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Using multi-criteria decision-making and machine learning for football player selection and performance prediction: A systematic review

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Abstract

Evaluating and selecting players to suit football clubs and decision-makers (coaches, managers, technical, and medical staff) is a difficult process from a managerial-financial and sporting perspective. Football is a highly competitive sport where sponsors and fans are attracted by success. The most successful players, based on their characteristics (criteria and sub-criteria), can influence the outcome of a football game at any given time. Consequently, the D-day of selection should employ a more appropriate approach to human resource management. To effectively address this issue, a detailed study and analysis of the available literature are needed to assist practitioners and professionals in making decisions about football player selection and hiring. Peer-reviewed journals were selected for collecting published papers between 2018 and 2023. A total of 66 relevant articles (journal articles, conference articles, book sections, and review articles) were selected for evaluation and analysis. The purpose of the study is to present a systematic literature review (SLR) on how to solve this problem and organize the published research papers that answer our four research questions.

Keywords: multi-criteria decision-making, machine learning, football player selection, managerial-financial and sporting performance.

1. Introduction

Soccer has been the world's most influential most and popular sport for over a century. For the past thirty years, it has also become the most gainful industry, 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 are complex businesses that exclusively deal with financial issues (Morrow and Howieson, 2014). However, Katzenbach (2009) explored the counter-intuitive features comprising high-performing teams, such as selecting team members based on their skills rather than their compatibility. Club success is determined by the score on the field, which depend on the line-up of the chosen players. Therefore, the selection should be based on a more relevant human resource management strategy.

In a football match, in addition to preparing the team to participate in competitions, the role of decision-makers (managers, coaches, technical, and medical staff) is to hire and select players to form the team line-up by relying, technical, and tactical factors (Carmichael et al., 2000). Most importantly, the goal of the player selection process for a particular team is to choose the most suitable player for a particular playing position and role (Dezman et al., 2001; Trninic et al., 2008). Accordingly, decision-makers constantly search for the most efficient technique to identify outstanding players and build elite teams (Katzenbach and Smith, 1993). One strategic decision decision-makers should made is choosing players for certain football match. The starting line-up comprises 11 players among the 28 available to coaches to play at the beginning of a game. This decision influences the success of a team in achieving financial and sports performance (Szymanski and Smith, 1997; Carmichael et al., 2011; Rohde and Breuer, 2016). This strategic process is part of a conventional approach that does not refer to a thorough scientific method; it is carried out mainly by intuition, common sense, and an uncertain methodology (Boon and Sierksma, 2003; Dadelo et al., 2014; Purwanto et al., 2018; Salles et al., 2019).

This process is complex and challenging to manage because it must consider a large number of qualitative and quantitative criteria and sub-criteria that describe the performance and position of each player (Arnason et al., 2004; Tavana et al., 2013; Nasiri et al., 2018). To solve this issue, decision-makers do not refer to modern methods used in other areas, such as health, software packages, transportation, and environment, which consist of multi-criteria decision-making (MCDM) methods. MCDM approaches could be beneficial and useful in assisting decision-makers, providing more objective decisions, especially when combined with machine learning algorithms. Historical research on football player selection and performance prediction oscillated between the traditional coaching experience and data-driven approaches. MCDM methods have gained traction in recent years because they provide a multi-criteria perspective for informed decision making (Dadelo et al., 2014). Simultaneously, machine learning based on large datasets may provide granular predictions of player performance using models, such as neural networks and random forests (Azeman et al., 2021). The potential fusion of MCDM for selection and machine learning for predictive insights remains underexplored area of research. Addressing this research gap is critical, and motivates 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. The remainder of this paper is as organized as follows: The following section presents the research method and details of the

protocol used to plan and conduct the proposed research. Section 3 shows the analysis results to answer the research questions related to the topic. Section 4 and concludes.

2. Research method

For the present study follows an SLR protocol based on Kitchenham's guidelines (Barbara Kitchenham and Charters, 2007). Figure 1 shows three sequentialplans reflecting the components of the SLR: planning, conducting, and reporting the review.
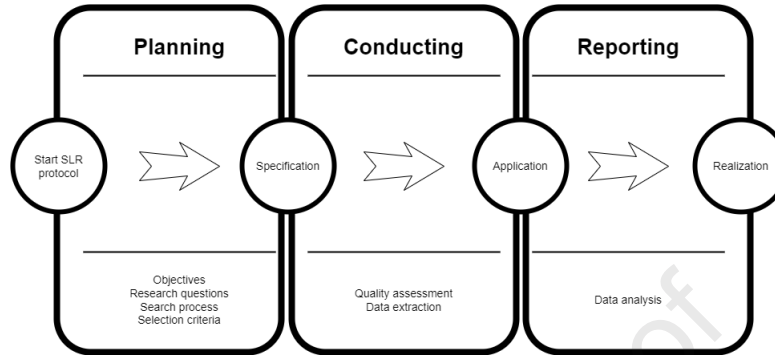

Fig. 1. SLR general process

2.1 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 keywords for downloading the relevant papers from the selected digital libraries, and identify the selection criteria.

(1) Objectives: This study examines research out in 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 significant challenge for all clubs, involving multiple criteria that should be evaluated simultaneously. Therefore, 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 a SLR of books and papers published in journals and conference proceedings related to our research topic.

(2) Research questions: After determining the purpose and motivation of our research, the SLR proposes a process to answer the following research questions:

RQ1: 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.

RQ2: 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.

RQ3: The effectiveness of sports clubs is influenced by players' and coaches' talents. The most crucial elements of a sports organization are the athletic resources that constitute its human capital. MCDM approaches couldbe of interest to support decision makers and provide more objective decisions. This study investigates the applicability and utility of MCDM approaches in the selection process for football players.

RQ4: How can we build a hybrid model combining MCDM approaches and machine learning algorithms by integrating all technical and managerial-financial variables to help decision makers select the best players for a game?

(3) Search process: For planning the SLR process, an appropriate mechanism must be followed to ensure the retrieval

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of rele[...]cles 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 essencial. 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 1). The first attempt in this search process has yielded the following results: IEEE $\rightarrow$802, ScienceDirect $\rightarrow$1432, Springer $\rightarrow$398, Taylor and Francis $\rightarrow$221, and Wiley Online Library $\rightarrow$137. To refine the results we assigned a subset of keywords (S1, S2, S3, S4) 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.

Table 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")
RQ1	S1 = ("football" OR "soccer") AND ("management" OR "managerial") AND ("financial sporting performance")
RQ2	S2 = ("football" OR "soccer") AND ("player") AND ("criteria" OR "attribute")
RQ3	S3 = ("Multi-criteria Decision Making") AND ("selection problems")
RQ4	S4 = ("Multi-criteria Decision Making") AND ("prediction") AND ("machine learning") AND ("football player selection")

(4) 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 2 summarizes the essential inclusion and exclusion criteria for the proposed SLR.

Table 2 Selection criteria of the relevant papers

Inclusion criteria
- 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
- Published outside the 2018-2023 period
- Other language than English
- Content of the paper not providing satisfactory information of the main topic and research questions
- Informal literature surveys
- Duplicate papers

2.2 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 (Fig. 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). Second, the inclusion/exclusion criteria are applied to a subset of primary studies (Table 4). Third, the remaining studies are analyzed in depth and filtered by title and paper keywords, abstracts, and content (Table 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, 2023) 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 and 4 show the research trends in the selected period and the percentage of digital libraries, respectively.

Fig. 2. Review process

Table 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 4 Search process with inclusion/exclusion criteria

Digital libraries	Journal papers	Conference papers	Book section	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

Table 5 Filtering papers by title and paper keywords, abstract, and contents

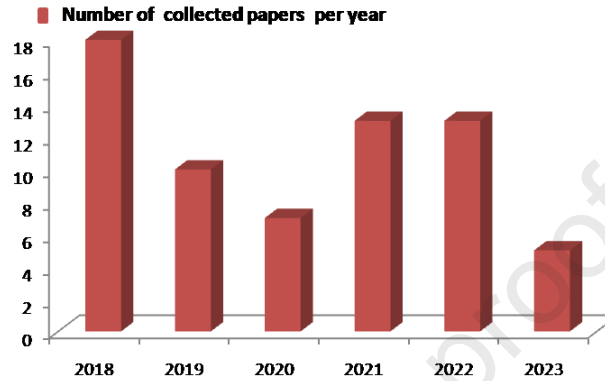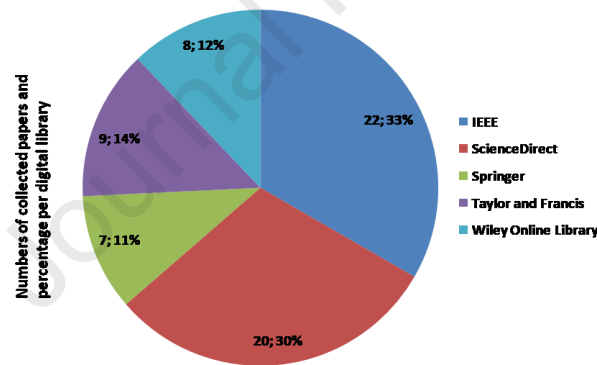| Digital libraries	Title and paper keywords	Abstract	Content
IEEE	30	28	22
ScienceDirect	31	28	20
Springer	10	8	7
Taylor and Francis	11	11	9
Wiley Online Library	10	10	8
Total	92	85	**66**

Fig. 3. Research trends 2018–2023

Fig. 4. Contribution share of each database

(5) 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.

(6) 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 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 of the inclusion/exclusion decisions and ensure the quality of the selected studies (Table 7).

We also consider books and book sections on sports management and decision-making: (Saaty and Vargas, 1982; Katzenbach and Smith, 1993; Saaty, 1996; J. Katzenbach, 2009; Dobson and Goddard, 2001; Tzeng and Huang, 2011; Ishizaka and Nemery, 2013). 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 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 Eitan et al., 2023), a visual tool that helps researchers.

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Table 6 Data extraction form

Data item	Description
Ref.	Reference ID/Number of the paper under
Studyyear	year of publication
RQ1	Does the paper relate to our RQ1?
RQ2	Does the paper relate to our RQ2?
RQ3	Does the paper relate to our RQ3?
RQ4	Does the paper address RQ4?
Case Study	Does the Study Apply any Case?
DataBase	Does the paper include dataset from any DataBase?

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.

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. Section 1 reports the contribution of the literature to the study of the relationship between managerial and financial performance and sports performance (RQ1). Section 2 describes the main criteria and sub-criteria related to the football players involved in the selection problem (RQ2). Section 3 presents the decision-making methods used to assist decision-makers in solving selection problems, referring to player criteria and sub-criteria (RQ3). Section 4 highlights hybrid models that integrate all technical and economic variables to help decision makers select the best players for a game (RQ4).

(1) *RQ1: 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) highlights that selecting personnel in an organizations is usually tricky . The process becomes even more complicated when selection occurs in complex organizations where different areas can work toward multiple 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) measures economic-financial performance using net revenue and other revenue sources such as broadcasting, matchday, commercial, and player sales. Using panel data analysis, they find that team performance positively and significantly affects the clubs' economic and financial performance in the subsequent 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) analyzes 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) emphasizes 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) identifies 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) proposes a method to determine the economic value of professional football players in the event of a purchase or sale. Dimitropoulos and Scafarto (2021) examines the relationship between the athletic and financial performance of Greek football clubs. They deduce that sports and financial performance are linked through investments in players. Frick and Simmons (2008) establishes a positive correlation between spending on team payroll (managerial compensation) and team performance. Using stochastic analysis, they demonstrated that coaching and playing inputs contribute to team success in the league. Boon and Sierksma (2003) discusses in their model how to support the design of optimal teams and assesses the value-added of a team's potential.

Table 7 Summary of the reviewed literature

Authors	Year	RQ 1	RQ 2	RQ 3	RQ 4	Case study	Data Source	N°
Xia et al. (2018)	2018	✓	-	-	-	✓	National Football League & National Basketball Association	1
Blanco et al. (2018)	2018	✓	-	✓	✓	✓	Spanish ACB Basketball League	2
Lepschy et al. (2018)	2018	✓	-	-	-	-	-	3
Flegl et al. (2018)	2018	✓	✓	✓	✓	✓	sofifa	4
Danisik et al. (2018)	2018	✓	✓	✓	-	-	-	5
Purwanto et al. (2018)	2018	-	✓	✓	✓	✓	interviews	6
Parida et al. (2022)	2018	✓	✓	-	-	-	-	7
Rohde and Breuer (2018)	2018	✓	-	-	-	✓	Big five clubs owners from 2003 to 2014	8
Samur (2018)	2018	✓	-	-	-	-	-	9
Hervert-Escobar et al. (2018)	2018	✓	✓	-	-	✓	FIFA world cup 2018	10
Wadjdi et al. (2018)	2018	-	-	✓	-	-	-	11
Buhagiar et al. (2018)	2018	✓	-	-	-	-	-	12
Galariotis et al. (2018)	2018	-	-	✓	✓	-	-	13
Chatterjee et al. (2018)	2018	-	-	✓	✓	✓	ABP (Media company in india)	15
Farshidi et al. (2018)	2018	-	-	✓	✓	✓	Software companies	16
Nasiri et al. (2018)	2018	✓	✓	✓	✓	✓	Questionnaire	17
Chen et al. (2018)	2018	-	-	✓	✓	✓	Location Selection	18
Lepschy et al. (2018)	2018	-	✓	✓	✓	✓	American/Canadian basketball league NBA	19
Bhat et al. (2019)	2019	✓	-	-	✓	-	-	20
Shahriar et al. (2019)	2019	-	✓	✓	✓	✓	Bangladesh Soccer Team	21
Mohanta et al. (2019)	2019	-	-	✓	✓	-	-	22
Nsolo et al. (2019)	2019	-	-	-	✓	✓	WhoScored - Opta	23
Ouahli and Cherkaoui (2019)	2019	-	-	✓	✓	✓	-	24
Purwanto et al. (2018)	2019	-	-	-	✓	-	Wysout (soccer-logs)	25
Patnaik et al. (2019)	2019	-	✓	-	-	✓	OPTA	26
Saeed et al. (2019)	2019	-	-	✓	-	-	-	27
Gu et al. (2019)	2019	✓	-	-	-	✓	Major League Soccer from 2004 to 2015	28
Gomez-Gonzalez et al. (2019)	2019	-	-	✓	✓	-	-	29
Alaminos et al. (2020)	2020	✓	-	-	-	-	-	30
Cacho-Elizondo (2020)	2020	-	✓	-	-	-	-	31
Gonçalves et al. (2020)	2020	✓	-	-	-	✓	Brazilian sports clubs from 2013 to 2017	32
Yang et al. (2020)	2020	-	✓	✓	✓	-	-	33
Valenti et al. (2020)	2020	✓	-	-	-	✓	Data from 55 UEFA members from 2011-2017	34
Salih et al. (2020)	2020	-	✓	✓	✓	✓	Data from (Raheela et al., 2016)	35
Di Simone and Zanardi (2020)	2020	✓	-	-	-	✓	European football companies (59 firms from 2013 to 2018).	36
Romero et al. (2021)	2021	-	✓	✓	✓	✓	2018 European Men's Handball Championship	37
Bai and Bai (2021)	2021	-	✓	-	-	-	-	38
Manish. et al. (2021)	2021	✓	✓	-	-	-	-	39
Azeman et al. (2021)	2021	-	✓	✓	✓	✓	English Premier League Season 2005-2006	40
Rahman and Asadujjaman (2021)	2021	-	-	✓	✓	-	-	41
Wieckowski and Watróbski (2021)	2021	-	-	✓	✓	✓	Formula 1	42
Zhao et al. (2021)	2021	-	-	-	✓	✓	Sofifa	43
Aydemir et al. (2021)	2021	✓	✓	✓	-	-	-	44
Li et al. (2021)	2021	✓	✓	-	-	✓	National Basketball Association 2012 to 2015	45
Fry et al. (2021)	2021	✓	-	-	-	-	-	46
Kaczynska et al. (2021)	2021	-	-	✓	✓	✓	ratings.fide.com (chess)	47
Dimitropoulos and Scafarto (2021)	2021	✓	-	-	-	-	-	48
Garcia-delBarrio and Agnese (2022)	2022	✓	-	-	-	✓	Premier League, La Liga, Serie A, and Ligue 1, 201- 2019	49
Steve Arrul et al. (2022)	2022	✓	-	-	-	✓	FIFA 2019	50
Morciano et al. (2022)	2022	✓	✓	-	-	-	-	51
Rose et al. (2022)	2022	✓	-	-	-	-	-	52
Jenifer and Sundarrajan. (2022)	2022	-	-	✓	✓	-	-	53
Datta and Rudra (2022)	2022	✓	✓	-	-	-	-	54
Parida et al. (2022)	2022	✓	✓	✓	-	✓	Football Club Barcelona	55
Hu and Fu, (2022)	2022	-	-	-	✓	✓	Premier League & La Liga data	56
Karakaya et al. (2022)	2022	-	✓	✓	-	-	-	57
Mahmood et al. (2021)	2022	✓	-	-	-	✓	National Basketball Association	59
Wieckowski and Watróbski (2021)	2022	-	-	✓	✓	✓	Randomly generated decision matrix	60
Ribeiro et al. (2022)	2022	✓	✓	-	-	✓	Portuguese First League from 2016 to 2018	61
Manju and Philip (2023)	2023	-	-	✓	✓	✓	Dataset of cricket matches 2008-2022	62
Peddii and Jain (2023)	2023	-	✓	✓	✓	✓	Historical data	63
Athish V et al. (2023)	2023	-	-	✓	✓	✓	kaggle.com & Sofia.com.	64
Joe Anand et al. (2023)	2023	-	-	✓	-	-	-	65
McHale and Holmes (2023)	2023	✓	✓	✓	-	✓	transfermarkt.com, Instat, sofifa. com	66

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.

(2) *RQ2: 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 (Raheela et al., 2016; Cacho-Elizondo, 2020). In selecting the best player, Nikjo et al. (2015) defines six criteria after questioning ten experts and three decision-makers. These criteria include technical and tactical skills, experience of professional play, average number of goals scored per game, 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) discusses 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) presents a methodology for evaluating and ranking football players based on anthropometric, fitness, and ability tests. Tavana et al. (2013) proposes 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. (2018) examines 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 (Charnes et al., 1978; Carmichael et al., 2000, 2011). 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) *RQ3: 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 Et choix traduisant la réalité (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 measure the performance of decision-making units (DMUs) that convert multiple inputs into multiple outputs.

This research aims to review articles demonstrating the use of multiple criteria decision-making methods in sports, particularly in football player selection (Table 8). Mavi et al. (2012) measures the sporting performance of 18 professional football teams in the German Bandesliga by collecting data for the season 1999/2000. Seungbum and Ross (2012) ranks the criteria and sub-criteria to identify the decision making factors in sports sponsorship in the global market context. (Blanco et al., 2018) applies 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) contents 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) develops 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. (2018) proposes 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) selects 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) develops 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) proposes 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-meter speed running. Ballı 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 Turkey. The findings of this SLR contribute to a deeper understanding of several MCDM methods used in sports.

Table 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
Fuzzy-AHP 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 attruibutes (Communication, Pattern of distribution, Team experience, Global synergy) distribution)
Fuzzy-ANP-PROMETHEE II-DEA Nasiri et al. (2018)	• 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 line-up selection	Physical, technical, tactical, mental
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. . .

Table 8 Summary of studies related to our RQ3 (Continued)

Methods References	Category	Application	Goal	Criteria (Sub-criteria)
TOPSIS Raheela et al. (2016)	• 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
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
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, 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 Criket.	Ranking of faster-bowlers and spinners	Economy rate, bowling average, bowling strike rate

Table 8 Summary of studies related to our RQ3 (Continued)

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 can we create a hybrid MCDM model that incorporates all technical and economic variables to help decision-makers select the best players for a game?* Our model uses machine learning algorithms to predict players' (sporting and financial) performances based on historical data collected from official club websites set of criteria and sub-criteria is then weighted using an MCDM method such as AHP, and football players required for the line-ups are ranked using an appropriate MCDM approach. This hybrid model allows for a complete analysis by integrating the strength of machine learning algorithms to predict criteria and sub-criteria for decision-making models.

This research question focuses on studies (samples) that construct a model to select or rank the best players (Table 9).

Table 9 A samples of studies related to RQ4

References	Model/System	Application
Feng et al. (2010)	Multi-objective 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 multi-objective 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.
Ballı and Korukoğlu (2014)	Fuzzy decision support framework port framework	Developed a fuzzy multi-attribute 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.

Table 9 A samples of studies related to RQ4 (Continued)

References	Model/System	Application
Ozceylan (2016)	A mathematical model for player selection	Study proposes a two-phase approach for selecting football players. In the first phase, the attributes of each player at each position were prioritized using AHP. In the second phase, a 0-1 integer linear programming model was developed using the weights of player attributes and the best players were determined for inclusion in the team. The proposed solution was applied to a Turkish football club to demonstrate its applicability and performance.
Blanco et al. (2018)	Quantitative tool based on the PROMETHEE	A quantitative ranking system was constructed to aggregate basketball players using the PROMETHEE methodology. A case study of 191 players who participated in the Spanish ACB basketballleague 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 integrated qualitative and quantitative data to select Mexican football teams for the 2018 World Cup in Russia.
Purwanto et al. (2018)	System for Line-upSelection	A system was developed to select the starting lineup of football playersbased on the AHP method.
Ouahli and Cherkaoui (2019)	Team performance model using the Fuzzy-AHP	Three performance teams in industrial and safety critical systems were developed based on individual performance, job attributes and teamattributes using the fuzzy-Ahp method.
Nasiri et al. (2018)	A bi-objective integer programming model	proposed an integrated approach that combines a multi-criteria decision-making analysis (FANP-PROMETHEE II-DEA) and mathematical programming to assist decision-makers in their selection process.
Nsolo et al. (2019)	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)	It has been argued that when faced with a set of alternatives, multi-criteria decision making is one of the most appropriate decision-making tools. Combining deep learning algorithms with multi-criteria decision making has proven beneficial for Big Data.
Zhao et al. (2021)	Multi-objective optimization - genetic algorithm	The team composition issue was formulated as a multi-objective optimization problem and, a variant of the genetic algorithm was proposed that can automatically output and recommend a football team with a high win rate by quantifying the players' abilities under a givenbudget constraint.

Table 9 A samples of studies related to RQ4 (Continued)

References	Model/System	Application
Wieckowski and Watróbski (2021)	Complex MCDM model based on 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 can reduce the number of characteristic objects (COs) pair comparisons that must be performed by an expert (from 1111 to 111), while maintaining its efficiency.

4. Discussion and conclusion

This SLR allowed 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 et al. (Barbara 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. To successfully perform the proposed SLR, all resources listed in Tables 7, 8, and 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., 2018; Purwanto et al., 2018; Shahriar et al., 2019; Kizielewicz and Dobryakova, 2020; Romero et al., 2021). We could conclude that line-up selection using MCDM methods was a relevant research area and topical subject, especially when combined with machine learning algorithms. This study identified new ways to develop a decision support system for player selection problems using multiple and conflicting criteria. This study's results may help the research community in this area to better understand and design models, decision support systems based on several criteria, and integrated machine learning algorithms.

Selecting a line-up of teams 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 comprehensive report on the relationship between managerial-financial and sporting performance, and the application of MCDM and machine learning algorithms in football team formation.

Future research directions: 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.

Data availability
There are no data available.
Conflicts of interest
There are no conflicts of interest related to this article.

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Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: