It aims to improve the efficiency and objectivity of football player selection processes, taking into account financial and managerial aspects. This contribution is embodied in a DSS, aimed at providing a more objective and data-driven approach that can help managers and decision makers in sports organizations make more informed and effective decisions.

Our research does not aim to replace the skills of coaches with AI. It is intended as a technical decision-making aid, based on a plurality of criteria and supported by AI and MCDM techniques. In this way, the expertise and experience of the technical and medical staff are enhanced by the contribution of multi-criteria models and AI. This integration of the skills of sports decision makers with AI is part of a global management framework aimed at improving financial and sporting performance. Furthermore, the criteria mentioned are not limited to athletic and footballing considerations alone. They also encompass insights derived from theories and lessons learned from major works in finance, human resources management, and marketing.

7.2 Main contributions and hypothesis validation

The main contributions of this research to the field of sports management and data-driven decision-making can be summarized as follows. These contributions directly address the hypotheses outlined in chapter 2.

Integration of AI and MCDM (H1): "The selection of the starting lineup, recruitment and transfer based on the integrated model, incorporating machine learning techniques and MCDM approaches, contribute effectively to yield optimal results."

This study integrates machine learning techniques and multi-criteria decision-making methods to model the process of football player selection. By combining Random Forest, Entropy, and CRITIC algorithms to prioritize criteria, and the TOPSIS method to rank players, the research confirms Hypothesis 1 by providing a new approach that improves the objec-

tivity and efficiency of the player selection process, leading to relatively optimal results.

Application to the current football landscape (H2): "The integrated model can be effectively applied and helpful in the current football landscape."

The development of a decision support system that helps football club managers make more relevant decisions demonstrates that the integrated model can be applied in today's football landscape. The system's ability to use a data-driven approach to evaluate and rank players corresponds to Hypothesis 2, showing that the model is practical in today's football environment. This modeling could be very useful when complemented by the knowledge and expertise of sports decision-makers, offering a global solution that integrates the objectivity derived from a scientific approach with a dose of subjectivity resulting from sporting experience.

Departing from conventional methods (H3): "The integrated model departs from conventional selection methods, offering a more scientific, comprehensive, and efficient approach to player selection."

By applying scientific methods to the player selection process, the research complements traditional subjective decision-making. The integration of various criteria ensures a comprehensive assessment of players, reducing bias and improving the accuracy of selections. This approach confirms Hypothesis 3, showing that the integrated model departs considerably from conventional methods, offering a more scientific and effective approach to player selection.

Beyond sport: financial and managerial aspects (H4): "The scope of MCDM goes beyond the sports dimension; it extends to the financial and managerial aspects."

The study shows that the scope of MCDM extends beyond the sporting dimension to include financial and managerial aspects. Our research work confirms Hypothesis 4, illustrating that the integrated model can be used to evaluate player performance and manage financial and personnel decisions within a football club.

7.3 Limitations and future research directions

While the research has made significant contributions, it is not without restrictions. These limitations provide avenues for future research to build upon and enhance the findings presented in this thesis.

Data limitations: Despite our efforts to manage a large database containing twenty thousand players, five hundred clubs, and approximately forty attributes, there are still other types of data that need to be considered. These include player injuries, psychological states, sanctions (yellow/red cards), on-field performance, optimal timing for substitutions, whether the team is playing at home or away, and data on the opposing team. Football, unlike other fields, is rich in data, making it challenging to manage for both sports decision-makers and the proposed solution. The accuracy and effectiveness of the DSS are heavily dependent on the quality and comprehensiveness of the data used. It is crucial to leverage the advantages of big data and AI to update all necessary data instantaneously, as this management involves hidden complex variables and information. Future research could focus on incorporating larger and more diverse datasets to improve the robustness of the system.

Dynamic nature of football: Football is a dynamic sport where player performance can fluctuate due to various factors such as injuries, form, and external conditions. Future research could explore the incorporation of real-time data and adaptive algorithms that can update player rankings and recommendations as new information becomes available.

Incorporation of additional criteria: The current system prioritizes and ranks players based on a set of predefined criteria. Future research could explore the incorporation of additional criteria, such as psychological factors, marketability, and fan engagement, to provide a more comprehensive evaluation of players.

Expansion to other sports: While this research focuses on football, the principles and methodologies developed can be adapted to other sports. Future studies could explore the application of AI and MCDM techniques to different sports to assess their effectiveness in various contexts.

By considering these limitations and exploring new directions, future research can improve the effectiveness and applicability of AI and MCDM techniques in sport management, leading to more effective and strategic decision-making in this field.

Appendix A

Decision Matrices

Table A.1: Decision matrix (Part 1)

N°	Name	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
P1	L. Messi	4	85	95	70	91	88	96	93	94	91	96	91	80	91	94	95	86	68
P2	Neymar Jr	5	85	83	63	86	86	95	88	87	81	95	93	89	96	89	84	80	64
P3	K. Mbappé	5	78	93	72	85	83	93	80	69	71	91	97	97	92	93	83	86	78
P4	G. Donnarumma	1	12	12	12	36	8	28	12	14	34	30	50	55	64	85	38	59	72
P5	Sergio Ramos	3	66	65	92	82	69	65	74	76	83	83	71	69	77	92	66	79	93
P6	K. Navas	1	11	15	11	40	11	24	21	15	37	30	54	53	60	85	61	56	74
P7	Á. Di María	5	88	79	51	84	78	88	91	88	82	87	83	83	94	84	76	83	73
P8	M. Verratti	4	82	60	57	90	64	91	85	64	89	92	68	60	91	87	94	60	67
P9	Marquinhos	3	68	51	88	84	35	69	58	32	85	79	81	81	69	87	67	65	92
P10	A. Hakimi	3	86	73	68	81	60	84	68	55	73	83	95	95	86	84	79	77	80
P11	G. Wijnaldum	4	72	75	78	87	73	85	78	73	81	88	78	76	84	86	88	78	81
P12	M. Icardi	3	47	87	85	76	85	76	76	52	54	80	70	68	68	84	75	85	91
P13	P. Kimpembe	2	59	31	80	80	33	63	50	32	75	78	80	81	69	80	60	70	79
P14	I. Gueye	3	60	54	69	80	32	76	60	66	76	79	70	69	79	81	82	80	86
P15	Juan Bernat	4	83	65	56	81	61	82	78	51	73	82	82	82	86	81	88	67	75
P16	Danilo Pereira	3	58	57	83	81	55	75	54	53	78	77	60	67	54	75	60	74	77
P17	L. Paredes	4	79	61	60	84	71	79	80	78	85	81	67	66	71	78	75	88	66
P18	Rafinha	4	74	71	55	85	75	86	80	61	80	84	74	68	83	77	80	80	75
P19	J. Draxler	4	79	74	64	81	77	83	77	76	77	84	76	73	80	78	74	80	77
P20	Ander Herrera	3	71	68	63	80	64	78	79	64	77	81	68	62	76	80	76	78	62

Table A.2: Decision matrix (Part 2)

N°	Name	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
P21	A. Diallo	3	69	38	78	78	39	75	58	32	76	78	72	76	73	77	71	51	84
P22	Nuno Mendes	3	74	45	67	71	54	72	66	59	68	75	82	88	82	76	76	80	71
P23	Sergio Rico	1	17	14	11	28	15	15	24	20	26	13	48	46	51	72	43	58	63
P24	L. Kurzawa	3	75	66	72	75	61	76	69	53	67	80	77	71	72	69	70	69	85
P25	T. Kehrer	2	64	37	76	73	32	65	54	38	66	67	68	68	68	69	64	65	84
P26	C. Dagba	3	72	43	54	77	39	76	63	41	68	78	82	82	83	69	86	68	67
P27	J. Dina Ebimbe	3	58	59	59	76	51	75	59	49	70	77	84	82	77	70	73	71	75
P28	A. Letellier	1	13	10	11	28	13	11	19	13	23	16	37	39	32	67	20	47	57
P29	X. Simons	3	60	57	39	69	49	70	71	61	65	69	70	66	73	63	84	59	56
P30	É. Michut	3	55	50	45	70	48	70	61	48	66	70	68	62	75	62	80	58	45
P31	B. Fadiga	3	48	46	55	67	37	71	52	47	61	69	77	73	86	65	77	52	55
P32	I. Gharbi	3	55	54	35	62	49	71	68	52	57	67	75	68	81	55	88	60	49
P33	N. Bitumazala	3	47	39	53	64	38	62	52	41	60	65	68	67	64	54	71	53	57

Table A.3: Decision matrix (Part 3)

N°	Name	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31	C32	C33	C34	C35
P1	L. Messi	72	69	94	44	40	93	95	75	96	20	35	24	6	11	15	14	8
P2	Neymar Jr	81	53	81	63	37	86	90	93	93	35	32	29	9	9	15	15	11
P3	K. Mbappé	88	77	82	62	38	92	82	79	88	26	34	32	13	5	7	11	6
P4	G. Donnarumma	34	72	18	30	26	14	60	24	68	20	14	16	91	83	79	85	90
P5	Sergio Ramos	78	84	64	90	87	73	71	92	88	84	89	91	11	8	9	7	11
P6	K. Navas	39	75	13	32	22	16	68	25	67	28	14	14	89	84	75	87	89
P7	Á. Di María	78	62	86	73	42	84	88	73	86	41	55	52	10	7	11	12	11
P8	M. Verratti	76	54	58	89	85	78	89	64	94	78	82	84	12	12	15	15	10
P9	Marquinhos	83	78	45	81	88	68	74	52	86	89	89	89	6	6	12	10	13
P10	A. Hakimi	91	73	70	75	78	78	75	46	80	75	78	76	10	8	14	6	8
P11	G. Wijnaldum	93	74	73	75	80	79	79	74	86	79	80	70	16	6	14	12	6
P12	M. Icardi	67	73	71	58	22	91	72	82	83	45	24	20	13	9	5	7	9
P13	P. Kimpembe	81	87	37	90	84	47	64	57	80	81	86	84	7	8	14	15	9
P14	I. Gueye	85	69	68	83	86	69	68	55	79	82	87	83	8	6	8	12	13
P15	Juan Bernat	79	58	62	75	79	78	77	53	78	75	81	78	8	9	12	11	16
P16	Danilo Pereira	85	89	67	80	80	71	72	57	78	81	81	68	9	7	13	14	15
P17	L. Paredes	79	77	77	89	75	76	84	64	84	79	78	80	9	14	6	9	10
P18	Rafinha	66	67	79	70	70	77	83	67	82	70	74	66	11	6	15	13	7
P19	J. Draxler	68	67	78	56	66	78	81	65	82	48	64	44	11	13	5	13	8
P20	Ander Herrera	81	70	68	81	82	75	79	74	82	79	80	76	9	12	15	9	8

Table A.4: Decision matrix (Part 4)

N°	Name	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31	C32	C33	C34	C35
P21	A. Diallo	74	77	24	77	78	61	69	41	81	77	78	81	12	7	7	7	8
P22	Nuno Mendes	81	69	63	67	75	72	59	45	75	73	76	73	7	8	8	12	15
P23	Sergio Rico	36	53	12	25	17	11	53	24	55	16	13	11	77	74	77	74	80
P24	L. Kurzawa	72	69	62	75	74	74	75	54	74	70	75	73	14	10	7	9	15
P25	T. Kehrer	74	80	40	76	76	53	59	41	69	75	78	79	9	9	14	10	12
P26	C. Dagba	70	53	61	68	75	69	65	45	70	73	73	74	7	6	9	11	11
P27	J. Dina Ebimbe	81	75	56	69	72	64	67	57	66	65	69	56	6	11	14	12	5
P28	A. Letellier	31	72	14	25	24	14	22	20	51	15	13	11	68	67	62	67	72
P29	X. Simons	61	55	55	72	61	67	68	58	70	56	64	52	9	11	5	8	10
P30	É. Michut	50	45	55	60	61	58	67	55	70	55	60	51	9	13	11	8	9
P31	B. Fadiga	68	40	43	65	61	58	62	50	62	55	63	56	12	14	14	15	15
P32	I. Gharbi	41	34	54	51	40	57	64	60	68	37	45	38	7	9	13	15	8
P33	N. Bitumazala	49	55	36	68	60	41	49	45	53	57	63	59	7	14	14	11	11

Appendix B

User Interfaces

Decision Support System for Selecting Professional Football Players

Criteria Selection:

Select a club:

Paris Saint-Germain

Select a position:

Defender

Select the attributes/criteria:

Weak Foot × Crossing × HeadingAccuracy × ShortPassing × Dribbling ×

LongPassing × BallControl × Acceleration × SprintSpeed × Agility ×

Reactions × Balance × ShotPower × Jumping × Stamina × Strength ×

Aggression × Interceptions × Composure × Marking × StandingTackle ×

Figure B.1: Main user interface

Weights Calculation:

Choose a method to calculate weights:

- Random Forest (Machine Learning)
- ENTROPY (MCDM)
- CRITIC (MCDM)

Calculate Weights

Rank Players

Figure B.2: Weight option interface

- Random Forest (Machine Learning)
- ENTROPY (MCDM)
- CRITIC (MCDM)

Calculate Weights

The coefficient of determination (R2): 0.9199860676597333

The model can predict 92.0 of the variability in players' salaries based on their attributes.

	Weight
StandingTackle	0.0375
Acceleration	0.0366
SlidingTackle	0.0306
SprintSpeed	0.0306
Agility	0.0246
Stamina	0.0226
Dribbling	0.0211
Balance	0.0204
ShotPower	0.0166
Strength	0.0106

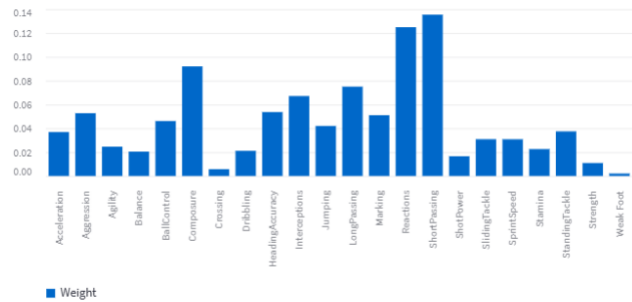


Figure B.3: Weights calculation using random forest algorithms

Choose a method to calculate weights:

- Random Forest (Machine Learning)
- ENTROPY (MCDM)
- CRITIC (MCDM)

Calculate Weights

	Weight
Weak Foot	0.1476
HeadingAccuracy	0.0921
Strength	0.0725
Crossing	0.0667
Stamina	0.0560
Reactions	0.0525
ShotPower	0.0525
Jumping	0.0511
Composure	0.0445
Balance	0.0391

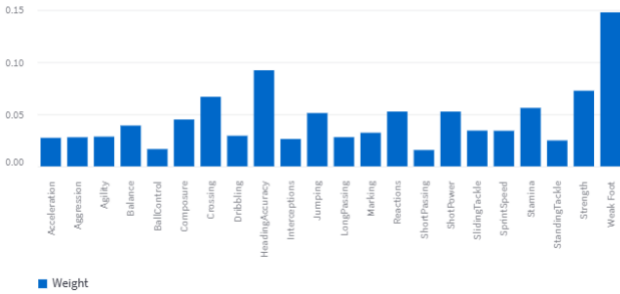


Figure B.4: Weights calculation using ENTROPY method

Choose a method to calculate weights:

- Random Forest (Machine Learning)
- ENTROPY (MCDM)
- CRITIC (MCDM)

Calculate Weights

	Weight
Balance	0.0847
Weak Foot	0.0706
Dribbling	0.0680
Agility	0.0611
SprintSpeed	0.0580
Aggression	0.0578
Acceleration	0.0554
Strength	0.0546
HeadingAccuracy	0.0531
ShotPower	0.0502

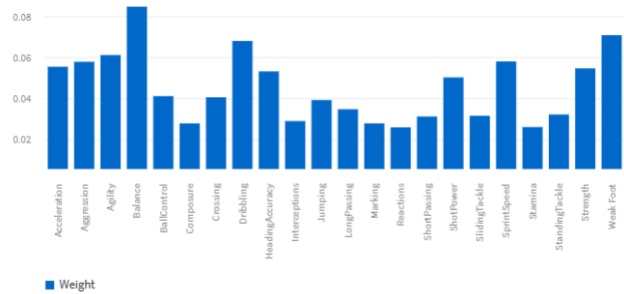


Figure B.5: Weights calculation using CRITIC method

TOPSIS

Rank Players

Weights used for ranking are calculated using: Random Forest

	Player	Score	Rank
0	Marquinhos	0.8446	1
1	Sergio Ramos	0.8416	2
2	P. Kimpembe	0.7016	3
3	A. Hakimi	0.6960	4
4	A. Diallo	0.6350	5
5	Juan Bernat	0.6218	6
6	Nuno Mendes	0.5065	7
7	L. Kurzawa	0.4707	8
8	T. Kehrer	0.4424	9
9	C. Dagba	0.4290	10

Player ranking with TOPSIS calculated successfully.

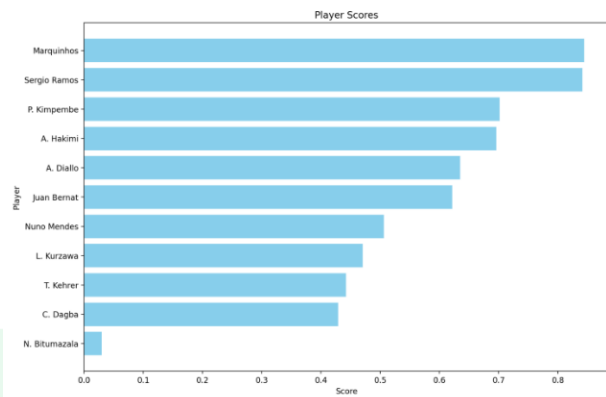


Figure B.6: Players ranking using TOPSIS and random forest

TOPSIS

Rank Players

Weights used for ranking are calculated using: ENTROPY

	Player	Score	Rank
0	T. Kehrer	0.7495	1
1	A. Hakimi	0.6613	2
2	Nuno Mendes	0.6168	3
3	Sergio Ramos	0.5047	4
4	Marquinhos	0.4882	5
5	P. Kimpembe	0.4541	6
6	A. Diallo	0.4312	7
7	L. Kurzawa	0.4089	8
8	Juan Bernat	0.4034	9
9	N. Bitumazala	0.2552	10

Player ranking with TOPSIS calculated successfully

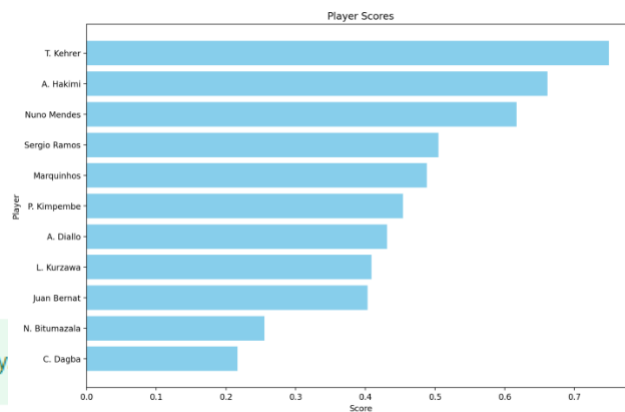


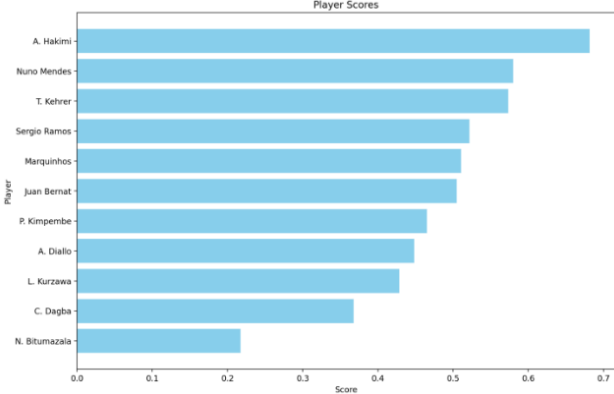
Figure B.7: Players ranking using TOPSIS and ENTROPY

TOPSIS

Rank Players

Weights used for ranking are calculated using: CRITIC

	Player	Score	Rank
0	A. Hakimi	0.6816	1
1	Nuno Mendes	0.5800	2
2	T. Kehrer	0.5733	3
3	Sergio Ramos	0.5216	4
4	Marquinhos	0.5107	5
5	Juan Bernat	0.5049	6
6	P. Kimpembe	0.4651	7
7	A. Diallo	0.4482	8
8	L. Kurzawa	0.4285	9
9	C. Dagba	0.3678	10



Player ranking with TOPSIS calculated successfu

Figure B.8: Players ranking using TOPSIS and CRITIC

Appendix C

Tables of matches and player selections

Table C.1: Table of actual matches

PSG vs Metz		PSG vs RC Lens	
21 May 2022, 5 substitutes, Won	22 September 2022, 3 substitutes, Won	23 April 2022, 2 substitutes, Null	4 December 2021, 3 substitutes, Null
K. Navas	K. Navas	K. Navas	K. Navas
A. Hakimi	Numo Mendes	A. Hakimi	A. Hakimi
Marquinhos	P. Kimpembe	P. Kimpembe	Bernat
Sergio Ramos	Marquinhos	Sergio Ramos	P. Kimpembe
P. Kimpembe	A. Hakimi	Marquinhos	Marquinhos
T. Kehrer	J. Draxler	Numo Mendes	Numo Mendes
M. Verratti	G. Wijnaldum	M. Verratti	M. Verratti
Danilo Pereira	Danilo Pereira	I. Gueye	Danilo Pereira
G. Wijnaldum	Rafinha	Danilo Pereira	L. Paredes
I. Gueye	A. DiMaria		G. Wijnaldum
Ander Herrera	Ander Herrera		
A. DiMaria	Neymar Jr	K. Mbappé	A. DiMaria
L. Messi	M. Icardi	Neymar Jr	M. Icardi
K. Mbappé	K. Mbappé	L. Messi	L. Messi
Neymar Jr		A. DiMaria	K. Mbappé
PSG vs Real Madrid		PSG vs Reims	
Champions league, 3 substitutes, Lost	2 substitutes, Won	23 January 2022, 3 substitutes, Won	29 August 2022, 5 substitutes, Won
Donnarumma	Donnarumma	K. Navas	K. Navas
A. Hakimi	A. Hakimi	T. Kehrer	A. Diallo
Numo Mendes	Marquinhos	Marquinhos	Marquinhos
P. Kimpembe	P. Kimpembe	Sergio Ramos	T. Kehrer
Marquinhos	Numo Mendes	Numo Mendes	A. Hakimi
M. Verratti	Danilo Pereira		P. Kimpembe
L. Paredes	Danilo Pereira	Danilo Pereira	M. Verratti
Danilo Pereira	L. Paredes	L. Paredes	I. Gueye
J. Draxler	M. Verratti	M. Verratti	G. Wijnaldum
I. Gueye	I. Gueye	Ander Herrera	L. Paredes
		J. Draxler	Ander Herrera
			J. Draxler
K. Mbappé	A. DiMaria	A. DiMaria	Neymar Jr
L. Messi	L. Messi	M. Icardi	K. Mbappé
Neymar Jr	K. Mbappé	K. Mbappé	A. DiMaria
A. DiMaria	Neymar Jr	L. Messi	L. Messi

Table C.2: Table of actual matches (Continued)

PSG vs OM		PSG vs Manchester City	
17 April 2022, 3 substitutes, Won	24 October 2022; 5 substitutes, Won	Champions league, 2 substitutes, Won	29 August 2022, 3 substitutes, Won
G. Donnarumma	K. Navas	G. Donnarumma	K. Navas
A. Hakimi	Numo Mendes	A. Hakimi	Numo Mendes
Marquinhos	P. Kimpembe	Marquinhos	P. Kimpembe
P. Kimpembe	Marquinhos	P. Kimpembe	Marquinhos
Numo Mendes	A. Hakimi	Numo Mendes	T. Kehrer
Sergio Ramos	T. Kehrer		
Danilo Pereira	Danilo Pereira	Ander Herrera	L. Paredes
M. Verratti	M. Verratti	M. Verratti	I. Gueye
I. Gueye	I. Gueye	I. Gueye	Ander Herrera
G. Wijnaldum	G. Wijnaldum	G. Wijnaldum	Danilo Pereira
		Danilo Pereira	
L. Messi	A. Di Maria	L. Messi	Neymar Jr
K. Mbappé	Neymar Jr	K. Mbappé	K. Mbappé
Neymar Jr	L. Messi	Neymar Jr	L. Messi
M. Icardi	K. Mbappé		A. DiMaria
PSG vs Rennes			
3 October 2021, 3 substitutes, Lost	11 February 2022, 3 substitutes, Won		
K. Navas	K. Navas		
A. Hakimi	Numo Mendes		
Marquinhos	P. Kimpembe		
Sergio Ramos	Marquinhos		
P. Kimpembe	A. Hakimi		
T. Kehrer	J. Draxler		
M. Verratti	G. Wijnaldum		
Danilo Pereira	Danilo Pereira		
G. Wijnaldum	Rafinha		
I. Gueye	A. DiMaria		
Ander Herrera	Ander Herrera		
A. DiMaria	Neymar Jr		
L. Messi	M. Icardi		
K. Mbappé	K. Mbappé		

Table C.3: Player selection provided by the model

Random Forest-TOPSIS	ENTROPY-TOPSIS	CRITIC-TOPSIS
Goalkeeper		
K. Navas	K. Navas	K. Navas
G. Donnarumma	G. Donnarumma	G. Donnarumma
Sergio Rico	Sergio Rico	A. Letellier
A. Letellier	A. Letellier	Sergio Rico
Defender		
Marquinhos	T. Kehrer	A. Hakimi
Sergio Ramos	A. Hakimi	Nuno Mendes
P. Kimpembe	Nuno Mendes	T. Kehrer
A. Hakimi	Sergio Ramos	Sergio Ramos
A. Diallo	Marquinhos	Marquinhos
Juan Bernat	P. Kimpembe	Juan Bernat
Numo Mendes	A. Diallo	P. Kimpembe
L. Kurzawa	L. Kurzawa	A. Diallo
T. Kehrer	Juan Bernat	L. Kurzawa
C. Dagba	N. Bitumazala	C. Dagba
N. Bitumazala	C. Dagba	N. Bitumazala
Midfielder		
G. Wijnaldum	G. Wijnaldum	G. Wijnaldum
L. Paredes	L. Paredes	L. Paredes
Rafinha	Danilo Pereira	Rafinha
Ander Herrera	Ander Herrera	M. Verratti
J. Draxler	Rafinha	Ander Herrera
I. Gueye	J. Draxler	J. Draxler
M. Verratti	M. Verratti	I. Gueye
Danilo Pereira	J. Dina Ebimbe	Danilo Pereira
J. Dina Ebimbe	I. Gueye	J. Dina Ebimbe
X. Simons	X. Simons	X. Simons
É. Michut	B. Fadiga	B. Fadiga
B. Fadiga	É. Michut	É. Michut
I. Gharbi	I. Gharbi	I. Gharbi
Forward		
K. Mbappé	Neymar Jr	K. Mbappé
L. Messi	K. Mbappé	Neymar Jr
A. DiMaria	L. Messi	M. Icardi
Neymar Jr	M. Icardi	L. Messi
M. Icardi	A. Di Maria	A. Di Maria

Appendix D

Source code

```
1     import streamlit as st
2     import numpy as np
3     import pandas as pd
4     import matplotlib.pyplot as plt
5     from sklearn.ensemble import RandomForestRegressor
6     from sklearn.model_selection import train_test_split
7     from pyDecision.algorithm import ahp_method, critic_method
8     #from sklearn.metrics import mean_squared_error
9     from sklearn.metrics import *
10    from sklearn.model_selection import cross_val_score
11
12    # Charger les donn\ees
13    @st.cache
14    def load_data():
15        data = pd.read_excel("D:/Kaggle data/Data_By_Position_V2/
16                            Clean_Data_2022_V1.xlsx")
17        return data
18
19    data = load_data()
20
21    st.title('Decision Support System for Selecting Professional
22            Football Players')
```

```
23     attributes_by_position = {
24         'Foreword': ['Weak Foot', 'Skill Moves', 'Crossing',
25                     'Finishing', 'HeadingAccuracy', 'ShortPassing',
26                     'Volleys', 'Dribbling', 'Curve', 'BallControl',
27                     'Acceleration', 'Agility', 'Reactions', 'Balance', '
28                     ShotPower', 'Jumping', 'Stamina', 'Strength', '
29                     LongShots', 'Aggression',
30                     'Positioning', 'Vision', 'Penalties', 'Composure', '
31                     SprintSpeed'],
32         'Defender': ['Weak Foot', 'Crossing', '
33                     HeadingAccuracy', 'ShortPassing', 'Dribbling', '
34                     LongPassing', 'BallControl', 'Acceleration', '
35                     SprintSpeed',
36                     'Agility', 'Reactions', 'Balance', 'ShotPower', '
37                     Jumping', 'Stamina', 'Strength', 'Aggression', '
38                     Interceptions', 'Composure', 'Marking',
39                     'StandingTackle', 'SlidingTackle'],
40         'Midfielder': ['Weak Foot', 'Crossing', 'Finishing',
41                       'HeadingAccuracy', 'ShortPassing', 'Volleys', '
42                       Dribbling', 'Curve',
43                       'LongPassing', 'BallControl', 'Acceleration', '
44                       SprintSpeed', 'Agility', 'Reactions', 'Balance',
45                       'ShotPower', 'Jumping',
46                       'Stamina', 'Strength', 'LongShots', 'Aggression', '
47                       Interceptions', 'Positioning', 'Vision', '
48                       Penalties', 'Composure', 'Marking', '
49                       StandingTackle'],
50         'Gokeeper': ['Weak Foot', 'Reactions', 'Jumping', '
51                     Strength', 'GKDividing', 'GKHandling', 'GKKicking',
52                     'GKPositioning', 'GKReflexes']
53     }
54
55     st.title('Criteria Selection:')
```

```
38     selected_club = st.selectbox('Select a club:', data['Club'].
        unique())
39     data_club = data[data['Club'] == selected_club]
40
41     selected_position = st.selectbox('Select a position:',
        data_club['Position'].unique())
42     data_position = data_club[data_club['Position'] ==
        selected_position]
43
44     selected_attributes = st.multiselect('Select the attributes/
        criteria:', attributes_by_position[selected_position],
45     default=attributes_by_position[selected_position])
46
47     data_position_filtered = data_position[selected_attributes +
        ['Wage player']]
48     data_position_filtered.replace([np.inf, -np.inf], np.nan,
        inplace=True)
49     data_position_filtered.dropna(inplace=True)
50
51     st.title('Weights Calculation:')
52
53     method = st.radio("Choose a method to calculate weights:", [
        "Random Forest (Machine Learning)", "ENTROPY (MCDM)", "
        CRITIC (MCDM)"])
54
55     if st.button('Calculate Weights'):
56
57         if method == 'Random Forest (Machine Learning)':
58             X_position = data_position_filtered.drop('Wage player', axis
                =1)
59             y_position = data_position_filtered['Wage player']
60             #X_train_position, _, y_train_position, _ = train_test_split
                (X_position, y_position, test_size=0.2, random_state=42)
61             X_train_position, X_test_position, y_train_position,
                y_test_position = train_test_split(X_position, y_position
```

```
        , test_size=0.2, random_state=42)
62 position_model = RandomForestRegressor(n_estimators=100,
        random_state=42)
63 position_model.fit(X_train_position, y_train_position)
64 weights = position_model.feature_importances_
65 title = "Weights by Random Forest"
66 st.session_state.weights = weights
67 st.session_state.weight_method = "Random Forest"
68 y_pred = position_model.predict(X_test_position)
69 #mse= mean_squared_error(y_test_position, y_pred)
70 #st.write("MSE:", mse)
71
72 R2= position_model.score(X_train_position, y_train_position)
73 st.write("The coefficient of determination (R2):", R2)
74 percentage_value = round(R2 * 100, 2)
75 st.write("The model can predict", percentage_value, "of the
        variability in players' salaries based on their
        attributes.")
76 #cv_scores = cross_val_score(position_model, X_position,
        y_position, cv=4, scoring='neg_mean_squared_error')
77 #mse_cv = cv_scores.mean()
78 #st.write("Cross-Validation MSE:", mse_cv)
79
80
81
82
83 elif method == 'ENTROPY (MCDM)':
84 decision_matrix = data_position_filtered[selected_attributes
        ].values
85
86 # Step 1: Normalize Decision matrix
87 norm_matrix = decision_matrix / decision_matrix.sum(axis=0)
88
89 # Step 2: Compute the Entropy Values
90 k = -(1 / np.log(norm_matrix.shape[0]))
```

```
91
92     def entropy(X):
93     return (X * np.log(X)).sum() * k
94
95     entropy_values = np.apply_along_axis(entropy, axis=0, arr=
96         norm_matrix)
97
98     # Degree of Differentiation
99     dod = 1 - entropy_values
100
101     # Calculate weights
102     weights = dod / dod.sum()
103
104     title = "Weights by ENTROPY"
105     st.session_state.weights = weights
106     st.session_state.weight_method = "ENTROPY"
107
108     elif method == 'CRITIC (MCDM)':
109     decision_matrix = data_position_filtered[selected_attributes
110         ].values
111     criteria_type = ['max'] * decision_matrix.shape[1]
112     weights = critic_method(decision_matrix, criteria_type)
113     title = "Weights by CRITIC"
114     st.session_state.weights = weights
115     st.session_state.weight_method = "CRITIC"
116
117     weight_df = pd.DataFrame({
118         'Attribute': selected_attributes,
119         'Weight': weights
120     }).sort_values(by='Weight', ascending=False)
121
122     # Afficher les poids
123     st.write(weight_df.set_index('Attribute'))
124     st.bar_chart(weight_df.set_index('Attribute'))
```

```
124
125     # Sauvegarder les poids pour une utilisation ultérieure
126     st.session_state.weights = weights
127
128
129     # Ajoutez une condition pour vérifier si les poids ont été
130     # calculés avant de permettre le calcul TOPSIS
131     if hasattr(st.session_state, 'weights'):
132         st.title('Player Ranking with MCDM:')
133
134         ranking_method = st.radio("Choose a ranking method:", ["
135             TOPSIS"])
136
137     # Fonction pour TOPSIS
138     def topsis(matrix, weights):
139         # 1. Normalisation
140         norm_matrix = np.linalg.norm(matrix, axis=0)
141         normalized_matrix = matrix / norm_matrix
142
143         # 2. Pondération
144         weighted_matrix = normalized_matrix * weights
145
146         # 3. Identifier les solutions idéales
147         ideal_positive = np.max(weighted_matrix, axis=0)
148         ideal_negative = np.min(weighted_matrix, axis=0)
149
150         # 4. Calculer les distances
151         dist_positive = np.linalg.norm(weighted_matrix -
152             ideal_positive, axis=1)
153         dist_negative = np.linalg.norm(weighted_matrix -
154             ideal_negative, axis=1)
155
156         # 5. Calculer les scores
157         score = dist_negative / (dist_positive + dist_negative)
```

```
155
156     return score
157
158
159     if st.button('Rank Players'):
160         if not hasattr(st.session_state, 'weights'):
161             st.warning("Please calculate the weights first.")
162             st.stop()
163
164         st.write(f"Weights used for ranking are calculated using: {
165                 st.session_state.weight_method}")
166
167         data_for_topsis = data_position_filtered.drop('Wage player',
168             axis=1).values
169         scores = topsis(data_for_topsis, st.session_state.weights)
170         ranked_indices = np.argsort(scores)[::-1]
171         ranked_players = data_position['Name'].iloc[ranked_indices].
172             values
173
174         ranking_df = pd.DataFrame({
175             'Player': ranked_players,
176             'Score': scores[ranked_indices],
177             'Rank': range(1, len(ranked_players) + 1)
178         })
179
180         st.write(ranking_df)
181         st.success("Player ranking with TOPSIS calculated
182                 successfully.")
183
184         # Visualisation avec Matplotlib
185         plt.figure(figsize=(12,8))
186         plt.barh(ranking_df['Player'], ranking_df['Score'], color='
187                 skyblue')
188         plt.xlabel('Score')
189         plt.ylabel('Player')
```

```

185 plt.title('Player Scores')
186 plt.gca().invert_yaxis() # Pour avoir le joueur avec le
    score le plus \'elev\'e en haut
187 st.pyplot(plt)

```

```

1 # Import necessary library
2 from typing import Set
3
4 # Function to calculate Jaccard Index
5 def jaccard_index(set1: Set[str], set2: Set[str]) -> float:
6     intersection = set1.intersection(set2)
7     union = set1.union(set2)
8     index = len(intersection) / len(union)
9     return round(index, 1) # Round to the nearest tenth
10
11 # PSG vs Metz
12
13 # Define the sets
14 # Model selection match 1
15 rf_set_metz1 = {"K. Navas", "G. Donnarumma", "Marquinhos", "
    Sergio Ramos", "P. Kimpembe", "A. Hakimi", "A. Diallo",
16     "G. Wijnaldum", "L. Paredes", "Rafinha", "Ander
    Herrera", "J. Draxler",
17     "K. Mbapp\'e", "L. Messi", "A. DiMaria", "Neymar Jr"
    }
18
19 entropy_set_metz1 = {"K. Navas", "G. Donnarumma", "T. Kehrer
    ", "A. Hakimi", "Numo Mendes", "Sergio Ramos", "
    Marquinhos",
20     "G. Wijnaldum", "L. Paredes", "Danilo Pereira", "
    Ander Herrera", "Rafinha", "Neymar Jr", "K. Mbapp
    \'e",
21     "L. Messi", "M. Icardi"}
22
23 critic_set_metz1 = {"K. Navas", "G. Donnarumma", "A. Hakimi"

```



```
24     , "Numo Mendes", "T. Kehrer", "Sergio Ramos", "Marquinhos",
25     ",
26     "G. Wijnaldum", "L. Paredes", "Rafinha", "M.
27     Verratti", "Ander Herrera", "K. Mbapp'e", "
28     Neymar Jr",
29     "M. Icardi", "L. Messi"}
30
31 # Model selection match 2
32 rf_set_metz2 = {"K. Navas", "Marquinhos", "Sergio Ramos", "P
33     . Kimpembe", "A. Hakimi", "A. Diallo", "G. Wijnaldum",
34     "L. Paredes", "Rafinha", "Ander Herrera", "J.
35     Draxler", "K. Mbapp'e", "L. Messi", "A. DiMaria"
36     }
37
38 entropy_set_metz2 = {"K. Navas", "T. Kehrer", "A. Hakimi", "
39     Numo Mendes", "Sergio Ramos", "Marquinhos", "G. Wijnaldum",
40     "L. Paredes", "Danilo Pereira", "Ander Herrera", "
41     Rafinha", "Neymar Jr", "K. Mbapp'e", "L. Messi"}
42
43 critic_set_metz2 = {"K. Navas", "A. Hakimi", "Numo Mendes",
44     "T. Kehrer", "Sergio Ramos", "Marquinhos", "G. Wijnaldum",
45     "L. Paredes", "Rafinha", "M. Verratti", "Ander
46     Herrera", "K. Mbapp'e", "Neymar Jr", "M. Icardi"
47     }
48
49 # Coach selection match 1
50 coach_set_metz1 = {"K. Navas", "A. Letellier", "A. Hakimi",
51     "Marquinhos", "Sergio Ramos", "P. Kimpembe", "T. Kehrer",
52     "M. Verratti", "Danilo Pereira", "G. Wijnaldum", "I.
53     Gueye", "Ander Herrera",
54     "A. DiMaria", "L. Messi", "K. Mbapp'e", "Neymar Jr"
55     }
```

```
42     # Coach selection match 2
43     coach_set_metz2 = {"K. Navas", "Numo Mendes", "P. Kimpembe",
44                       "Marquinhos", "A. Hakimi", "J. Draxler", "G. Wijnaldum",
45                       "Danilo Pereira", "Rafinha", "A. DiMaria", "Ander
46                       Herrera", "Neymar Jr", "M. Icardi", "K. Mbapp\'e"
47                       }
48
49     # Calculate and print Jaccard Indices
50
51     metz_index1 = jaccard_index(rf_set_metz1, coach_set_metz1)
52     metz_index2 = jaccard_index(entropy_set_metz1,
53                               coach_set_metz1)
54     metz_index3 = jaccard_index(critic_set_metz1,
55                               coach_set_metz1)
56
57     metz_index4 = jaccard_index(rf_set_metz2, coach_set_metz2)
58     metz_index5 = jaccard_index(entropy_set_metz2,
59                               coach_set_metz2)
60     metz_index6 = jaccard_index(critic_set_metz2,
61                               coach_set_metz2)
62
63     print(f"JI for match 1 Metz: {metz_index1, metz_index2,
64           metz_index3}")
65     print(f"JI for match 2 Metz: {metz_index4, metz_index5,
66           metz_index6}")
```

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Titre : Optimisation de Sélection en Football par l'Intégration des Théories de Management, de l'IA et de Décision Multi-critères

Mots clés : Management du football; Sélection des joueurs; Prise de décision axée sur les données; Apprentissage automatique; Prise de décision multicritères; Optimisation des performances sportives

Résumé : Le travail de recherche présenté dans cette thèse s'inscrit dans le contexte de la gestion des clubs professionnels de football, où l'établissement d'un équilibre humain et financier est essentiel pour assurer la viabilité à long terme des organisations sportives. Les méthodes traditionnelles de sélection des joueurs ont historiquement guidé les processus de prise de décision au sein des clubs, souvent de manière subjective et incertaine. Avec l'évolution du football vers un sport axé sur les données, il devient nécessaire de compléter les approches traditionnelles par des méthodes scientifiques basées sur l'intelligence artificielle (IA) et les méthodes de prise de décision multicritères (MCDM) pour optimiser la sélection des joueurs et améliorer les

performances sportives et financières. Cette thèse propose un modèle combinant le machine learning et l'analyse multicritères pour améliorer l'efficacité et l'objectivité de la sélection des joueurs, en prenant en compte les considérations financières et managériales.

Nous priorisons les critères techniques, physiques, tactiques et comportementaux des joueurs avec des algorithmes tels que Random Forest, Entropy et CRITIC, puis classons les joueurs selon leurs performances avec la méthode TOPSIS. Un système d'aide à la décision est conçu pour aider les décideurs sportifs en proposant les joueurs par ordre de performance, intégrant des évaluations subjectives et objectives.

Title : Football Selection Optimization through the Integration of Management Theories, AI and Multi-criteria Decision Making

Keywords : Football management; Player selection; Data-driven decision making; Machine learning; Multi-criteria decision making; Sports performance optimization

Abstract: The research work presented in this thesis is set in the context of managing professional football clubs, where establishing a human and financial balance is essential to ensure the long-term viability of sports organizations. Traditional player selection methods have historically guided decision-making processes within clubs, often subjectively and uncertainly. As football evolves into a more data-driven sport, it becomes necessary to complement traditional approaches with scientific methods based on artificial intelligence (AI) and multi-criteria decision-making (MCDM) to optimize player selection and improve both sporting and financial performance.

This thesis proposes a model combining machine learning and multi-criteria analysis to enhance the efficiency and objectivity of player selection, considering financial and managerial aspects. We prioritize the technical, physical, tactical, and behavioral criteria of players using algorithms such as Random Forest, Entropy, and CRITIC, then rank players based on their performance using the TOPSIS method. A decision support system is designed to assist sports decision-makers by proposing players in order of performance, integrating subjective and objective evaluations.