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Sport Performance Analysis with a Focus on Racket Sports: A Review

Sarka Krizkova [1], Hana Tomaskova [1,*] and Erfan Babaee Tirkolaee [2]

[1] Faculty of Informatics and Management, University of Hradec Kralove, 500 03 Hradec Kralove, Czech Republic; sarka.krizkova@uhk.cz
[2] Department of Industrial Engineering, Istinye University, Istanbul 34010, Turkey; erfan.babaee@istinye.edu.tr
* Correspondence: hana.tomaskova@uhk.cz

Abstract: Athletes, both professional and amateur, are always looking for ways to improve their performance. With the introduction and increasing availability of modern technologies and smart devices arose the need to measure and analyze performance, but likewise, the use of these innovations as a competitive advantage also arose. Scientific publications reflect the wide range of available approaches and technologies, as well as the growing interest in various sports. As a result, we concentrated on a systematic review of publications that presented performance analysis tools and methods in all sports, with a final focus on racket sports. Clarivate Analytics' Web of Science (WoS) and Elsevier Inc.'s SCOPUS databases were searched for 1147 studies that conducted performance analysis and sports research and were published in English. The data in the systematic review are current, up until 18 May 2021. A general review was performed on 759 items, and then 65 racket sports publications were thoroughly scrutinized. We concentrated on performance data, data collection and analysis tools, performance analysis methods, and software. We also talked about performance prediction. In performance research, we have identified specific approaches for specific sports as well as key countries. We are also considering expanding performance analysis in to E-sports in the future.

Keywords: performance analysis; racket sports; sports; systematic review

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1. Introduction

As technology has become more accessible to athletes across a wide range of sports, performance analysis has evolved over the last few decades. As a result, performance analysis has proven to be an important part of an athlete's development, coaching process, and a significant competitive advantage. Even though they do not fully utilize all available technologies, performance analysts are a unified approach that examines the interactions between players and their individual skill elements. The scientific analysis of sports performance seeks to advance our understanding of game behavior to improve future outcomes and performance. Without the use of performance analysis, the coaching process is incomplete. Most people agree that psychological fitness, psychological preparedness, physical development, biomechanical proficiency, and tactical awareness all play a role in sports performance. Just a few examples include psychological fitness, psychological preparedness, physical development, biomechanical ability, and tactical awareness (nutrition, genetics, general health and well-being, socio-cultural factors, etc.).

The purpose of this systematic literature review is to provide a detailed and comprehensive description of the relevant aspects of performance analysis, as well as to present the results of a bibliometric analysis of the documents that were discovered.

The following sections outline the structure of the paper. Systematic search, including entry criteria, exclusion criteria, and limitations, is described in Section 2, titled "Research Methodology". The findings from the analysis of articles that met the criteria for the systematic review are summarized in the section titled "Results". Section 3.1, "SR1: An overview of sport performance analysis in general", contains a selection of research articles that are relevant to sport performance analysis. This section provides a concise summary of the most important information about the approaches that were used in this systematic review. Section 3.2 "SR2: A systematic review of publications on racket sports" examined publications based on their publication date, citation count, scientific fields, author collaboration, and keyword density. Furthermore, we looked at the articles for their methodology, approach, and research areas. In Section 4, "Discussion", we discuss scientific gaps and the direction of future research. We present a research area in which we anticipate an increase in publications, as well as the components of those publications. In addition, we discuss the potential evolution of applied methods and approaches in the future. Finally, in Section 5 titled "Conclusion", the findings and benefits of the study are summarized.

2. Research Methodology

Three of the most important elements of a systematic literature review were identified by Kitchenham and Charters [1]. The formulation of a research hypothesis, or hypotheses, the organization of an unbiased and extensive analysis and review of related publications, and the formulation of precise criteria for inclusion and exclusion from the study were all components of this process.

We came up with five research hypotheses, which are as follows:

- Research hypothesis 1 (R1): The number of publications has steadily increased over time.
- Research hypothesis 2 (R2): The relationship between the number of publications and the Summer Olympics is significant.
- Research hypothesis 3 (R3): In performance analysis processes, the observation method is the most commonly used method.
- Research hypothesis 4 (R4): Rackets Sports performance analysis research is primarily conducted in Europe.
- Research hypothesis 5 (R5): Performance analysis research necessitates the participation of multiple authors.

The procedure and criteria for conducting the analysis are described in detail in the following relevant subsections.

2.1. Eligibility Criteria

The primary characteristics of the study are publications that have been indexed in Clarivate Analytics' Web of Science (WoS) and Elsevier Inc.'s SCOPUS databases. This search has a data range that extends until 18 May 2021. All exclusion criteria are listed below (EC). The study began with a global systematic review of performance analysis in sport (EC1-EC5), and subsequently, we focused on racket sports (EC6).

- EC1 = The article is available in both databases.
- EC2 = The publication is available in a language other than English.
- EC3 = The publication is a specific type (Book Chapter, Data Paper, Book, Conference Review, Editorial, Editorial Material, Letter, Meeting Abstract, Note, Review, Short Survey).
- EC4 = This publication does not have full access.
- EC5 = The publication is unrelated to the topic of systematic research.

=> SR1: An overview of sport performance analysis in general.

- EC6 = No racket sports are mentioned in the article.

=> SR2: A systematic review of publications on racket sports

2.2. Information Sources and Search

The primary sources of information for the study were Clarivate Analytics' WoS and Elsevier Inc.'s SCOPUS databases. Results of the performed advanced search are shown in Table 1 for the search query listed below. The investigation was carried out in the Topics (TS) section of WoS and the TITLE-ABS-KEY section of SCOPUS. The search was conducted with no time constraints and for "All document types" and "All languages." Because the investigation was completed on the 18th of May 2021, the statistics for the year 2021 are only partial.

Table 1. SCOPUS and WoS databases search queries.

Query	Nb. of Outcomes
TS = ("performance analysis" AND sport)	824
TITLE-ABS-KEY = ("performance analysis" AND sport)	978

The results from both databases are shown in Figure 1.

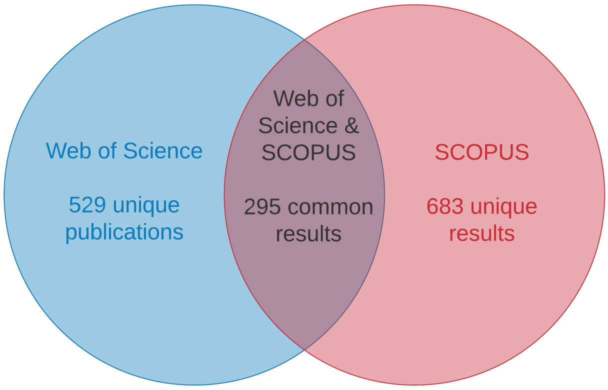


Figure 1. Venn diagram illustrating two distinct sets of results extracted from the Web of Science and SCOPUS databases.

2.3. Study Selection

For articles that were not definitively excluded after the title and abstract screening, a full-text review was conducted. The screening of the title and abstract, as well as the full-text review, was independently verified by two independent assessors.

Articles were accepted if they fulfilled all the following criteria: (i) performance analysis is a major topic; (ii) the analysis is focused on one of the racket sports; and (iii) the analysis is available in English and in full-text format (i.e., abstracts, commentaries, letters, and unpublished data were excluded). The inclusion of studies was not based on the methodological quality of the studies. In this study, selected publications were examined from various perspectives, and each contribution was coded according to a variety of criteria. This study aims to improve the discipline's fundamental understanding of performance analysis methods/approaches/software for specific sports. The study's findings may encourage scientists to apply current performance analysis methods to sports.

The review's limitation is that it only includes publications in English. Because of this restriction, some relevant studies written in other languages or published after 18 May 2021 may have been overlooked.

2.4. Data Collection Process

Performance analysis and technology will be a hot topic in the near future as more advanced sports analysis technologies are implemented. This fact has already had an impact on the literature. Because more platforms or software, including smart devices, are available for easier analysis, more casual users have begun to employ specialized technology. Keywords for increased technological involvement in sport were selected in this case. Performance, analysis, and sport were the three keywords.

3. Results

The initial search returned 1802 results, which is a significant number. Figure 2 depicts the process of conducting a systematic review, including steps for partial exclusion. After duplicates, non-English publications, and off-topic items were removed, 759 items were subjected to general review (SR1). Finally, 65 racket sports articles were thoroughly reviewed (SR2).

Figure 2. The systematic review process.

3.1. SR1: An Overview of Sport Performance Analysis in General

There are several parts in this section that discuss the objectives of performance analysis, the methods of gathering data, and tools for data collection and automation analysis. Then there is a list of performance analysis methods. Following that, we will go over the software that was used to conduct the performance analysis in detail. Finally, we will discuss the predictions of performance analysis results.

Performance analysis objectives can be captured in a variety of ways and for a variety of sports. For example, we can mention the following: identification of potential by: Arede et al. [2], Woods et al. [3], Waldron and Worsfold [4], Woods et al. [5,6], Lago-Fuentes et al. [7], specific performance of a young player by Saphie et al. [8], Brito et al. [9,10], Karakulak [11], Gimenez-Egido et al. [12], Analysis of technical skills (movement patterns, for example) by: Santos et al. [13], Nassis [14], Mangan et al. [15], Saavedra et al. [16], Challis et al. [17], Hökelmann and Richter [18]. Player's performance analysis during the game (match analysis that includes stroke position, ball movement, match sequence, and player's substitutions) is covered in detail in: Pereira et al. [19], Michael et al. [20], Caballero et al. [21], Slawson et al. [22], Belli et al. [23], Gal et al. [24]. Some of the authors, such as Tromp and Holmes [25], Monteiro et al. [26], Franchini et al. [27], Gimenez-Egido et al. [12], García-de Alcaraz et al. [28] and Ortega-Toro et al. [29], attempt to provide a solution for estimating the impact on performance after rule changes, process model analysis by presenting a solution as an example. The approaches to team analysis are discussed in detail by a number of authors.Young et al. [30], Ortega et al. [31], Travassos et al. [32], Korte and Lames [33], Clemente et al. [34] and Laporta et al. [35] discussed a social network analysis. Paulo et al. [36], Kusmakar et al. [37], Woods et al. [38], Araújo and Davids [39] and Vilar et al. [40] offer the ecological dynamics approach for team analysis.

Summary: Several different objectives have been addressed throughout the performance evaluation. The topics listed below are more frequently discussed: detection of potential, specific performance of a young player, analysis of technical skills, player's performance analysis during a game, and the impact of rule changes on player performance. Those topics have already been thoroughly discussed. The reviewers believe there is room for improvement in senior player development, as more athletes can stay competitive into their late thirties. Another area for future research is performance analysis and mental health. As demonstrated recently at the Olympics in Japan, an increasing number of top athletes are starting to experience this problem. It is, therefore, necessary to conduct research into improving training regimes, early detection of mental health problems, and how to plan for posttraumatic stress disorder recovery.

3.1.1. Performance Data

Regarding performance evaluation, data collection and analysis are critical components of the process. It has an impact on the number of sources and databases that are available, depending on how popular sports are among people. The following sources of information were considered for inclusion in the selection:

- Among the authors who use match records and tournament statistics are the following: Laporta et al. [41], García-de Alcaraz and Usero [42], Marcelino et al. [43] and Drikos et al. [44];
- The following authors conduct an investigation into the official ranking analysis: Mertz et al. [45], Lemmer [46], Longo et al. [47], Russomanno et al. [48] and Hansen et al. [49].
- The following authors presented their findings on video/image observation: Tian [50], Raiola et al. [51] and Callaway [52];
- The data collected from wearable devices are used in the analysis described by Stetter et al. [53], Jahren et al. [54], Caporaso et al. [55], Goud et al. [56], Büthe et al. [57], Mahmoud et al. [58] and Yahya et al. [59].

Summary: The chapter on data sources has been a particularly interesting one in this review. Generally, common data sources such as match records, tournament statistics, and ranking information were used in the majority of the studies. Still, only a few studies relied on surveys as their primary data source. The use of more customised data sources and the combination of multiple data sources are two possibilities for future research, particularly in an era in which analysis tools are widely available.

3.1.2. Tools Used for Data Collection/Automation Analysis

The method used to collect data varies from sport to sport. Because of the public and scientific interest, articles about football use the most advanced tools and data collection techniques. Funding is also an important consideration in the development of tools.

Three viable approaches have been identified in the articles. Video/image tracking/recording, geographical positioning system (GPS) tracking, or wearable device tracking are all used to collect data. To accomplish this, only a few systems combine video tracking with wearable sensors. Table 2 contains a list of possible approaches organized by sport. GPS are the most widely used data collection technique in sports.

The Video Tracking Camera System (VTCS) is a technology that captures two-dimensional position data (x and y) at high sampling rates (over 25 Hz). VTCS can collect technical and tactical parameters as well as external load variables. Reily et al. [60] demonstrated a system that uses a single Microsoft Kinect 2 camera to automatically evaluate a gymnast's performance on the pommel horse apparatus, specifically the consistency of the gymnast's timing and body angle. The depth at each pixel determined by the camera provides information not available to traditional sports analysis approaches based solely on RGB data. Amisco Pro, as described by Di Salvo et al. [61], is a multicamera match performance analysis system. During the game, the movements of all 20 players (excluding goalkeepers) are recorded. Amisco Pro tracks players' distance traveled, time spent in five different intensity categories, and time spent in various positions. DigitalStadium (R) is a performance analysis device defined by Beato et al. [62] as a video tracking multiple system with a semi-automatic performance analyst process. Ramón-Llin et al. [63] captured the data with two video cameras and analyzed it with the SAGIT tracking system. The SAGIT algorithm is based on a movement/position analysis. The system recognized the posture from an RGB image, performed an overall evaluation, and returned the information in real time. Tamaki and Saito [64] proposed system for reconstructing the 3D trajectories of table tennis balls using RGB camera data. The introduced method could be used for a match analysis because it has already been demonstrated to provide accurate information for service analysis.

Table 2. Data collection tools.

Tools	Sports	No. of Articles
Amisco Pro	football, running	2
Babolat Play	tennis	1
Digital.Stadium (R)	football	1
Garmin (TM) Heart Rate Band	basketball	1
GPS	cycling, horse racing, sailing, running, surfing, tennis, basketball, football (13), handball (3), hockey, netball, rugby (6), volleyball	32
IMSs	cycling	1
Microsoft Kinect 2	gymnastics	1
Pliance (TM) electronic saddle mat, Casio high speed camera with Quintic (TM) biomechanical software	horse racing	1
Remote, RowX	rowing	1
RGB camera	skeleton, table tennis	2
RTLS	skiing	1
SAGIT	table tennis	1
Sony Smart Tennis	tennis	1
VERT	volleyball	1
Vicon Motion Systems	football	1
Wimu (TM)	basketball	1

Wearable devices provide an excellent opportunity not only to measure the player's motion and position, but also to track the player's physical stage in real time. Garmin (TM) Heart Rate Band and Wimu (TM) inertial devices were used for data collection and real-time monitoring of physical activity and movement during citereina2019training. Heart rate, player load, step counts, and jumps are all outputs from these devices. Wimu (TM) was used by Poureghbali et al. [65] to collect external load and positional data for basketball performance analysis. The kinematic coupling algorithm of inertial motion capture systems (IMSs) used by Cockcroft and Scheffer [66] can measure human kinematics both outdoors and in a laboratory. Magnetic interference is a concern for the system. Swarén et al. [67] used a real-time locating system (RTLS) to track cross-country skiers during a competition. Three RTLS tags have been attached to the antenna of a real-time kinematics global navigation satellite system (RTK GNSS) carried by a skier who skied the course three times at three different intensities. Mahmoud et al. [58] conducted research using the VERT (TM) (Mayfonk Athletic Company) wearable sensing device to measure height jump in volleyball. Bluetooth transmits real-time data to a smartphone or tablet. Last jump, best jump, jump average, and jump amounts can all be recorded. Both the Babolat Play and the Sony Smart Tennis Sensor mentioned by Büthe et al. [57] have been used as wearable devices to track various types of tennis shots and provide a performance analysis to the player. The paper by Llosa et al. [68] offered two different wearable devices for rowing (Remote and RowX). Both devices used sensors from the boat and a person on the boat. These sensors allow for the evaluation of a boat's movement, individual rower performance, or performance in comparison to other crew members.

Hampson and Randle [69] used a combined approach to record all trials and show the influence of the rider on the horse by using a wearable device (Pliance (TM) electronic saddle mat) and a Casio high-speed camera with Quintic (TM) biomechanical software.

Summary: GPS is the most commonly used approach across all 32 projects because it is a simple and cost-effective tool that is easily accessible. It was no surprise that football was the most popular sport using more advanced data collection tools. The popularity of sport has been shown to play a significant role in the income generated by performance analysis tools. It is necessary to conduct technical development across various sports, with a particular emphasis on racket sports. Wearable data collection tools for squash and badminton, for example, must be implemented. One area of concern is the use of wearable devices and the data collected, as data is typically not collected during tournaments because the extra weight affects the stroke.

3.1.3. Methods of Performance Analysis

There are many different performance analysis methods that can be used depending on what is being measured, what data is being analyzed, and what sport is being investigated. Following are some of the techniques that have been identified:

- Statistics methods including ANOVA, one-way ANOVA, two-way MANOVA, linear model, cluster analysis, k-means clustering, logistic regression, Chi-square analyses, Mann-Whitney U-test, discriminant analysis, Matched Paired *t*-test, mixed linear method and Markov chain: Waldron and Worsfold [4], Castellano et al. [70], Torres-Luque et al. [71], Iván Fernández-García et al. [72], Ibañez et al. [73], Douglas et al. [74], Wedding et al. [75], Saavedra et al. [16], Escobar-Molina et al. [76], Konings and Hettinga [77], Croft et al. [78], García-de Alcaraz and Marcelino [79], Gómez et al. [80], Sarajärvi et al. [81], Francis et al. [82], Liu et al. [83], Pawista and Saphie [84], Conte et al. [85], Vencúrik et al. [86], Leicht et al. [87];
- Machine learning: Kusmakar et al. [37], Wenninger et al. [88], García-Aliaga et al. [89], Khan et al. [90], Wang and Hsieh [91], Metulini [92], Rangel et al. [93], Lai et al. [94];
- Neural networks including recurrent neural network (RNN) with long short-term memory (LSTM): Rahmad and As'ari [95], Brock et al. [96], Rahmad et al. [97], Xu and Yan [98], Rahmad et al. [99], Fok et al. [100];
- Decision tree including partial decision tree (PART) and random forest: James et al. [101], Woods et al. [5], McIntosh et al. [102,103];
- Social network analysis: Ortega et al. [31], Travassos et al. [32], Korte and Lames [33], McLean et al. [104], Ramos et al. [105];
- Notational analysis: Saphie et al. [8], Van Maarseveen et al. [106], Raiola et al. [107], Lupo et al. [108], Sampaio et al. [109], Folgado et al. [110], Winter and Pfeiffer [111];
- Self-organising maps: Croft et al. [78], Chassy et al. [112], Croft et al. [113];

Summary: In general, a significant amount of work has been done in the area of performance analysis methods. Statistical methods have been implemented across various sports and data sources, followed by large implementations of notational analysis. Three regions can be explored further: neural network analysis, social network analysis, and the use of self-organizing maps.

3.1.4. Software Used to Analyze Performance

As their primary data input, the following software used video/image data collection, wearable devices, or GPS. FRAMI, a computer software for judo matches, was introduced by Sherwood et al. [114]. The system is used to analyze both technical and tactical behaviors in a video match. FUT-SAT is a tactical assessment system designed specifically for football/soccer that is used by Moreira et al. [115] and Machado et al. [116]. The system allows for the progression of player movement in the game across all age groups and levels. FUT-SAT analyzes the player's actions during the game, with ball possessions serving as the primary unit of analysis, followed by tactical action assessments. Bagadus is a real-time prototype of a sports analytics system described in Stensland et al. [117]. Using a video camera array, the system integrates a sensor system, a soccer analytic annotations system, and a video processing system. In their study, citelegg2012matchpad presented visualisation software, MatchPad. The MatchPad assisted coaches in examining actions and events in detail while maintaining a clear overview of the match, and it also assisted them in making decisions during the matches. It also enables coaches to communicate critical information to players in a visually engaging manner, thereby improving their performance. In their article, Zhang et al. [118] outlined a computer vision technology to establish a sport detection and analysis system using an RGB camera and deep learning models. SportVU is an optical tracking technology used in basketball by Wu and Bornn [119]. The system enabled performance statistics by extracting coordinates of players and the ball with statistical algorithms to provide greater match insights and generate data for the most recent AI analysis software. Silva et al. [120] presented Ultimate Performance Analysis Tool (uPATO) enabling observing, codifying, importing, visualizing, computing measures, and exporting data from observed games. The tool enabled the introduction of data based on adjacency matrices as well as the integration of various metrics used for team sports analysis. The ability to analyze GPS data is a significant advantage of this tool.

Summary: There has not been much progress in the development of performance analysis software until recently. In the studies that were reviewed, less than ten different pieces of software were used. All the above software is used as the primary input video or image collected by a player's integrated camera or software working with a GPS. This area has been identified as having significant potential for new development. One of the suggestions is to use a combined approach of GPS and video/image as the primary data input, which would be more accurate. The second option is to use historical data to compare it to data collected during a live in-game session. In addition, analysis from GPS or wearable technology must be more automated and personalised to provide in-game advice to players.

3.1.5. Performance Prediction

Performance prediction is a topic that has been extensively discussed in a number of articles and books. In this paper, the authors describe the various approaches that were used, starting with standard statistical methods and progressing to sport-specific software at the end. The following questions have been addressed by researchers in an attempt to provide answers:

- Which performance indicator best predicts success?
- Can game statistics be used to forecast success?
- How can a successful player be identified?
- How much of an impact does travel/match location have on player/team performance?

Wei et al. [121] used Hawk-Eye ball and player tracking data to identify unique player styles and predict within-point events. The study used spatial and temporal information to better characterize each player's tactics and tendencies, in addition to coarse match statistics (i.e., serves, winners, number of shots, and volleys). To model player behavior, a probabilistic graphical model is used. Because player behavior is affected by the opponent, model adaptation was used to improve our prediction. As a new measure for table tennis players, Ley et al. [122] proposed the mutual point-winning probabilities (MPW) as server and receiver. The MPWs quantify a player's chances of winning a point against a given opponent and thus complement the traditional match statistics history between two players nicely. These new quantities are based on a statistical model of the type Bradley-Terry, which takes into account the significance of individual points. A random forest algorithm with parameters such as acceleration, rally duration, and time between rallies was used in a study by Dieu et al. [123] for prediction of conative stages with a prediction accuracy possibility for badminton. To demonstrate the potential impact of home vs away matches, Lo et al. [124] used general and generalised mixed linear models for rugby points difference and match won or lost prediction. Article published by Linthorne et al. [125] proposed prediction method combines the equation for the range of a projectile in free flight with the measured relationships between the athlete's take-off speed, take-off height, and take-off angle. The results of this method agreed well with the athletes' competition take-off angle.

Prediction of an Athlete's Career Path

Kłys et al. [126] took an interesting approach to optimizing sport skill level predictors for female judo athletes using Probabilistic Neural Network (PNN). In a research conducted by Lai et al. [94], network analysis and machine learning are used to estimate the contribution of the network of matches in predicting an athlete's success. Li et al. [127] research also discusses career path prediction. The introduced prediction method is based on thirty years of longitudinal data that included 82 top ten professional players between 2007 and 2017. The practical implications of the above-mentioned articles' findings, specifically informing career planning, predicting professional success, monitoring, and assessing emerging tennis players, are discussed.

Summary: Prediction performance is an area of study that has been debated in many publications and books due to the high level of interest in the subject that has been expressed not only by players and coaches but also by team leaders, bookmakers, and team supporters. Despite the high level of interest in this subject, there is no reliable solution for result prediction in the literature. Since large databases are available, a machine learning approach that is potentially fuzzy has a great opportunity to be used, as we have stated earlier. While it is true that many predictions had as their goal the prediction of the athlete's career path, there is room for improvement, such as the inclusion of more sophisticated computing methods.

3.2. SR2: A Systematic Review of Publications on Racket Sports

The 65 publications that were analyzed were published in 38 different sources between 1997 and 2021. Since publication, the average number of years since publication is 3.86, the average number of citations per document is 7.092, and the average number of citations per year per document is 1.496. There are a total of 123 references in these publications.

Taking a look at the different types of documents, there are 53 articles, one publication that is marked as an Early Access Article, one publication that is marked as an article and conference paper, and ten publications that are marked as conference or proceedings documents.

All four of the most well-known racket sports have been taken into consideration in the reviewed papers. There have also been some publications that have mentioned a novelty sport called paddle tennis, as well. A total of 65 publications has been evaluated.

3.2.1. Classification by Racket Sport and Methodology

The distribution of publications for each racket sport is represented in Table 3. Tennis is the most widely represented racket sport in the publications studied.

Table 3. Distribution of the performance methodology for each racket sport.

Sports	Performance Analysis Method	Publications
badminton	combine approach (observation+statistical)	[123]
	n/a	[128]
	neural network	[95,97,99,129,130]
	observation	[131–134]
	statistical approach	[71,135–137]
padel tennis	neural network	[138]
	observation	[139–143]
	observation (tracking software)	[63,144]
	statistical approach	[145–147]
squash	observation (tracking software)	[148]
	statistical approach	[149]
table tennis	neural network	[94]
	observation	[150,151]
	observation (tracking software)	[64]
	statistical approach	[122,152,153]
tennis	observation	[12,23,57,121,154–158]
	observation (tracking software)	[159]
	statistical approach	[72,127,160–176]

We could divide the selected works into four broad categories:

- publications that use observation as the primary tool;
- publications that use a standard statistical approach;
- publications that use a combination of observation and statistics;
- non-statistic methods, primarily neural networks.

Figure 3 illustrates the distribution over time of the methodology for selected publications.

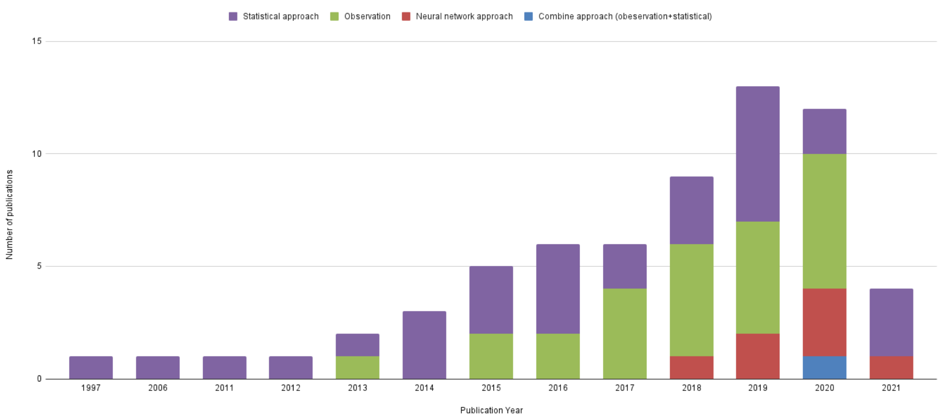


Figure 3. Performance analysis methods of selected publications given the publication year.

Observation

Despite technological advancements, the observation methodology remains an important tool for quick and cost-effective performance analysis across racket sports. Torres-Luque et al. [131] provides an example of technical and tactical analysis for badminton. The primary goal of this study was to create, validate, and estimate the dependability on an observational instrument for analyzing tactical and technical actions in individual badminton. Aiken's V coefficient was used to calculate the validity.

Roberts et al. [130] present a frame-by-frame analysis to distinguish between skilled and less skilled athletes. The current study seeks to address this issue by observing measures of anticipation in purely naturalistic match-play. The influence of skill level corresponds to empirically derived suggestions of skilled athletes accessing domain-specific knowledge for future event prediction.

Valldecabres et al. [133] created an ad hoc observational tool for badminton singles games that consists of 13 criteria and 47 mutually exclusive categories. There were 287 actions from the 2015 Badminton World Championship that were studied. Cohen's Kappa and generalizability theory were used to evaluate the tool's validity.

Yong and Tan [137] provides an example of the regression analysis method. The study looks into the connection between movement accuracy and heart rate data collected by the Microsoft Kinect tool.

Chiminazzo et al. [134] presented observational analyses of technical and timing variables to provide critical information for understanding the match. The technical and timing variables of badminton men's singles matches in the 2016 Olympic Games were examined and compared between groups and play-off stages. The study's findings are important for comprehending the game and providing information for training planning.

Statistical Approach

Barreira et al. [135] illustrate the statistical approach. The purpose of that work is to calculate the point difference between winners and losers in badminton games. To characterize the data collected from the tournament platform, the published analysis employs average, median, standard deviation, quartiles, minimum, and maximum values. The Shapiro Wilk statistical test was used to confirm the data's normality. The Mann-Whitney test was used to compare the maximum difference in points established by the game's winners and losers.

In [136], the Crosstabs-Command and binomial logistic regression methods were used to determine the interactive effects of each contextual variable on challenge success (gender, requester player, next point winner, score-line, game, game interval, games in favor, challenges left per game, match-outcome, and player's international experience). The main findings revealed that the request affects the success of a challenge with less efficiency when the player requests the hawk-eye (odds ratio [OR] = 0.65) and when the player who requests the hawk-eye is the loser of the match (OR = 0.21). The identified trends enable players to improve strategic plans that include determining the best time to request a Line Review.

Torres-Luque et al. [71] found statistical differences in a set of badminton competition matches in five different modalities in terms of competition level (Group Phase vs. Eliminatory Phase). Non-parametric data were subjected to a descriptive analysis and a univariate test (Mann-Whitney U). The findings of the analysis presented here could assist players and coaches in planning and implementing various types of workouts or, more specifically, competition schedules tailored to the characteristics of badminton.

Combine Approach

Dieu et al. [123] combined observational approach (10 expert coaches) with a random forest algorithm. The publication emphasized the benefits of performance analysis from the juxtaposition of subjective and objective data to design training plans based on the participants' level of expertise.

Neural Networks

The recent work of Gómez et al. [129] on bipartite networks for modeling racket sport performance. Non-linear and ecological approaches are associated with bipartite networks. Badminton stroke networks (BSN) were created by analyzing a player's and their opponents' match activities. The model was able to recognize various playing patterns. The identification of each player's network and its association with point outcomes, in particular, provided a better understanding of stroke performance and individual characteristics of world-class badminton players.

Rahmad et al. [97] focused on creating an automated system that used Faster Region Convolutional Neural Network (Faster R-CNN) to track the position of the badminton player from the sport broadcast video. Several different trained Faster R-CNN detectors were generated from the dataset before being tested on a variety of videos to assess detector performance. The study found that when the detector is fed a more generalised dataset, it successfully detects the player.

Rahmad et al. [99] used a pretrained Convolutional Neural Network (CNN) method to create an automated system for badminton smash recognition on widely available broadcasted videos. The CNN models were built using smash and other badminton actions from the video, such as clear, drop, lift, and net.

Summary: Tennis is primarily depicted as a racket sport in the literature that has been reviewed. Considering that it is famous worldwide, as opposed to badminton, which is the most popular at the competitive level in Asia, this is not a surprising outcome. Four broad groupings of performance analysis categories have been identified across 65 publications reviewed. Although tennis is the most researched sport, only one paper addressed tracking software as a tool for performance evaluation. The publications for badminton, padel tennis, and table tennis feature all four groups, followed by tennis publications with three groups, and finally squash publications with only two ways. For racquet sports, a significant opportunity has been identified to apply machine learning, decision trees, and neural networks (particularly for tennis and squash, where no reviewed literature has used this method) for performance analysis (especially for tennis and squash). Looking at Figure 3 it can be seen that the neural network technique is showing some promising patterns. Greater participation of software technologies, such as automatic in-game movement recognition and evaluation and in-game wearable devices for badminton, table tennis, and squash, should be considered in future research efforts.

Result. *Research hypothesis R3-not confirmed.*

3.2.2. Source Title Categorization

The specific source title is assigned to publications covered by the Web of Science Core Collection and SCOPUS databases. For the sixty-five selected English-language publications, thirty-nine distinct sources have been identified. Eight of the title sources have multiple publications. The first twenty sources are listed in Table 4.

Surprisingly, all nine publications published in the "International Journal of Sports Science and Coaching" were about tennis. Publications from the second most countable source, the "International Journal of Performance Analysis In Sport", cover all five sports.

Figure 4 displays a bar graph for the selected publications, displaying the total number of publications, the average number of citations per publication, and the corresponding average number of pages per publication. The graph displays the results according to the type of source. The first section displays the frequency of documents for various research areas. The second section focuses on the average number of citations, while the third section displays the average number of pages per article. The International Journal of Sports Science and Coaching received the fewest citations. German Journal of Exercise And Sport Research publications have the fewest pages on average.

Table 4. The 20 most relevant sources.

Sources	Articles
International Journal of Sports Science and Coaching	9
International Journal of Performance Analysis In Sport	7
Frontiers In Psychology	5
Journal of Sports Sciences	5
International Journal of Environmental Research And Public Health	3
German Journal of Exercise And Sport Research	2
Journal of Human Kinetics	2
Ricyde-Revista Internacional De Ciencias Del Deporte	2
2013 IEEE Conference on Computer Vision And Pattern Recognition Workshops	1
2016 IEEE 13th International Conference on Wearable And Implantable Body Sensor Networks	1
2017 International Conference on Robotics Automation And Sciences	1
2017 International Electrical Engineering Congress	1
2018 19th IEEE Mediterranean Electrotechnical Conference	1
2018 25th International Conference on Systems Signals And Image Processing	1
Applied Sciences-Basel	1
Big Data	1
Computational Intelligence In Information Systems	1
Computer Vision And Image Understanding	1
Chaos Solitons and Fractals	1
Children-Basel	1

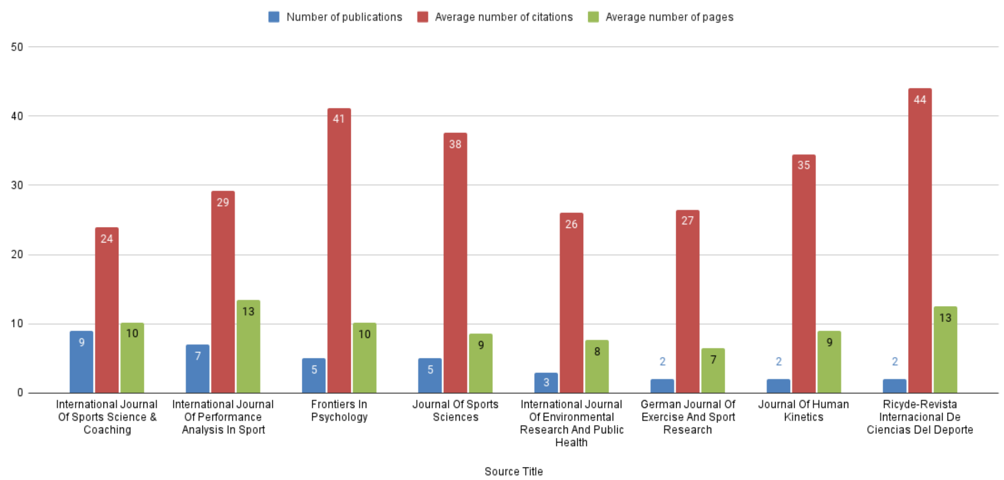


Figure 4. Sources of selected publications, average citations and average number of pages.

Summary: Source title categorization showed the expected results with the International Journal of Sports Science and Coaching as a top source followed by the International Journal of Performance Analysis In Sport. Looking at the source analysis with more than two publications, the minimum is 24 average number of citations, and the maximum is 44 average number of citations. The number of pages varies from seven to thirteen. Those numbers could be a good indicator for future work in terms of the quality of the sources and the ideal length of the publications.

3.2.3. Analysis of Publication Year

Figure 5 depicts the distribution of the selected publications over time. The distribution of publications is influenced by a major sporting event. The peak was recently recognized for the Olympic games. It could be for a variety of reasons, including:

- data are easily accessible to large groups;
- data are collected in a more advanced manner;
- more funding is available for performance analysis to achieve a gold medal;
- widespread public interest.

Indeed, it depends on the Olympic priority for each sport, but in general, the Olympics are the most important event. A similar relationship could be found between football and the World Championship event. The first publication, in 1997, examined the competitiveness of elite professional tennis athletes. After a long 14-year wait, the first publication for another racket sport was published in 2011 for table tennis, followed by squash in 2014 and padel tennis in 2015. In 2016, badminton was the most recent racket sport to be included in publications.

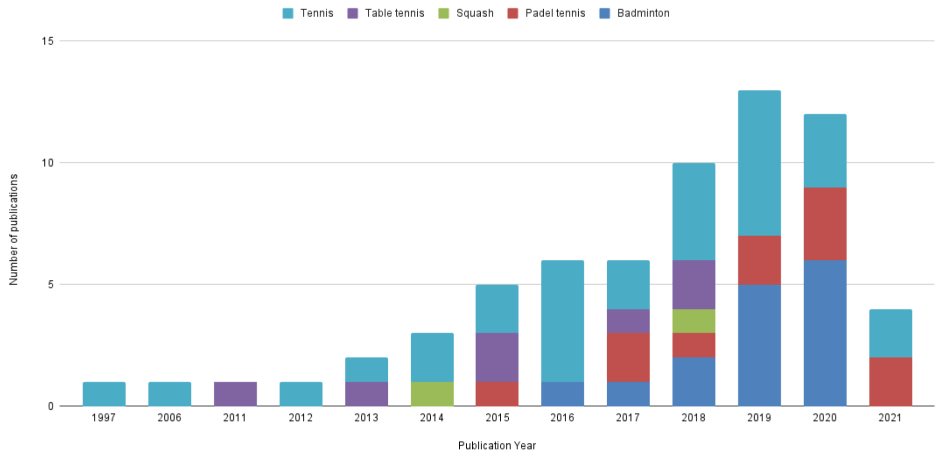


Figure 5. Year of publication, categorized by sport.

Summary: Except for 2020, the analyses of the published years confirm that the R1 and R2 research problems have been answered. When considering how to organize the research to have participants collaborate and have sufficient data for the study, this tendency could be an indicator.

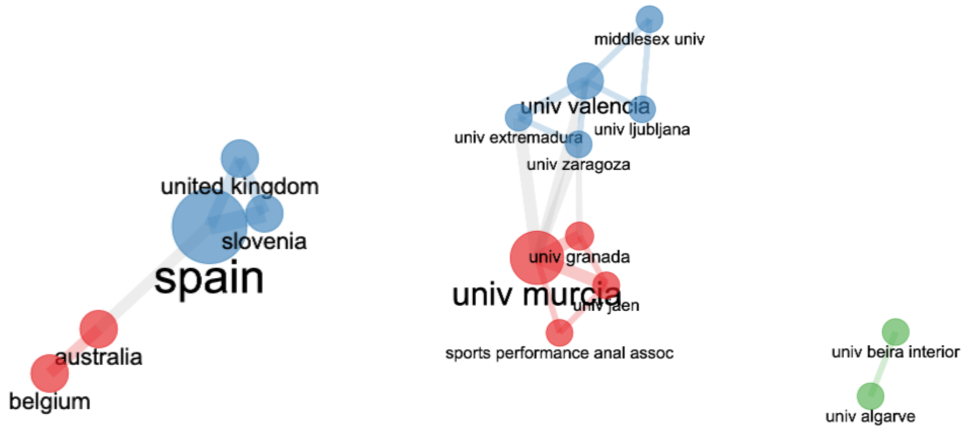
Result. *R1 and R2 research hypotheses were confirmed, with the exception of data from 2020. This anomaly occurred as a result of the pandemic, which caused the majority of sporting events, including the Summer Olympic Games, to be canceled.*

3.2.4. Analysis of the Authors' Teams, Affiliations, and Countries

Bibliometric analysis cannot be performed without the authors' approval. There were a total of 197 authors identified, with a total of 257 times that an author appeared in the database. There has been no publication of a separate author's work, with an average of 3.03 authors per document published. Table 5 contains a list of the top twenty authors in the field.

Result. *Research hypothesis R5—confirmed.*

We concentrated on demonstrating co-authorship. As illustrated in Figure 6a, these authors are organized into larger or smaller groups.



(**a**) Country collaboration (**b**) Affiliations cooperating

Figure 6. Cooperation on the basis of country and affiliations.

Table 5. Top 20 most relevant authors.

Authors	Articles	Authors	Articles
Ramon-Llin J	7	Kondric M	3
Torres-Luque G	6	Martinez-Gallego R	3
Sanchez-Alcaraz B	5	Munoz D	3
Gimenez-Egido J	4	Ortega-Toro E	3
Sanchez-Pay A	4	Rahmad N	3
As'ari M	3	Araujo D	2
Blanca-Torres J	3	Barreira J	2
Canas J	3	Cabello-Manrique D	2
Courel-Ibanez J	3	Carvalho J	2
Guzman J	3	Davids K	2

We divided the authors into groups based on their collaboration with their co-authors, with a curve connecting the co-authors. The size of each connection's node corresponds to the number of documents written by the given author. The average year of publication of the author's papers was used to create the color distinction of the authors. The majority of the authors are from Spain, and all of them are related. More than four documents have been published in Spain, the United Kingdom, Australia, France, and Malaysia.

When we look at the number of times a country is mentioned in the author affiliates, we find that Spain is mentioned 67 times, the United Kingdom is mentioned 13 times, Australia is mentioned 11 times, France is mentioned 9 times, Portugal is mentioned 8 times, Brazil is mentioned 7 times, Italy is mentioned 7 times, the United States of America is mentioned 7 times, Belgium is mentioned 6 times, Malaysia is mentioned 6 times, Slovenia is mentioned 6 times, Turkey is mentioned 3 times, Croatia is mentioned twice, and Germany is mentioned once. Germany is mentioned once.

The university collaboration is depicted in Figure 6b and with the additional indications detailed in Table 6. While it is interesting to note that there are only two distinct clusters, it is also worth noting that racket sports are found all over the world. Padel tennis was invented in Mexico and is currently the most popular in Spain, Mexico, Italy, and countries in the Hispanic American region, according to the International Tennis Federation.

Table 6. 20 Corresponding author's country (SCP: single country publications, MCP: multiple country publications) and 20 Most Relevant Affiliations.

Country	A	SCP	MCP	Affiliations	A
Spain	17	12	5	Univ Murcia	12
United Kingdom	6	6	0	Univ Valencia	10
Australia	4	1	3	Univ Estadual Campinas	6
France	4	4	0	Univ Granada	5
Malaysia	4	4	0	Univ Jaen	5
Argentina	3	3	0	Univ Ljubljana	5
Belgium	3	1	2	Univ Extremadura	4
Brazil	3	3	0	Univ Politecn Madrid	4
Italy	3	2	1	Univ Zaragoza	4
Slovenia	3	2	1	Universiti Teknologi Malaysia	4
Portugal	2	0	2	Sheffield Hallam Univ	3
USA	2	2	0	Univ Caen Normandy	3
Croatia	1	0	1	Univ Ghent	3
Germany	1	1	0	Univ Loughborough	3
China	1	1	0	Univ Politecn Catalunya	3
Japan	1	1	0	Auckland Univ Technol	2
Lebanon	1	1	0	Catholic Univ Valencia San Vicente	2
New Zealand	1	1	0	Middlesex Univ	2
Switzerland	1	1	0	Queensland Univ Technol	2
Thailand	1	1	0	So Cross Univ	2

It is possible that Rafael Nadal is one of the biggest male tennis players in the world and the best Spanish singles player.Surprisingly, few badminton publications have come from Asia, despite the fact that the region has the greatest interest in the sport among the general public. Since Spanish badminton singles player Carolina Marin won the gold medal at the Olympics, the country has shown increased interest in the sport.

Summary: It was discovered that a total of 197 authors were identified; however, only three were found to be authors of more than five papers. The average number of authors per article is only 3.03 individuals. The fact that only two unique clusters have been identified due to the academic collaboration is noteworthy. This came as a complete surprise because the level of racket sports varies from one region to the other. Spain's success in tennis and badminton isn't a surprise because the country has some of the best players in the world. More communication could be proposed for future work in this area.

Result. *Research hypothesis R4—confirmed.*

3.2.5. Keyword Analysis

Overall, there were 180 Keywords Plus in the examined documents, along with 158 Authors' Keywords.

Tableau Software generated a keyword word cloud, which is depicted in Figure 7. The size of the keywords represents how frequently authors use keywords. Not only are the keywords divided by size, but they are also divided by sport. The performance analysis phrase is most commonly used in tennis. As a result, this phrase is the longest and greenest. Except for squash, performance analysis is the most frequently used keyword in the majority of racket sports, with the highest frequency of twenty-two for tennis. Tennis publications provide the most keywords (114), followed by badminton (62), padel tennis (49), table tennis (29), and squash (21). (9). As more technology for in-game analysis becomes available, the keywords used in tennis publications become more specific. Surprisingly, the statistical approach was used first, followed by the observation approach, which is simpler than any statistical analysis. In 2018, neural networks were introduced into the analysis, and more advanced methods and software became available. It is very interesting that the number of publications using the observation methodology has remained consistent over time, whereas the statistical approach may have shifted to more advanced methods such as neural networks.

Figure 7. Keyword analysis based on the frequency for a specific racket sport.

Table 7 shows the most frequent words defined by authors and the most frequency words in title. It is interesting that only 44 publications mention performance analysis as a keyword. Only 8 of the 25 tennis publications mention tennis, a similar ration could be found for badminton where only 5 out of 15 publications mention badminton. It is interesting to compare those results with the keywords in title. More than 50% of tennis publications define tennis and all of the 15 badminton publications mention badminton in the title.

Table 7. Most frequent words—author keywords and title words.

Author Keywords	Occurrences	Title Words	Occurrences
performance analysis	44	tennis	35
racket sports	13	analysis	20
tennis	8	players	16
racket sport	7	badminton	15
badminton	5	performance	13
match analysis	5	padel	11
racquet sports	4	professional	9
sport analytics	4	elite	8
deep learning	3	match	8
notational analysis	3	table	8
sport performance analysis	3	serve	6
sports	3	success	6
table tennis	3	data	5
accuracy	2	game	5
coaching	2	network	5
disability	2	outcome	5
elite success	2	vision	5
equipment scaling	2	differences	4
fatigue	2	characteristics	4
hawk-eye data	2	player	4

Figure 8 depicts a hierarchical cluster of keywords defined by authors. There are two major clusters that have been identified. There is a large cluster around tennis and a smaller cluster around badminton. The main reason for the larger tennis cluster is that table tennis and padel tennis include keyword tennis, as demonstrated in previous publications.

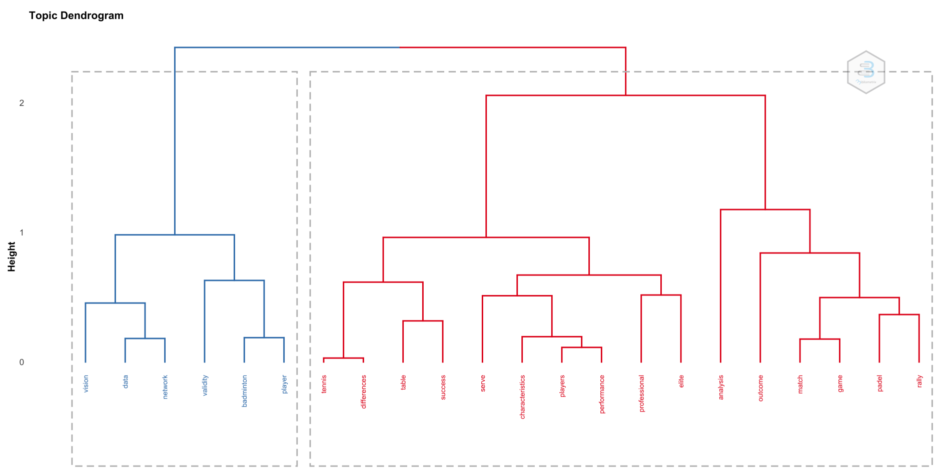


Figure 8. Dendrogram.

Summary: Results from a review of the keywords and title were quite interesting. As of this writing, only 44 articles use the term "performance analysis". More than half of tennis publications define the sport, and all 15 badminton publications have the word "badminton" in the title. It is highly suggested that any future research should include the term "performance analysis" as a keyword and mention the sport's name in the title. These enhancements make it possible to search for information more precisely and accurately.

3.2.6. Analysis of Citations

Table 8 shows the twenty most cited documents. The top two publications conduct research on padel tennis, which is a surprising result given the sport's low popularity when compared to other sports. Padel tennis is not even an Olympic sport, like tennis, table tennis, or badminton, and it is the most recent racket sport to be introduced to the world.

Table 8. The 20 most-cited documents on a global scale.

Paper	Total Citations	TC per Year	Normalized TC
Courel-Ibáñez et al. [143]	42	8.4	3.761
Courel-Ibáñez et al. [146]	38	5.429	2.676
Rhodes et al. [177]	36	4.5	2.25
Mecheri et al. [168]	19	3.167	1.754
Carvalho et al. [161]	18	2	1.636
Houston et al. [163]	17	0.68	1
Hammond and Smith [172]	16	1	1
Hizan et al. [170]	15	2.143	1.056
Ramón-Llin et al. [144]	14	4.667	2.676
McRae and Galloway [162]	14	1.4	1
Kilit et al. [169]	13	2.167	1.2
Büthe et al. [57]	13	2.167	1.2
Chiminazzo et al. [134]	12	3	3.529
Munivrana et al. [155]	11	1.571	0.775
Sánchez-Alcaraz et al. [141]	10	5	3.243
Renò et al. [154]	10	2	0.896
Barreira et al. [135]	10	1.667	0.923
Carvalho et al. [164]	10	1.25	0.625
Rahmad et al. [97]	9	3	1.721
Sánchez-Alcaraz et al. [140]	9	4.5	2.919

Summary: A look at this aspect of the review revealed that the top two most cited writers think of padel tennis as a research topic. This result demonstrated a general interest in the newly-formed sports across a broad spectrum of disciplines. To achieve a significant number of citations, it is recommended that future studies examine novel sports (for example, padel squash, or outdoor badminton) or develop performance analysis (which may incorporate machine learning, artificial intelligence, or fuzzy neural networks).

4. Discussion

We have identified a number of future research opportunities. Standard statistical methods were used in the publications, but only a few of the 1001 publications mentioned artificial intelligence, cloud computing, or machine learning. As a result, the main area of development is considered the implementation of more advanced techniques, such as the use of the fuzzy approach. Racket sports are an excellent example of a sport in which traditional methods based on neural networks are used. In comparison, neural networks are widely used in football publications. The number of publications using observation methodology has remained consistent over the years, while the statistical approach has shifted to more advanced methods such as neural networks. Publications with more advanced methodologies are expected in the coming years.

Football is the most widely discussed sport in performance analysis publications, followed by basketball and rugby. The performance analysis of team sports used more advanced techniques for data collection, analysis, and prediction of results. As the automation system becomes available, publications from this sports environment usually describe a larger data set. According to the previous assertion, the distinction between well-analyzed sports such as football and racket sports is the emphasis on junior development. More work needs to be done to identify and develop junior talent.

Furthermore, more automation for data collection, cleaning, and analysis can be included, as some of the articles mentioned manually data collection/observation and expert analysis may result in misjudgment due to the human factor. No complex solution for performance analysis that connects the results and training plan was identified in the publications, indicating a large opportunity here.

Because the majority of publications have been distributed across only a few countries, there is definitely room for more cross-country collaboration.

E-Sport and Virtual Reality

Only a handful of publications mention e-sports as a component of sports performance analysis in general. It is critical to investigate performance analysis for e-sport athletes, as this will aid in the evolution of standard performance analysis techniques over time. E-sports is a developing field that presents a significant opportunity, primarily due to the increased availability of funding and technological resources. E-sports could be viewed as a more straightforward method of implementing tracking and evaluation systems. When compared to the usual athletes, it is easier to keep track of their performance. Another reason why e-sports should be taken into consideration is their popularity among the younger generation. Rarely do publications discuss the use of augmented and virtual reality as an environment for evaluating and improving performance. It is a fantastic opportunity because this topic has not been discussed extensively across a wide range of publications.

5. Conclusions

In the field of sports performance research, performance analysis is becoming increasingly important. Its growth has been aided by the availability of cutting-edge technologies and smart devices.

The collection and analysis of data from 759 analyzed publications on various sports revealed that data collection and analysis are critical components of athlete performance evaluation. Sixteen performance analysis tools were identified and classified based on the sport in which they were used. Statistical methods, machine learning, neural networks, decision trees, social network analysis, notational analysis, and self-organizing maps were identified as the seven groups of performance analysis methods. We also presented the various types of performance analysis software that were discussed. Predicting performance was accomplished by focusing not only on predicting the trajectory of an athlete's athletic career and extracting four key questions.

The second part of the results concentrated solely on racket sports, which were the subject of 65 publications. These publications confirmed the assumptions that the number of publications is increasing and is influenced by the Summer Olympic Games, that publications on performance analysis require a multiauthor team, usually composed of a specialist in the sport and an expert in the analysis method used, and that performance analysis of racket sports is exclusively published by European authors. The assumption that the observation method is the most commonly used method, on the other hand, has not been confirmed. Four methods of performance analysis were identified for the racket sports (badminton, padel tennis, squash, table tennis, and tennis), as well as their frequency of use. We identified key publication sources and author teams based on the bibliometric analysis. This is where the predominance of European authors emerged, along with the dominance of Spain. The keyword analysis revealed only two clusters for the author's keywords: a large cluster centered on tennis and a smaller cluster centered on badminton. It was surprising to discover that the most cited articles are about Padel tennis, the youngest racket sport.

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