

Beyond Traditional Metrics: A Systematic Review of Spatial and Spatiotemporal Indicators in 5-on-5 Basketball

Yana Liu, Wenlong Zhang, Mingquan Zhang, Qi Su and Xiao Xu ✉

¹ College of Physical Education, Dalian University, Dalian, China

Abstract

Basketball performance analysis has traditionally relied on event-based statistics and box-score-derived metrics. Although these measures describe performance outcomes, they provide limited information about how actions are shaped by player location, movement, and interaction during play. With the growing availability of court-referenced player and ball location data, spatial and spatiotemporal indicators have become increasingly common for describing game behavior in basketball. For the purposes of this review, spatial indicators were defined as location-based measures captured at a given moment, such as shot location, defender distance, or team spacing. Spatiotemporal indicators were defined as measures that capture movement or changes in spatial configuration over time, such as dyadic coordination, team expansion, or changes in possession value. This systematic review examined how these indicators have been operationalized and applied, and how their outputs have been interpreted in relation to tactical performance. This systematic review was conducted in accordance with the PRISMA guidelines. Searches were conducted in PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar for studies published through 15 September 2025. Studies were eligible if they examined standard, regulation 5-on-5 basketball, used court-referenced player and/or ball location data during match play, and derived spatial or spatiotemporal indicators relevant to tactical, technical-tactical, or game-performance questions. Reporting completeness and transparency were appraised using a STROBE-based framework for empirical/observational studies and an adapted TRIPOD-informed checklist for modeling/analytics studies. A total of 759 records were identified, of which 16 studies met the inclusion criteria. The included studies addressed offensive, defensive, and combined offensive-defensive contexts. Five studies used a state-based measurement approach, eight used a sequence-based approach, and three used both. Individual/local spatial indicators most commonly included shot location, distance to the basket, defender distance, shot angle, and shot-trajectory factors. Interactional indicators included dyadic coupling, attacker-defender distance, passer-receiver relations, and secondary-assist-related measures. Collective indicators included team spatial center, stretch index, court-area occupation, team width, and centroid movement. Defensive-impact indicators included defensive shot frequency and shot-efficiency effects, whereas model-derived and complexity indicators included expected possession value, player gravity, and intrinsic dimension. Spatial and spatiotemporal indicators extend basketball performance analysis beyond traditional outcome-based metrics by revealing where players were located, how they interacted spatially, and how team structure changed during possessions. However, they should not be interpreted as direct measures of tactical effectiveness. Their interpretation should be anchored in possession phase, shot or pass event, defender proximity, offensive or defensive context, and whether the indicator was derived from a single game state or a sequence of play.

Key words: Basketball, positional data, spatial indicators, spatiotemporal indicators, tactical performance.

Introduction

Basketball performance analysis has traditionally relied on event-based statistics and box-score-derived metrics to describe game outcomes and key actions (Hughes and Bartlett, 2002; Kubatko et al., 2007; Oliver, 2004). These measures typically include event counts, efficiency ratios, and possession-based metrics (Angel Gomez et al., 2008; Kubatko et al., 2007; Lorenzo et al., 2010). Event counts, such as rebounds, assists, and turnovers, quantify how often key actions occur. Efficiency ratios, such as field-goal percentage and opponent field-goal percentage, summarize the success with which actions are completed. Possession-based metrics use the possession as the unit of analysis and therefore provide a closer approximation of game flow, but they still provide limited information about the spatial and temporal conditions under which actions are generated. These outcome-based indicators provide coaches with useful information for identifying team strengths and weaknesses, monitoring game dynamics, and informing in-game adjustments (Courel-Ibáñez et al., 2017; Hughes and Bartlett, 2002; Oliver, 2004). However, although these measures provide relatively stable summaries of performance, they offer limited insight (Bourbousson et al., 2010a; Cervone et al., 2016; Courel-Ibáñez et al., 2017). Accordingly, they are effective for describing discrete events and outcomes, but less effective for explaining how those outcomes emerge during play (Cervone et al., 2016; Courel-Ibáñez et al., 2017; Lamas et al., 2015).

Early research using player and ball positional data was limited by the difficulty of collecting reliable movement data, and only a small number of studies initially examined the spatiotemporal rhythm and interaction structure of basketball (Bourbousson et al., 2010a; Courel-Ibáñez et al., 2017; Perše et al., 2009). With advances in optical tracking, video-based analysis, and automated positioning technologies, the availability of positional data has increased substantially, and basketball research has increasingly incorporated analyses of spatial and spatiotemporal structure (Gudmundsson and Horton, 2017; Torres-Ronda et al., 2022; Van der Kruk and Reijne, 2018). For example, Goldsberry (2012) used shot-location distributions to characterize the spatial conditions of offensive attempts, showing that spatial information can complement traditional statistics when assessing shot quality. Bourbousson et al. (2010a; 2010b) extended this line of work by analyzing

spatiotemporal coordination from player trajectories and identifying dynamic coupling within and between teams. Measures derived from player and ball locations are now used to describe positioning, movement, and interaction during play, allowing performance analysis to move beyond discrete events and final outcomes (Cervone et al., 2016; Courel-Ibáñez et al., 2017; Lamas et al., 2015). Game behavior can therefore be examined not only in terms of results but also in relation to the contexts and processes through which those results emerge (Cervone et al., 2016; Gudmundsson and Horton, 2017; Lamas et al., 2015). In practical terms, positional information is important because the tactical meaning of an action is not determined by the event alone. The same successful shot may reflect a well-organized possession in which the defense has been displaced, or it may result from an individual solution late in the shot clock. Similarly, a completed pass may help maintain an offensive advantage, but it may also be made primarily to release pressure after the initial option has been denied. In this sense, positional context helps connect observable actions to tactical performance by showing whether players used space, timing, and teammate-opponent relations to create, maintain, or limit advantage during play (Franks et al., 2015; Sampaio et al., 2016).

The increasing use of spatial and spatiotemporal indicators has not necessarily resolved the problem of interpretation. The central issue is no longer whether these indicators can describe basketball behavior, but the extent to which they can justify credible inferences about tactical performance. In the current literature, similar indicators are often used to support different levels of inference, ranging from straightforward descriptions of game situations to broader interpretations of tactical behavior (Chen et al., 2025; Mackenzie and Cushion, 2013; Rein and Memmert, 2016). In many cases, however, the link between a measured spatial pattern and its tactical meaning remains insufficiently specified. This interpretive problem is compounded by heterogeneity in indicator construction across studies. Some indicators focus on the spatial conditions surrounding individual actions, whereas others address local player interactions or team-wide organization (Duarte et al., 2012; Fewell et al., 2012; Miller et al., 2014). Some indicators capture brief game states at specific moments, whereas others describe processes that unfold over time (Perše et al., 2009; Reich et al., 2006; Santos-Fernandez et al., 2022). In addition, model-based studies introduce further assumptions about how space, interaction, and analytical relevance are represented (Cervone et al., 2016; Franks et al., 2015; Zuccolotto et al., 2023). These differences are consequential because they shape the strength with which an indicator can support tactical interpretation (Chen et al., 2025; Mackenzie and Cushion, 2013; Rein and Memmert, 2016).

In the present review, tactical performance is understood as the organization of player actions through positioning and movement in relation to teammates, opponents, and the evolving game situation (Araújo et al., 2006; Lamas et al., 2015; Vilar et al., 2012). From this perspective, spatial and spatiotemporal indicators can describe ob-

servable behavioral patterns, but they do not directly measure tactical intent or tactical effectiveness. This distinction is important because location-based analysis is better understood as a way of representing tactical behavior rather than as direct evidence of tactical effectiveness. In this review, possession context refers to the situational conditions within a possession that shape how an indicator should be interpreted. These conditions include the phase of play, action type, player-ball relations, defensive pressure, and the surrounding sequence of actions before and after the measured event. This operational definition was used to ensure that each indicator was interpreted in relation to the possession from which it was derived.

Previous basketball and team-sport reviews have described collective behavior, positional data, and analytical approaches in invasion games more broadly (Chen et al., 2025; Courel-Ibáñez et al., 2017; Gudmundsson and Horton, 2017; Rico-González et al., 2021). However, these reviews have not specifically examined how indicators derived from player and ball locations are used to interpret tactical performance in standard regulation 5-on-5 basketball. This issue is important because, during full-game match play, actions unfold under the combined influence of possession phase, shot-clock pressure, teammate-opponent relations, and defensive response. This issue is particularly important in 5-on-5 basketball, where possessions involve continuous interaction, repeated reorganization, and simultaneous processes operating at multiple analytical levels (Bourbousson et al., 2010b; Duarte et al., 2012; Lamas et al., 2015; McGarry et al., 2002). The focus on standard regulation 5-on-5 basketball was therefore deliberate. Small-sided games, drills, 3-on-3 formats, and simulated tasks were not included because changes in player number, court use, task goals, decision options, and defensive organization can alter the spatial relations from which these indicators are derived. Findings from modified, training-based, or simulated settings are also closely shaped by the constraints imposed by the task or model. Including these formats could therefore obscure whether an indicator reflects tactical behavior in standard regulation 5-on-5 match play or the design features of a modified context. These characteristics make positional analysis valuable, but they also increase the risk of over-interpreting indicators when they are detached from the possession context (Chen et al., 2025; Gudmundsson and Horton, 2017; Rein and Memmert, 2016; Rico-González et al., 2021).

Against this background, the present review examines how spatial and spatiotemporal indicators have been used in standard regulation 5-on-5 basketball research and how their outputs have been interpreted in relation to tactical performance. Its main contribution lies in providing a basketball-specific synthesis of these indicators and clarifying how different indicator types support and constrain tactical interpretation. More specifically, the review identifies the main types of indicators used in the literature, examines how they represent game behavior across analytical levels and contexts, analyzes how their outputs are translated into tactical claims, and considers the factors that shape their interpretability in research and applied settings.

Methods

Search strategy

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021). The review protocol was registered with PROSPERO on September 19, 2025 (CRD420251146172). Preliminary searches had been initiated before protocol registration; this timing is reported here for transparency. The PROSPERO record was subsequently updated to reflect the eligibility criteria, search sources, and review procedures reported in the present manuscript.

A comprehensive search was conducted across PubMed/MEDLINE, Scopus, and Web of Science, with Google Scholar used as a supplementary source. The search covered studies published through September 15, 2025. The search strategy was structured around two core concept blocks: basketball and spatial/spatiotemporal data. Search strings were adapted to the indexing structure of each database, with field tags and controlled vocabulary used where appropriate. Full database-specific search strategies are provided in Supplementary Table 1, together with details of the supplementary Google Scholar search, including the search date, search terms, screening range, sorting method, stopping rule, and de-duplication procedure. Searches were conducted independently by two reviewers and verified by a third reviewer.

Eligibility criteria

Eligibility criteria were developed using the PICOS framework and refined to identify studies that used court-referenced player and/or ball location data to derive indicators relevant to tactical analysis in standard regulation 5-on-5 basketball. Studies were included only when such location data formed an essential part of the analysis, rather than

being reported only descriptively or incidentally (Methley et al., 2014; Schiavenato and Chu, 2021). The eligibility criteria are summarized in Table 2 according to population/context, data type, indicator requirement, tactical relevance, and source type.

The screening process was conducted independently by two trained reviewers, with EndNote used for reference management. Before formal screening, both reviewers completed a calibration exercise using a random sample of 62 records, corresponding to approximately 10% of the 621 records retained after deduplication. The calibration sample was selected using a computer-generated random sequence. These records were used to harmonize reviewers' interpretation of the eligibility criteria and were not included in the κ estimate for formal title/abstract screening. During title/abstract screening and full-text assessment, the reviewers made decisions independently and were masked to each other's decisions until the consensus stage. Inter-rater agreement was high for the calibration exercise, title/abstract screening, and full-text assessment (Cohen's $\kappa = 0.88, 0.86,$ and $0.90,$ respectively). Disagreements were resolved through consensus, with a third reviewer consulted when necessary. The study selection process is presented in the PRISMA flow diagram.

Assessment of reporting completeness

The included studies were appraised for reporting completeness and transparency, rather than methodological quality or risk of bias, because the aim of this review was to examine how spatial and spatiotemporal indicators were defined, operationalized, and interpreted, rather than to synthesize intervention effects or estimate pooled outcomes. Empirical/observational studies were appraised using a STROBE-based framework (Rösch et al., 2022; Von Elm et al., 2007; Von Elm et al., 2014), whereas studies in which modeling or analytics formed a central part of the research design were appraised using an adapted TRIPOD-

Table 1. Database-specific search strategies

Database	Search fields	Search strategy
Concept blocks	-	Sport concept: basketball; data concept: tracking, player tracking, positional data, positional, spatial, spatiotemporal, and trajectory
PubMed/MEDLINE	MeSH + Title/Abstract	("Basketball"[Mesh] OR basketball[Title/Abstract]) AND (tracking[Title/Abstract] OR "player tracking"[Title/Abstract] OR "positional data"[Title/Abstract] OR positional[Title/Abstract] OR spatial[Title/Abstract] OR spatiotemporal[Title/Abstract] OR trajectory[Title/Abstract])
Scopus	TITLE-ABS-KEY	TITLE-ABS-KEY(basketball) AND TITLE-ABS-KEY(tracking OR "player tracking" OR "positional data" OR positional OR spatial OR spatiotemporal OR trajectory)
Web of Science	Topic (TS)	TS = (basketball) AND TS = (tracking OR "player tracking" OR "positional data" OR positional OR spatial OR spatiotemporal OR trajectory)
Google Scholar	Supplementary search	Searched on 4 September 2025 using the following combinations: "basketball" "positional data"; "basketball" "tracking data"; "basketball" "spatial analysis"; "basketball" "spatiotemporal analysis"; "basketball" "tactical analysis"; "basketball" "performance analysis" "spatial"; "basketball" "performance analysis" "spatiotemporal"; "basketball" "player tracking" "tactical". Results were sorted by relevance, and the first 20 pages were screened. Screening stopped after page 20 because subsequent pages did not yield records that appeared potentially eligible based on title and snippet screening. Records identified from Google Scholar were exported or recorded manually and imported into EndNote for de-duplication with records from the primary databases.
Limits applied	-	English language; peer-reviewed journal articles; searches conducted up to 15 September 2025. No study-design filter was applied during the search stage.

Table 2. Eligibility criteria for study inclusion and exclusion

Domain	Inclusion criteria	Exclusion criteria
Population/context	Studies examining performance in regulation 5-on-5 basketball, including professional, semi-professional, collegiate, or youth settings.	Studies that did not examine regulation 5-on-5 basketball, including small-sided games, drills, 3-on-3 formats, or other modified task formats.
Data type	Studies using court-referenced player and/or ball location data during play, including continuous tracking data or location-based event data.	Studies relying solely on conventional statistics, play-by-play records without location information, or general event data without player or ball location information during play.
Indicator requirement	Studies deriving one or more spatial or spatiotemporal indicators from court-referenced player and/or ball location data.	Studies reporting positional or movement data only descriptively, without deriving a spatial or spatiotemporal indicator for analysis.
Tactical relevance	Studies using these indicators to address a tactical, technical-tactical, or game-performance question, such as offensive organization, defensive behavior, player-player or team interactions, possession development, shot opportunities, or scoring-related outcomes.	Studies in which the derived variables were used only for biomechanical, physiological, or workload-monitoring purposes and were not interpreted in relation to basketball performance or tactical behavior.
Source type	Original empirical studies, including methodological or modeling work only where applied to real regulation 5-on-5 basketball player and/or ball location data and producing interpretable findings relevant to match analysis.	Studies based entirely on simulated data, conceptual examples, or algorithmic demonstrations without application to real match data. Non-original publication types and records that did not meet the peer-reviewed article requirement were also excluded.

informed reporting checklist (Collins et al., 2015; Moons et al., 2015). These tools were adapted to emphasize reporting features directly relevant to spatial and spatiotemporal indicators, including data source, sample definition, indicator construction, model specification, validation or performance checks, and interpretive limitations. The full item lists and decision rules are provided in Appendix 1A for empirical/observational studies and Appendix 2A for modeling/analytics studies. Study-level appraisal results are provided in Appendix 1B and Appendix 2B.

For empirical/observational studies, the STROBE-based appraisal focused on the clarity and completeness of reporting in relation to study setting and competitive context, participant description, definition and measurement of positional variables and spatial or spatiotemporal indicators, outcome specification, and analytical/statistical procedures. For modeling/analytics studies, the adapted checklist focused on reporting clarity in relation to data source and sample definition, specification of spatial or spatiotemporal inputs, model structure and assumptions, definition of model-derived outputs, validation or performance checks, and discussion of practical interpretation and limitations.

For each applicable item, studies were classified as adequately reported, partially reported, or not reported according to predefined decision rules. An item was rated as adequately reported when the information was sufficiently clear for readers to understand how the relevant data were obtained and how the indicator, model output, or interpretation was generated. An item was rated as partially reported when some relevant information was provided but one or more key details were missing. An item was rated as not reported when the information was absent or too unclear to support judgment. For example, data source was rated as adequately reported when the dataset, competition level, and sample source were all stated; as partially reported when only some of these elements were provided; and as not reported when the source could not be identified. Similar rating anchors were applied to indicator definition,

validation or performance checks, and study limitations. Items considered not applicable to a given study design were coded as non-applicable and excluded from percentage calculations.

The reporting appraisals were conducted independently by the same two reviewers who completed the study screening. Disagreements were resolved through discussion, with a third reviewer consulted when necessary. Inter-rater agreement for the appraisal process was high (Cohen's $\kappa = 0.89$). Item-level results were summarized descriptively as counts and percentages, and per-study totals were used only as descriptive summaries of reporting completeness. The appraisal results were used to inform evidence interpretation and contextualize reporting transparency; they were not used to exclude studies, rank study quality, or weight findings quantitatively.

Data extraction and study classification

Data extraction was performed using a standardized extraction template by one reviewer and independently verified by a second reviewer. Disagreements were resolved through discussion, with a third reviewer consulted when necessary. Extracted data included study characteristics, sample information, study design, analytical methods, spatial and spatiotemporal indicators, main findings, and reported limitations. Missing information was recorded as "not reported."

Indicators were extracted with a focus on how court-referenced positional information was translated into representations of tactical performance. This coding framework captured the tactical context of each study, the tactical unit addressed, the use of model-based analytical procedures were used, and the measurement approach adopted.

Studies were first classified according to tactical context as offensive or defensive. Studies with an offensive component were then further classified by tactical unit as individual, interactional, or collective. Studies using model-based analytical procedures to derive indicators or

represent game dynamics were identified separately.

A complementary coding framework was also applied to characterize how indicators were constructed and interpreted. This framework included analytical scale, modeling approach, and measurement approach. Measurement approach was classified as state-based when indicators were derived from discrete events or single time points, sequence-based when they were derived from trajectories or time windows, and mixed when both approaches were used (Gudmundsson and Horton, 2017; Low et al., 2020; Memmert et al., 2017).

Inter-rater reliability for coded data-extraction and classification items was assessed using Cohen's κ ($\kappa = 0.87$), indicating strong agreement. Final classifications were determined by consensus after all discrepancies had been resolved.

Results

Search results

A total of 759 records were identified through database and supplementary searches, including 342 from PubMed, 141 from Scopus, 206 from Web of Science, and 70 supplementary records from Google Scholar, with all searches conducted through September 15, 2025. After 138 duplicates were removed, 621 records remained for title/abstract screening. Of these, 579 were excluded on the basis of the predefined eligibility criteria, mainly because they were not directly relevant to standard regulation 5-on-5 basket-

ball ($n = 193$), did not include valid court-referenced player and/or ball location data from which game-based spatial or spatiotemporal indicators could be derived ($n = 216$), or did not meet the inclusion criteria for original empirical research ($n = 170$).

As a result, 42 reports were sought for retrieval. Three reports could not be retrieved and were therefore not assessed for eligibility. The availability and publication status of these reports were checked through database records and publisher or journal websites, and they were recorded as reports not retrieved in the PRISMA flow diagram. Because these reports were not available as retrievable full-text records, they were not included in the eligibility assessment or listed among the full-text exclusion reasons. The remaining 39 reports were assessed for eligibility.

Following full-text review, 23 reports were excluded for the following reasons: absence of valid court-referenced player and/or ball location data ($n = 6$), non-standard 5-on-5 basketball context ($n = 3$), absence of derived spatial or spatiotemporal indicators ($n = 5$), lack of relevance to basketball tactical performance analysis ($n = 4$), non-original or non-peer-reviewed publication type ($n = 3$), and insufficient methodological detail in the available report ($n = 2$). Ultimately, 16 studies met the inclusion criteria and were included in the qualitative synthesis and reporting-methodology analysis. The study selection process is presented in Figure 1.

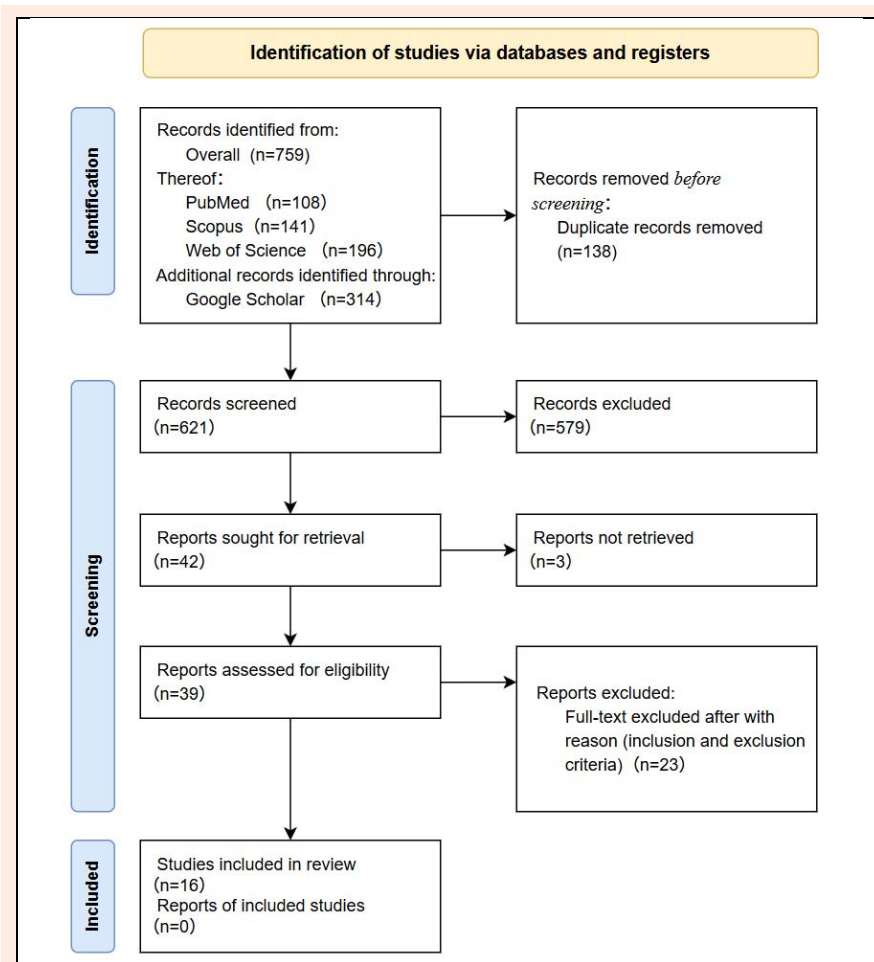


Figure 1. PRISMA flow diagram of the study selection process.

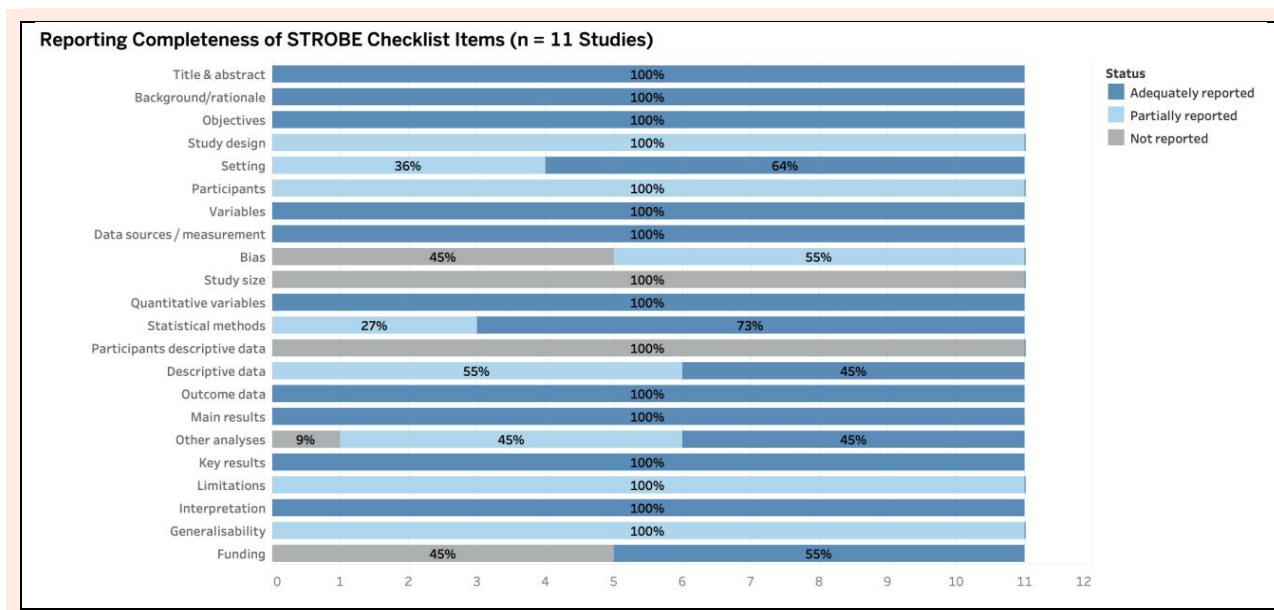


Figure 2. STROBE-based reporting completeness of empirical/observational studies.

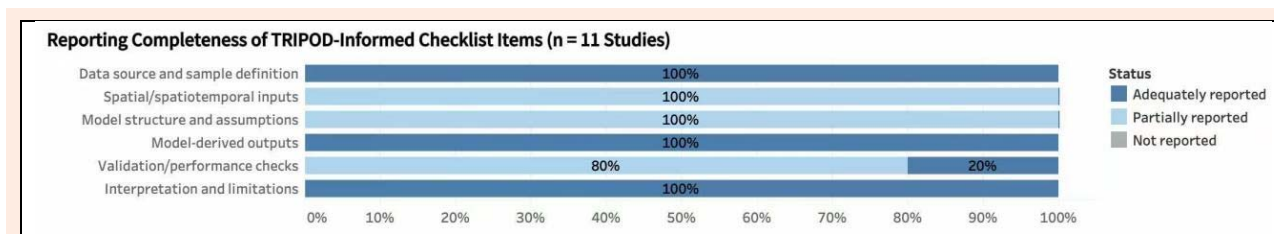


Figure 3. Reporting completeness of modeling/analytics studies based on the adapted TRIPOD-informed checklist

Assessment of reporting completeness

Reporting completeness and transparency were appraised separately for empirical/observational studies and modeling/analytics studies, reflecting the different methodological characteristics of the included research. Item-level results for the STROBE-based appraisal are presented in Figure 2, whereas those for the adapted TRIPOD-informed reporting checklist are presented in Figure 3. Detailed item definitions and decision rules are provided in Appendix 1A and Appendix 2A, Study-level appraisal results are provided in Appendix 1B and Appendix 2B.

Among the empirical/observational studies, reporting was generally more complete for basic descriptive study elements. Items related to the title and abstract, background and objectives, definition of key variables, data sources, outcome reporting, and presentation of the main results were most often classified as adequately reported. By contrast, items relating to study design, setting, participant description, and statistical methods were more often classified as partially reported. The least consistently reported items concerned potential sources of bias, study size, limitations, generalizability, and funding.

Among the modeling/analytics studies, core elements of the analytical workflow were generally reported more clearly than validation procedures and practical interpretation. Data source and sample description, specification of model inputs, and definition of model-derived outputs were usually classified as adequately reported. In contrast, reporting was less consistent for model assumptions, validation or performance checks, and discussion of practical interpretation and limitations.

Overall, the included studies generally reported their core data, indicators, and main findings clearly, but reporting was less consistent for elements related to bias, study size, validation, limitations, and generalizability. The reporting appraisals were used to inform evidence interpretation and contextualize reporting transparency across the included studies; they were not used to exclude studies, rank study quality, or weight findings quantitatively.

Classification of included studies

A total of 16 studies met the inclusion criteria and were retained for synthesis. All included studies examined performance in standard regulation 5-on-5 basketball and used court-referenced player and/or ball location data to derive indicators relevant to tactical performance.

The included studies covered four competition levels, as summarized in Table 3. Based on the participant-classification framework used in this review, 11 studies were classified as Tier 5, two as Tier 4, one as Tier 3, and two as Tier 2. In terms of sample source, 10 studies used only NBA data, one study combined simulated data with NBA offensive sequences, two studies used French professional match sequences, two used U14 competitive game sequences, and one used data from an Italian C-Gold League friendly match. Collegiate basketball was included in the tier framework but was not represented as a distinct sample source among the included studies.

Studies were first grouped according to tactical context as offensive, defensive, or combined offensive-defensive. Nine studies focused on offensive contexts, two focused on defensive contexts, and five addressed both offensive and

defensive contexts, including studies of team interaction. Studies were then classified by tactical unit as individual, interactional, collective, or defensive-only. Three studies focused on individual-level spatial conditions, such as positioning, defender proximity, and shot-related spatial constraints. Four studies examined interactional relations between players, including attacker-defender configurations and coordination within small groups. Seven studies described collective spatial organization, including measures of dispersion, centroid movement, and overall spacing structure. The two defensive-only studies were retained as a separate category and were not further subdivided by offensive tactical unit.

Nine studies also used modeling approaches to derive indicators or represent game dynamics. These studies were identified across both offensive and defensive contexts and across different tactical units. Studies were further classified according to measurement approach. Of the 16 included studies, five used a state-based approach, eight used a sequence-based approach, and three used a combined state- and sequence-based approach. State-based approaches were more commonly used in studies focused on discrete events, such as shot attempts or possession outcomes, whereas sequence-based approaches were more often used in studies examining continuous spatial dynamics and coordination over time.

Beyond sample source and tactical focus, the included studies also differed in the analytical level at which spatial or spatiotemporal information was operationalized. Some studies used local shot-space indicators, such as shot location, distance to the basket, defender distance, shot angle, and shot-trajectory factors. Other studies focused on interactional or collective indicators, including dyadic coordination, attacker-defender distance, passer-receiver relations, team spatial center, stretch index, court-area occupation, and spatial phase structure. Several studies further used model-derived indicators, such as expected possession value, offensive network parameters, player-density

estimates, player gravity, and intrinsic dimension.

Table 4 provides a study-level synthesis of these indicators. It reports the principal spatial or spatiotemporal indicators or indicator families extracted from each study, together with the authors' main interpretation, the interpretive boundary considered in the present review, and the limitations reported in the original article. This structure separates the operational meaning of each indicator from broader tactical inference.

To integrate the study-level findings, the extracted indicators were organized according to their primary interpretive role. As shown in Table 5, five indicator categories were identified: individual/local spatial indicators, interactional indicators, collective organization indicators, defensive-impact indicators, and model-derived/complexity indicators. These categories summarize how spatial and spatiotemporal information has been used to describe basketball performance, ranging from immediate shot conditions to model-based representations of possession value, player interaction, and movement complexity.

The classification of each included study according to competition level, tactical context, tactical unit, modeling approach, and measurement approach is presented in Table 3. The overall distribution of studies across tactical unit and measurement approach is shown in Figure 4.

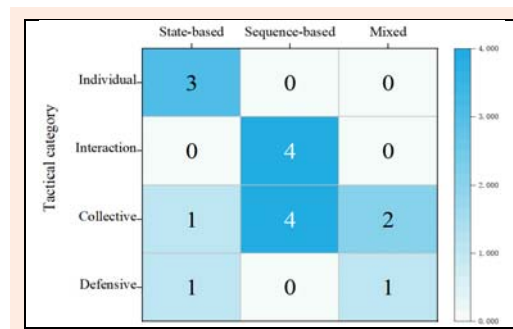


Figure 4. Distribution of included studies across tactical category and measurement approach.

Table 3. Classification of included studies by competition level, tactical context, tactical unit, modeling approach, and measurement approach.

Author	Competition level	Tactical context	Tactical unit	Modeling	Measurement approach
Bourbousson et al. (2010a)	Tier 4	B	R	-	Q
Bourbousson et al. (2010b)	Tier 4	B	C	-	Q
Shortridge et al. (2014)	Tier 5	O	I	M	S
Esteves and Arede (2015)	Tier 2	O	C	-	Q
Esteves et al. (2016)	Tier 2	O	C	-	Q
Franks et al. (2015)	Tier 5	D	-	M	MX
Sampaio et al. (2014)	Tier 5	O	I	M	S
Skinner et al. (2015)	Tier 5	O	C	M	S
Cervone et al. (2016)	Tier 5	O	C	M	MX
Santana et al. (2019)	Tier 5	O	R	-	Q
Manisera et al. (2019)	Tier 3	B	C	M	MX
Daly-Grafstein and Bornn (2021)	Tier 5	D	-	M	S
Santos-Fernandez et al. (2022)	Tier 5	B	C	M	Q
Supola et al. (2022)	Tier 5	O	R	-	Q
Barron et al. (2025)	Tier 5	B	R	M	Q
Jiao et al. (2025)	Tier 5	O	I	-	S

Participant competition levels are categorized based on the Participant Classification Framework (McKay et al., 2021): Tier 5 (World Class): Athletes from top global leagues (e.g., NBA) or Olympic/World Championship medalists, representing the highest competitive level; Tier 4 (Elite/International Level): Athletes from international professional leagues (e.g., French professional basketball league) or national team members; Tier 3 (Highly Trained/National Level): Athletes from national domestic leagues (e.g., Italian Serie C) or NCAA Division II/III programs; Tier 2 (Trained/Developmental): Youth competitive athletes (e.g., U14 championship participants) with regular sport-specific training and local/regional competition experience. Abbreviations: O = offensive; D = defensive; B = both; I = individual; R = interactional; C = collective; M = modeling study; - = not applicable; S = state-based; Q = sequence-based; MX = mixed.

Table 4. Study-level synthesis of spatial and spatiotemporal indicators and their interpretation.

Author	Objective	Sample	Methodology	Metric definition	Authors' interpretation	Review interpretive caution	Reported limitation
Bourbousson et al. (2010a)	To analyze spatiotemporal coordination between basketball players during match play using a dynamical systems approach.	Data were drawn from six game sequences in a 2008 French men's professional match, including 10 players, 20 intra-team pairs, and 25 inter-team pairs.	Relative Phase Analysis; Coordination Dynamics.	Dyadic relative phase: the phase relationship between two players' longitudinal or lateral displacement trajectories, used to quantify in-phase, anti-phase, or transitional coordination between player dyads.	Player dyads showed strong in-phase relations in the longitudinal direction, especially for matched player-opponent dyads, indicating movement coupling shaped by game demands.	This metric describes dyadic coordination, but it does not specify the tactical purpose of the coupling or whether the observed relation was beneficial for either team.	Based on six sequences from one professional match; player location was estimated from video tracking, and tactical context was not fully linked to the observed phase patterns.
Bourbousson et al. (2010b)	To examine spatiotemporal coordination between two teams during match play by analyzing team-level movement dynamics within a dynamical systems framework.	Data were drawn from one professional men's basketball match, including six selected game sequences involving two teams (10 players).	Relative Phase Analysis.	Team spatial center and stretch index: the geometric center of each team and the mean distance of players from that center, used to quantify team displacement, expansion, and contraction.	The two teams showed strong longitudinal in-phase coordination, while stretch-index patterns suggested reciprocal expansion and contraction between the attacking and defending teams.	These indicators describe team movement and spacing, but they should not be read as direct evidence of tactical effectiveness without information on possession phase and action context.	Based on one professional match and six selected sequences; team-level averages may mask individual roles and specific tactical actions.
Shortridge et al. (2014)	To quantify spatial variation in basketball shooting efficiency by developing spatially explicit metrics that account for shot location and league-wide shooting tendencies.	All field-goal attempts from the 2011–2012 NBA regular season, including more than 140,000 shots taken by players with at least 250 shot attempts.	Empirical Bayes Spatial Smoothing.	Spatial relative field-goal efficiency: empirical Bayes-smoothed shooting efficiency at court-specific locations, used to estimate location-adjusted shooting performance.	Spatially explicit metrics differentiated players' location-specific shooting ability and showed that players with similar overall shooting percentages may differ across court areas.	These metrics describe where shooting efficiency is higher or lower, but they do not show how the shot location was created within the possession.	Based on shot-location data from one NBA season; defensive pressure, passing sequence, and possession context were not directly included.
Esteves et al. (2015)	To examine collective spatial distribution patterns in basketball in relation to offensive and defensive performance outcomes.	Three U14 competitive basketball games, including 10 selected offensive sequences.	Multivariate Analysis of Variance; Mixed-design ANOVA.	Court-area occupation ratio: the number of attackers, the number of defenders, and the attacker-to-defender ratio within seven predefined court areas during offensive sequences.	Spatial distribution differed by court area; defensive numerical superiority near the basket was associated with successful offensive outcomes.	These measures describe local numerical distribution, but they do not identify the tactical actions that created the numerical pattern.	Exploratory analysis of three U14 games and 10 selected sequences; findings are limited by small sample size and youth competition context.
Esteves et al. (2016)	To examine how space occupation near the basket influences collective behaviors and performance outcomes in youth basketball.	Ten competitive games involving 13 U14 teams.	SMD; Cross-correlation; Multinomial Logistic Regression.	Local shot-space indicators: the number of attackers, the number of defenders, attacker-defender interpersonal distance, and shooter-to-basket distance measured around shot attempts.	Larger attacker-defender distance and shorter distance to the basket increased the likelihood of a converted shot; defensive numerical overload near the scoring target was also associated with offensive success.	These indicators describe local numerical and distance constraints near the basket, but they do not identify the specific offensive action that created the advantage.	Youth sample only; selected sequences from U14 games; two-dimensional video digitization; and limited generalizability to senior or professional basketball.

Table 4. Continue...

Author	Objective	Sample	Methodology	Metric definition	Authors' interpretation	Review interpretive caution	Reported limitation
Franks et al. (2015)	To quantify the independent influence of NBA defenders on opponents' shot selection and shooting percentages across court regions, and to describe spatially encapsulated individual defensive ability.	Approximately 115,000 half-court offensive plays lasting at least 5 seconds from the 2013–14 NBA regular season.	Log-Gaussian Cox Process; Hidden Markov Model.	Defensive shot frequency effect and defensive shot efficiency effect: model-based estimates of how a defender alters opponent shot frequency and shot success across court regions.	Defenders influenced shot frequency and shotefficiency in different ways, allowing defensive impact to be mapped across court regions.	These model-derived effects depend on inferred defensive assignments and should be interpreted within the team defensive context, rather than as fully isolated individual defensive ability.	Individual defensive effects could not be fully separated from team defensive strategy and teammate support; results were based on one NBA season of optical tracking data.
Sampaio et al. (2014)	To identify game performance profiles using NBA player-tracking and technical statistics, and to distinguish key performance characteristics of All-Star and non-All-Star players through clustering and discriminant analysis.	Tracking and non-tracking data from 548 players across 1,230 NBA regular-season games in the 2013–14 season.	Linear Discriminant Analysis; k-means Cluster Analysis.	Player-tracking performance profile indicators: NBA tracking and non-tracking variables describing shooting type, touches, passing, rebounding, speed–distance activity, and defensive actions.	All-Star players were mainly distinguished by elbow touches, defensive rebounds, close touches, close points, pull-up points, and lower defensive speed; cluster analysis identified scoring, passing, defensive, and all-around profiles.	These variables describe player performance profiles across a season, but they do not show the possession-level tactical process that produced each action.	All-Star grouping was based on media selection, full-court video was unavailable to verify tracking data, and the cluster analysis used only complete cases.
Skinner et al. (2015)	To estimate player-skill parameters and lineup-interaction patterns, and to use them to predict team offensive efficiency and assess how player skills contributed to team performance.	Simulated data for 5,000 possessions, together with 780 offensive sequences from the 2011 NBA playoff game between the Grizzlies and the Thunder.	Markov Chain Model.	Offensive network transition model: player-skill and lineup-interaction parameters used to represent possessions as transitions through offensive states and to predict lineup performance.	The model inferred player skills from simulated data and showed that limited real-game data could describe how a player interacted with different five-man lineups.	The model describes offensive structure under simplified network assumptions, but it does not directly identify observed tactical intent or specific play design.	Player-tracking data were not publicly available; the main validation used simulated data; and the real-game application was based on a limited playoff sample.
Cervone et al. (2016)	To construct a multiresolution stochastic process model to simulate changes in player movement during a possession and predict the possession outcome.	Tracking data from 461 players in the 2013–14 NBA season.	Multiresolution Stochastic Process Modeling; Markov Chain Modeling; Bayesian Inference; Maximum Likelihood Estimation.	Expected possession value: model-estimated expected points remaining in a possession, derived from multiresolution stochastic modeling of player movement and discrete game events.	The model showed that offensive value could be updated continuously during a possession and could reveal how player decisions and spatial strategies changed expected outcomes.	EPV describes model-estimated possession value, but its tactical meaning depends on how the model defines states, transitions, and relevant spatial information.	High computational complexity; reliance on high-quality optical tracking data; and model assumptions about possession states, transition kernels, and event segmentation.
Santana et al. (2019)	To analyze basketball offensive structure through concatenated space-creation dynamics and to characterize team tactical patterns.	Four NBA teams from the 2013–2014 season, including multiple matches and offensive possessions.	Chi-square Analysis.	Space-creation dynamics concatenation classes: isolated, independent concatenated, and dependent concatenated offensive tactical actions coded within ball possessions.	The framework differentiated team offensive structures; the Spurs showed longer sequences with more dependent concatenations, whereas other teams used shorter or more direct patterns.	The metric describes the sequence structure of offensive tactics, but it depends on manual coding and does not directly quantify spatial position or defender response.	Limited to four NBA teams; observational match analysis; reliance on expert-defined coding categories; and no direct use of tracking-derived spatial coordinates.

Table 4. Continue...

Author	Objective	Sample	Methodology	Metric definition	Authors' interpretation	Review interpretive caution	Reported limitation
Manisera et al. (2019)	To use tracking-data visualization and clustering analysis to reveal players' spatial distribution patterns and inform tactical optimization.	133,662 data points from a 2016 friendly match in the Italian C-Gold League.	k-means Cluster Analysis.	Spatial phase clusters and transition probabilities: clusters of homogeneous player-spacing configurations and transition matrices describing movement between game phases.	Cluster analysis identified different offensive and defensive game phases and showed how tracking data could support visualization and phase-based interpretation of team movement.	These clusters describe recurring spatial configurations, but their tactical meaning depends on how phases are labeled and linked to possession context.	Single friendly match from the Italian C-Gold League; home-team data only; device-based tracking; and no opponent or ball trajectory included in the final modeling.
Daly-Grafstein and Bornn (2021)	To analyze NBA shot trajectories to examine the impact of defense on shooting accuracy and to assess perimeter defenders' defensive ability and shooters' resilience under defensive pressure.	Data from 50,916 three-point shot trajectories in the 2014–15 NBA season.	Bayesian Regression; logistic Regression.	Shot-trajectory factors and trajectory-based shot-make probability: shot depth, left-right deviation, and entry angle derived from in-game ball trajectories and used to estimate shot-success probability.	Contested three-point shots showed greater variance in depth and left-right accuracy; trajectory-based metrics provided more stable estimates of perimeter defensive impact than opponent field-goal percentage.	These metrics explain how contests affect shot trajectories, but they do not fully identify the defensive scheme, closeout timing, or help-defense context behind the contest.	Restricted to NBA three-point shots; dependent on SportVU trajectory quality and modeled shot paths; and focused on perimeter defense rather than all defensive actions.
Santos-Fernandez et al. (2022)	To estimate the intrinsic dimension (ID) of high-resolution tracking data and reveal differences in movement complexity and behavioral structure at the player and team levels.	Tracking data from 15 randomly selected games in the 2015–16 NBA season.	Intrinsic Dimension Estimation; Bayesian Linear Models; Non-parametric Tests.	Intrinsic dimension: a Bayesian mixture-model estimate of the latent dimensionality of player-tracking data, used to quantify movement complexity and dependence in offensive sequences and shot-chart patterns.	ID values increased during phases such as creating space for passing and shooting, declined near the end of plays, and were higher in game-winning or closer-margin contexts.	ID captures movement complexity and unpredictability, but it does not specify which tactical action or player decision produced the observed complexity.	Fixed number of mixture components; temporal dependence not fully modeled; no measurement-noise component; and need for validation in larger samples.
Supola et al. (2022)	To analyze the characteristics of secondary assists and their impact on scoring efficiency.	Tracking data from the first half of the 2015–16 NBA season, covering 531 games.	Logistic Regression; Linear Regression.	Secondary-assist indicators: potential secondary assists, receiver openness, modeled Expected Points, and Average Points per Possession for shot opportunities created through pre-assist passing sequences.	Secondary assists were associated with more open shots, higher expected scoring value, and particularly productive corner-three opportunities.	These indicators describe the value of pre-assist ball movement, but they do not fully separate designed play execution from defensive breakdown or late-possession adaptation.	Reliance on public SportVU and event records; exclusion of some foul-related outcomes from the model; and systematic imprecision in modeled Expected Points for some shooting areas.
Barron et al. (2025)	To use density-functional fluctuation theory to describe NBA player-position distributions and interaction patterns during games, and to identify differences in player roles and tactical-structure features.	Player-tracking data from the 2022–23 NBA season through January 20.	Density-Functional Fluctuation Theory; Maximum Likelihood Estimation.	Density-functional fluctuation theory indicators: player-density fields, location-preference parameters, player–player interaction terms, and player-gravity estimates inferred from NBA tracking data.	DFFT predicted player locations, produced a team-position-based metric related to play outcomes, identified defensive positioning tendencies, and quantified offensive player gravity while accounting for teammate positioning.	These indicators describe spatial preference and interaction structure, but their tactical meaning depends on the density representation and does not directly encode play calls or defensive assignments.	Player influence was represented through two-dimensional Gaussian density fields; player-specific analysis was limited to selected high-minute players; and physical attributes such as height or leaping ability were not directly included in the model.
Jiao et al. (2025)	To identify spatiotemporal factors distinguishing successful and unsuccessful possessions using large-scale NBA tracking data.	Tracking data from 632 NBA games in the 2015–16 NBA season.	Independent t-test; Mann–Whitney U test.	Possession-level spatiotemporal indicators: ball kinematics, offensive and defensive team spatial structure, shooter-specific spatial variables, and contextual variables calculated for set-play possessions.	Successful shot outcomes were mainly distinguished by shooter-related spatial variables, including shorter shot distance, larger defender-related shot angle, and greater separation from the nearest defender.	These indicators identify spatial differences between made and missed shots, but they do not on their own explain the tactical process that created the shooting condition.	Observational design; single NBA season; no player-specific contribution analysis; and limited integration of technical, physical, and tactical variables beyond the tracking data.

Table 5. Interpretive scope of spatial and spatiotemporal indicator categories.

Local indicators	Main indicators	Primary descriptive use	Interpretive boundary
Individual actions and local spatial indicators	Shot location, spatial field-goal efficiency, shooter-to-basket distance, shot distance, nearest-defender distance, and shot angle.	Describe the immediate spatial conditions of a shot, including its location, the shooter's distance to the basket, and the space available at the moment of shooting.	These indicators describe the immediate shot condition, but not the full possession process that produced it. Stronger tactical interpretation requires information on the preceding pass, dribble, screen, or defensive rotation.
Interactional indicators	Dyadic relative phase, attacker-defender interpersonal distance, passer-receiver relations, secondary-assist indicators, and space-creation dynamics concatenations.	Describe player-player relations, including coordination, interpersonal spacing, passing links, and offensive action sequences within possessions.	These indicators show how players were related in space and time, but they cannot determine on their own whether the relation reflected planned execution, defensive breakdown, or late-possession adaptation.
Collective indicators	Team spatial center, stretch index, court-area occupation ratio, team area, team width, team length, centroid movement, spatial phase clusters, and transition probabilities.	Describe team shape, spacing, expansion, contraction, court occupation, and transitions between recurring spatial configurations.	These indicators characterize collective structure, but their tactical meaning depends on possession phase, ball location, opponent organization, and sequence outcome.
Defensive-impact indicators	Defensive shot frequency effect, defensive shot efficiency effect, nearest-defender distance, defender-related shot angle, contest-related shot-trajectory factors, and trajectory-based defensive impact.	Describe how defender location, proximity, and contest conditions are associated with shot selection, shot success, and shot trajectory.	These indicators can inform defensive evaluation, but individual defensive impact should be interpreted with caution because assignments, help defense, switching, and team coverage shape the observed effect.
Model-derived indicators and complexity measures	Expected possession value, offensive network transition parameters, density-functional player-density fields and interaction parameters, player gravity, and intrinsic dimension.	Estimate possession value, player-lineup interactions, spatial influence, player gravity, and movement complexity from high-dimensional tracking data.	These indicators provide model-based summaries rather than direct tactical labels. Their interpretation depends on model inputs, state definitions, segmentation rules, and validation evidence.

Discussion

Across the included studies, spatial and spatiotemporal indicators were used to extend basketball performance analysis beyond outcome description toward the analysis of game behavior as it unfolds in space and time. Their value lies in revealing the local conditions of actions, the relations between players, and the broader organization of teams during possessions. At the same time, their meaning depends on the analytical level at which they are constructed and the possession context in which they are observed. The following sections discuss how these indicators support interpretation at the individual, interactional, collective, defensive, and model-derived levels, with attention to the conditions under which spatial evidence can be linked to tactical-performance claims.

Local indicators and immediate action conditions

Individual spatial indicators are commonly used to describe the immediate spatial conditions surrounding a player at the moment of action, including nearest-defender distance, location relative to the basket, and available space at the time of a shot or pass (Franks et al., 2015; Goldsberry, 2012; Miller et al., 2014; Reich et al., 2006; Shortridge et al., 2014). Because they are anchored to specific game events, these indicators provide a relatively direct account of local playing conditions and are particularly useful for examining shot selection, shot difficulty, and the spatial constraints associated with immediate scoring opportunities. Their main analytical strength lies in the close

correspondence between the measured variable and the visible game situation. Goldsberry (2012), for example, showed how shot location can be used to differentiate the spatial conditions under which offensive attempts are taken, and Shortridge et al., (2014) extended this logic by using NBA shot-location data to estimate relative field-goal efficiency across court locations. Franks et al., (2015) used defender-shooter distance and related spatial features to characterize how tightly a shot was contested in a model of defensive shot frequency and shot efficiency based on NBA optical tracking data. At the youth level, Esteves et al., (2016) showed that attacker-defender interpersonal distance and distance to the basket were associated with converted shots in U14 competitive games. In these cases, the indicator refers to a condition that is directly observable in play, making it possible to describe what the player faced at that specific instant rather than inferring it indirectly from the final result alone.

However, this interpretive clarity should not be overstated. Individual spatial indicators describe the spatial state in which an action occurs, but they do not explain how that state was created. A shot taken with substantial space may reflect effective offensive creation through off-ball movement, screening, or ball circulation, but it may also arise from a late defensive rotation or a missed assignment (Sampaio et al., 2016; Stavropoulos et al., 2021). This distinction remains important even when large tracking datasets are used. For example, Jiao et al., (2025) identified shot distance, defensive angle, and nearest-defender distance as important variables associated

with possession outcomes, but these variables still describe the shot condition rather than the preceding tactical sequence. Thus, the indicator captures the endpoint condition of the action, not the tactical process through which that condition emerged.

Individual/local indicators remain analytically useful because they stay close to the visible game situation. They can describe where an action occurred, how much local space was available, and how closely it was contested, but they cannot by themselves explain how that situation developed.

This limitation becomes clearer when individual spatial indicators are considered alongside traditional outcome-based metrics. Measures such as field-goal percentage or opponent field-goal percentage provide limited information about how an action developed, but their meaning is relatively stable because they summarize the outcome itself (Kubatko et al., 2007; Lorenzo et al., 2010). By contrast, spatial indicators offer richer information about the immediate conditions of play, yet their interpretation depends more strongly on possession context (Correia et al., 2013; Rein and Memmert, 2016; McLean et al., 2017). An open shot identified through defender distance, for instance, may indicate effective offensive creation in one possession but a defensive error in another. The local spatial state may appear similar, whereas its tactical meaning may differ substantially. A further limitation is that these indicators are usually tied to discrete moments rather than to the temporal development of the possession (Correia et al., 2013; Gudmundsson and Horton, 2017; McLean et al., 2017). This makes them more compatible with state-based measurement than with sequence-based analysis. Measures of shot location, defender proximity, and local separation can describe critical instants with considerable precision, but they are less suited to showing how defensive structure was displaced over multiple actions or how favorable shot conditions were created through prior movement and interaction (Cervone et al., 2016; Gudmundsson and Horton, 2017; Jiao et al., 2025; Lamas et al., 2015).

When interpreted in isolation, individual spatial indicators can be overinterpreted. Their strength lies in showing the local conditions in which an action occurred rather than explaining the full tactical process that produced them. For applied analysis, this means that an apparently favorable spatial condition should be interpreted alongside the possession sequence, defensive response, and eventual outcome, rather than being taken as sufficient evidence of offensive quality. Individual indicators are most useful for clarifying the immediate spatial problem facing the player at the moment of action. They are less able to explain how that spatial problem developed. Broader interpretation therefore depends on the surrounding sequence and on how the possession unfolded.

Interactional indicators in offensive play

Offensive play rarely emerges from isolated player actions alone. Many tactical advantages in basketball begin to develop through local relations between players, such as those between a passer and receiver, a screener and ball-handler, or an attacker and a nearby defender (Bourbousson et al., 2010a; Santana et al., 2019; Supola et al., 2022).

For this reason, interaction-level spatial indicators provide a more tactically informative perspective than individual measures when the aim is to examine how local offensive actions are connected within the flow of play. These indicators are distinguished by the fact that they do not simply describe where a player is, but how players are positioned relative to one another at moments when an advantage may be developing (Bourbousson et al., 2010a; Santana et al., 2019; Supola et al., 2022). For example, Bourbousson et al., (2010a) used dyadic coupling to examine how player relations evolved during play, drawing on six game sequences from a French professional match and relative-phase analysis of intra-team and inter-team player dyads. Studies of passing networks and secondary assists have similarly shown how local offensive relations can reveal the development of actions before the final event is recorded. Santana et al., (2019) made this sequence logic more explicit by coding space-creation dynamics as isolated, independent concatenated, or dependent concatenated actions in possessions from four NBA teams, whereas Supola et al., (2022) used SportVU-based secondary-assist indicators to examine how pre-assist passing was related to receiver openness and expected scoring value. In this respect, interaction-level indicators move closer to the relational structure of offensive play than traditional outcome-based measures, which may indicate whether a possession ended in a score or turnover without showing how the local advantage was formed.

However, this closer connection to the offensive process does not, by itself, resolve the problem of interpretation. Local coordination does not carry a fixed tactical meaning, because similar interaction patterns may arise under different offensive conditions. A short passer-receiver distance, for example, may reflect a deliberate compact action designed to create an immediate connection, but it may also occur when offensive options have narrowed and the possession has become spatially compressed under defensive pressure. In both cases, the indicator captures the local relation, but not the reason that relation assumed its observed form (Gudmundsson and Horton, 2017; Lamas et al., 2015; McLean et al., 2017). The same caution applies to more structured sequence indicators. A dependent concatenation in Santana et al., (2019) may indicate a deliberately linked two-step action, but its tactical value still depends on whether it disrupted the defense or merely extended the possession. Similarly, a secondary assist in Supola et al., (2022) may indicate productive ball movement, but it does not, by itself, distinguish the designed creation of an advantage from a late defensive rotation. For this reason, interaction-level analysis is particularly dependent on temporal and situational framing. Unlike many individual indicators, which are often anchored to a single moment, interactional indicators derive much of their meaning from what occurs immediately before and after the observed relation (Bourbousson et al., 2010a; Correia et al., 2013; Santana et al., 2019). The same local pattern may therefore carry different tactical meanings depending on whether it occurs as part of a structured sequence, in response to a defensive rotation, or late in a possession after the initial action has broken down. These indicators show how local actions become linked, but their interpret-

tive value remains conditional on the sequence in which the relation is embedded (Bourbousson et al., 2010a; Lamas et al., 2015; Santana et al., 2019; Supola et al., 2022).

This also helps explain their relationship with traditional outcome-based metrics. Interaction indicators can reveal how an advantage begins to emerge before the final result is recorded, making them more informative about the offensive process than conventional measures such as assist rate or turnover count (Fewell et al., 2012; Santana et al., 2019; Supola et al., 2022). Yet precisely because they are tied more closely to the evolving structure of the possession, their interpretive meaning is less stable unless the surrounding context is specified. A passing relation that appears tactically productive in one offensive context may have a substantially different interpretation in another if the defensive response, possession phase, or local spacing pattern changes (Lamas et al., 2015; Sampaio et al., 2016).

For applied work, interaction indicators are most useful when the analytical question concerns how a local advantage begins to form before the possession outcome is decided. They are particularly helpful for examining how passing options, screening relations, and temporary spatial advantages develop within the flow of play. In this respect, they provide information that conventional outcome measures cannot capture directly. Even so, they do not carry a self-contained tactical meaning. The same local relation may reflect different offensive situations depending on timing, defensive reaction, and the wider sequence in which it occurs. Interaction-level indicators are therefore most informative when treated as relational evidence within a possession rather than as standalone markers of offensive quality.

Collective organization indicators in offensive play

At the collective level, collective organization indicators are used to describe how offensive organization emerges at the team level, rather than through isolated actions or short-range player relations. Measures such as team spread, stretch index, and centroid displacement are useful because they show how a team expands, contracts, and reorganizes over the course of a possession (Bourbousson et al., 2010b; Sampaio et al., 2014; Esteves and Arede, 2015). For example, Bourbousson et al. (2010b) analyzed six sequences from a professional match using team spatial center and stretch index, showing that these measures captured inter-team coordination and expansion-contraction patterns. This makes them particularly relevant when the aim is to describe offensive shape and team structure rather than the conditions of a single action. Studies based on centroid movement and dispersion-related measures have shown that team structure may shift from a more compact configuration in transition to a more expanded arrangement in half-court offense, reflecting the progression from initial advancement to organized setup (Bourbousson et al., 2010b; Esteves et al., 2016; Manisera et al., 2019). In youth basketball, Esteves and Arede (2015) used the number of attackers, number of defenders, and attacker-defender ratio across seven court areas to show that collective spatial distribution differed according to offensive and defensive outcomes. Manisera et al. (2019) used spatial clustering and transition probabilities to segment game phases from

tracking data, illustrating how recurring team configurations can be represented beyond single events. By contrast, conventional outcome-based measures can describe whether a possession ended successfully, but they provide much less information about how team structure changed before that outcome occurred (Kubatko et al., 2007; Gómez et al., 2008; Lorenzo et al., 2010).

The main limitation is that, once offensive behavior is summarized at the collective level, the local decisions that generated that structure become less visible. A wide offensive shape, for example, may reflect deliberate spacing and coordinated ball movement, but it may also emerge from defensive disorganization or temporary dispersal late in the possession. What the indicator captures is the resulting spatial arrangement, not the full tactical process through which that arrangement was created (Rein and Memmert, 2016; Gudmundsson and Horton, 2017; Chen et al., 2025). This limitation is particularly important for indicators such as team center, stretch index, and court-area occupation because they aggregate several player locations into a single team-level description. In this respect, collective indicators differ from individual and interactional measures. Individual indicators remain tied to specific actions, whereas interactional indicators preserve part of the local relational structure through which an advantage develops. Collective indicators, by contrast, provide a broader and more stable picture of team shape, but they do so by moving further away from the moment-to-moment processes that generated that shape (Bourbousson et al., 2010b; Manisera et al., 2019; Santos-Fernandez et al., 2022).

This limitation also explains why collective indicators require careful interpretation when they are used to make claims about tactical performance. Similar collective patterns may serve different offensive purposes under different game conditions. The same team spread, for instance, may be associated with effective half-court spacing in one possession and with disorganized or passive dispersion in another. Similarly, a larger stretch index may reflect purposeful floor spacing, but it may also indicate that players are disconnected from the ball or from the next action. For the same reason, their relationship with traditional outcome-based metrics is more indirect than that observed for individual or interactional indicators. A measure such as points per possession provides a stable summary of the outcome, whereas collective spatial indicators provide richer information about offensive structure but depend more heavily on how the possession phase is defined and which part of the sequence is analyzed (Manisera et al., 2019; Gudmundsson and Horton, 2017; Cervone et al., 2016).

For applied analysis, collective indicators are most useful when treated as descriptors of team structure rather than as direct evidence of tactical quality. They are most informative when interpreted alongside lower-level indicators and possession outcomes, so that team shape, local interactions, and action results can be interpreted as parts of the same sequence rather than as separate pieces of evidence. Used in this way, collective indicators help place offensive actions within the wider spatial structure of the possession and show how local behavior is embedded in broader team organization.

Defensive-impact indicators

From a spatial perspective, defensive tactics in basketball concern how space is controlled, denied, and redistributed in response to offensive actions. Positional-data studies therefore tend to represent defense not as a sequence of isolated reactions, but as a continuous process of spatial adjustment relative to the ball, offensive players, and key court areas (Bourbousson et al., 2010a; 2010b; Franks et al., 2015). This framing is important because it shifts defensive analysis away from outcomes alone and toward the spatial organization through which defensive pressure is generated. At the local level, many studies describe defensive behavior through proximity- and angle-based indicators, such as defender-ball distance, defender-shooter distance, and defensive angle. These measures are useful because they capture the immediate nature of defensive engagement in situations such as on-ball pressure and shot contests (Fernández et al., 2021). For example, Franks et al., (2015) used NBA optical tracking data to estimate defensive effects on shot frequency and shot efficiency across court regions. Jiao et al., (2025) used defensive angle and defensive distance difference as indicators of the direction and intensity of defensive pressure at the moment of shooting. In this respect, these indicators provide more process-relevant information than traditional defensive outcome metrics, such as opponent field-goal percentage, which summarizes defensive outcomes but reveals little about how those outcomes were generated. Daly-Grafstein and Bornn (2021) extended this point by using in-game shot trajectories to examine how contests changed shot depth, left-right accuracy, entry angle, and modeled shot-make probability, thereby showing that defensive impact may be reflected in shot-trajectory quality rather than only in the binary make-or-miss outcome. At the same time, the meaning of local defensive pressure is not fixed or self-evident (Chen et al., 2025; Low et al., 2020; Rein and Memmert, 2016; Rico-González et al., 2021). Similar spatial relations may correspond to different defensive situations, including deliberate sagging, late recovery, switching, or help coverage (Daly-Grafstein and Bornn, 2021; Franks et al., 2015; Sampaio et al., 2016). A short defender-shooter distance, for example, may indicate an effective closeout in one possession, whereas in another it may simply reflect a late reaction after the defense has already been compromised.

Defensive analysis becomes more tactically informative when attention shifts from isolated defender-attacker relations to coordination among defenders. Indicators based on inter-defender distance, relative phase, or synchronization provide insight into how defensive units move together, recover, and share responsibilities under offensive pressure (Bourbousson et al., 2010a; 2010b; Rico-González et al., 2021). For instance, Bourbousson et al., (2010a; 2010b) used player trajectories from selected professional match sequences to examine dyadic coordination, team spatial center, and stretch index relations, showing how defensive movement can be represented as coupled behavior rather than as isolated one-on-one responses. This interactional level is especially valuable for examining behaviors such as switching, hedging, and collective recovery because it captures how defenders respond as a unit rather than as separate individuals. Even at this level, however,

the tactical meaning of an observed pattern cannot be assumed directly. Comparable coordination patterns may arise from proactive tactical organization in one possession and reactive adaptation in another (Bourbousson et al., 2010a; 2010b; Silva et al., 2013). These indicators therefore reveal the relational structure of defensive movement, but not necessarily the defensive principle that explains that structure.

A further level of abstraction appears in collective and model-based approaches. Collective indicators such as defensive centroid displacement, stretch index, and compactness describe how defensive shape expands, contracts, and reorganizes across possessions (Bourbousson et al., 2010b; Manisera et al., 2019; Sampaio et al., 2014). In more recent possession-level work, Jiao et al., (2025) calculated defensive team centroid, team width, team length, and related spatiotemporal variables across set-play possessions, showing how defensive structure can be summarized beyond the immediate contest. Model-based representations, including spatial influence fields, defensive flow frameworks, and entropy-based measures, go further by translating defender positioning into continuous representations of control, uncertainty, or coverage (Barron et al., 2025; Daly-Grafstein and Bornn, 2021; Franks et al., 2015). Barron et al., (2025), for example, used density-functional fluctuation theory to infer player-density fields, player-to-player interactions, and player-gravity estimates from NBA tracking data, whereas Franks et al., (2015) modeled defensive impact through court-region-specific effects on shot frequency and shot efficiency. These approaches are valuable because they make broader defensive structure analytically visible and can summarize defensive organization over longer temporal scales than local event-based measures. Their interpretive challenge, however, is that they increasingly describe defense through aggregated structure or mathematical representation rather than through directly observable tactical action. As a result, the defensive meaning of these outputs depends not only on game context but also on how defensive space was modeled in the first place.

Defensive indicators do not all address the same analytical question. Proximity-based measures are most helpful when the analytical focus is immediate contest pressure, coordination metrics are better suited to examining how defenders move together, and collective or model-derived indicators provide information about the broader distribution of defensive control. Treating these measures as interchangeable can obscure the tactical question being asked. In practical analysis, defensive interpretation is usually strongest when these levels are considered together. Local indicators show where pressure was applied, interactional measures show how defenders adjusted collectively, and broader indicators place those actions within the overall defensive structure of the possession. Taken alone, each level provides only partial evidence.

Model complexity and interpretive clarity

As positional datasets have become richer, the models used to analyze them have also become more complex. Recent studies have moved beyond simple spatial descriptors and increasingly use models designed to capture possession

dynamics, defensive influence, movement complexity, and temporal changes in offensive value (Barron et al., 2025; Cervone et al., 2016; Franks et al., 2015; Santos-Fernandez et al., 2022). For example, Cervone et al. (2016) used a multiresolution stochastic process model to estimate expected possession value during a possession, Skinner and Guy (2015) represented offensive possessions as transitions through network states, and Santos-Fernandez et al. (2022) used intrinsic dimension to describe movement complexity in high-resolution tracking data. This development has broadened what can be measured, but it has also made it more difficult to judge how directly a model output corresponds to tactical interpretation. As models become more abstract, the pathway from measured input to tactical meaning is increasingly mediated by modeling assumptions (Barron et al., 2025; Franks et al., 2015; Skinner and Guy, 2015). Quantities such as expected possession value, spatial control, and movement complexity may provide analytically useful summaries, yet their tactical significance depends on how the model defines state, interaction, and relevance at the outset (Barron et al., 2025; Cervone et al., 2016; Santos-Fernandez et al., 2022). This is also evident in density-functional approaches, where player-density fields, spatial-preference parameters, and player-gravity estimates can make player interaction visible, but only through the representational assumptions of the model itself (Barron et al., 2025). These outputs therefore do not have self-evident tactical meaning. Their practical meaning depends on whether the modeling logic remains sufficiently transparent for analysts to understand which aspect of play is actually being represented.

A related issue concerns analytical scale. Highly detailed models may operate at a level of resolution that exceeds the level at which tactical behavior is typically interpreted or communicated in applied settings (Jiao et al., 2025; Torres-Ronda et al., 2022; Wu et al., 2023). Conversely, aggregated outputs may improve tractability while obscuring the local interactions and decision sequences through which tactical behavior is generated (Cervone et al., 2016; Manisera et al., 2019; Santos-Fernandez et al., 2022). For instance, expected possession value can summarize changes in possession value over time, but the resulting value trajectory still requires information about the action sequence, ball location, and defensive response before it can be translated into a tactical explanation. Similarly, intrinsic dimension can indicate increased movement complexity or unpredictability, but it does not specify which offensive action, spacing pattern, or defensive reaction generated that complexity. The problem is therefore not simply one of model complexity or sophistication, but one of alignment between the scale of modeling and the scale of explanation. When this alignment is weak, model complexity may increase descriptive precision without necessarily improving tactical understanding.

This point should not be read as an argument for using simpler models by default. Analytical sophistication is often necessary to capture the complexity of competitive team behavior, particularly when the aim is to represent evolving interactions rather than isolated events (Barron et al., 2025; Cervone et al., 2016; Wu et al., 2023). This is especially relevant in basketball, where a possession may

contain simultaneous off-ball movement, defensive adjustment, ball circulation, and changing shot opportunities that cannot be captured by a single event count. The more important issue is whether complexity serves an explanatory purpose. Models make their strongest contribution when they clarify how tactical patterns emerge, stabilize, or change during play, rather than merely producing technically sophisticated outputs that are difficult to interpret within a coaching or performance-analysis context (Andrienko et al., 2021; McLean et al., 2017; Vilar et al., 2012).

The main issue for future work is therefore not whether models should become more complex, but whether that complexity helps answer a recognizable tactical question. Model structure, inputs, temporal scale, and outputs should be chosen with the intended interpretation in mind. This requires researchers to report not only model performance but also the spatial inputs, state definitions, temporal windows, and validation checks that connect model outputs to basketball-specific interpretation. A model is most useful when it clarifies the game process it is intended to represent rather than simply producing a more sophisticated summary.

Limitations and Future Directions

Several limitations of this review should be acknowledged. The included studies differed in data sources, sampling rates, competition levels, and indicator definitions, which made direct comparisons difficult. Some studies used only shot-location or event-linked data, whereas others used full player-tracking data or model-based outputs. In addition, many studies reported what an indicator was associated with, such as shot outcome, spacing, or possession value, but provided less detail about the exact possession phase or action sequence in which the indicator was observed. Accordingly, the present review focused on how indicators were defined, operationalized, and interpreted rather than on ranking studies or quantitatively synthesizing their findings.

Future studies should make the link between spatial indicators and basketball actions more explicit. One useful approach would be to analyze complete possessions rather than isolated moments. For each possession, researchers could first identify the phase of play, such as transition, early offense, half-court offense, or shot creation. The key action type could then be coded, such as a screen, cut, handoff, drive, pass, closeout, switch, or defensive rotation. Spatial indicators could be calculated within the corresponding temporal window, including shooter-defender distance, passer-receiver distance, team width, team center, defensive spacing, and expected possession value. This would show not only the indicator value itself but also the basketball action and possession context in which that value emerged.

Future work should also compare these indicators against expert-coded tactical judgments and possession outcomes. For example, an open shot identified by defender distance could be compared with coaches' judgments of whether the possession reflected successful spacing, a missed defensive rotation, or a late-clock forced shot. Similarly, a large team spread could be compared against

expert judgments of whether it reflected effective floor spacing or disconnected offensive movement. These checks would help determine when a spatial indicator supports tactical interpretation and when it merely describes the visible arrangement of players.

To support this approach, future studies should report several core methodological details more clearly: the tracking system and sampling rate, how possessions started and ended, how phases of play were defined, how possessions were started and ended, who coded the basketball actions, whether coding reliability was checked, and how model outputs were validated. Clearer reporting of these details would make spatial and spatiotemporal indicators more comparable across studies and more interpretable for coaches, analysts, and researchers.

Conclusion

This review examined how spatial and spatiotemporal indicators have been used to analyze tactical performance in standard regulation 5-on-5 basketball. Compared with event counts, shooting percentages, and possession-based outcomes, these indicators provide a more detailed description of where players were located, how they were positioned relative to one another, how teams occupied space, and how spatial conditions changed during possessions.

The included studies show that different indicators support different levels of tactical interpretation. Local indicators, such as shot location, defender distance, and distance to the basket, describe the immediate conditions of an action. Interactional indicators capture relations among players, such as dyadic coordination, passer-receiver links, and linked offensive actions. Collective indicators characterize team spacing, court occupation, and changes in team shape. Defensive-impact indicators describe contest pressure, defensive positioning, and defender influence on shot selection or shot success. Model-derived and complexity indicators, such as expected possession value, player gravity, and intrinsic dimension, summarize possession value, player influence, and movement complexity under specific model assumptions.

These distinctions are important because similar indicator values or spatial configurations may be produced by different basketball situations. An open shot may result from effective off-ball movement, a late defensive rotation, or a broken play. An expanded team shape may indicate effective spacing, but it may also reflect disconnected offensive movement. Accordingly, spatial and spatiotemporal indicators should not be treated as direct evidence of tactical effectiveness unless the possession phase, action sequence, defensive response, and, where relevant, model assumptions are clearly specified.

Future studies should report the tracking data source and sampling rate, how possessions and phases of play were defined, how each indicator was calculated, which basketball actions were coded, how model outputs were validated, and what interpretive boundaries were placed on tactical claims. Clear reporting of these details would make spatial and spatiotemporal indicators more comparable across studies and more useful for linking positional data to basketball-specific performance interpretation.

Acknowledgements

The authors would like to thank all researchers whose work was included in this systematic review. No external assistance was received for study design, data extraction, data analysis, or manuscript preparation. This study did not involve any experiments on human participants or animals. As a systematic review of previously published literature, the study was conducted in accordance with internationally accepted standards for research integrity, transparency, and reporting, and complied with all applicable institutional and national regulations. This work was supported by the Liaoning Provincial Doctoral Research Start-up Fund Project [grant number: 2026-BS-0852]. No new data were generated or analyzed in this study. All data supporting the findings of this review are derived from published articles that are publicly available and appropriately cited within the manuscript. The authors declare that they have no conflicts of interest. Artificial intelligence tools were used to assist with language editing and clarity improvement. The authors take full responsibility for the integrity and accuracy of the content.

References

- Angel Gomez, M., Lorenzo, A., Sampaio, J., Jose Ibanez, S. and Ortega, E. (2008) Game-related statistics that discriminated winning and losing teams from the Spanish men's professional basketball teams. *Collegium antropologicum* **32**, 451-456.
- Araújo, D., Davids, K. and Hristovski, R. (2006) The ecological dynamics of decision making in sport. *Psychology of Sport and Exercise* **7**, 653-676. <https://doi.org/10.1016/j.psychsport.2006.07.002>
- Andrienko, G., Andrienko, N., Anzer, G., Bauer, P., Budziak, G., Fuchs, G., Hecker, D., Weber, H. and Wrobel, S. (2021) Constructing spaces and times for tactical analysis in football. *IEEE Transactions on Visualization and Computer Graphics* **27**, 2280-2297. <https://doi.org/10.1109/TVCG.2019.2952129>
- Bourbousson, J., Sève, C. and McGarry, T. (2010a) Space-time coordination dynamics in basketball: Part 1. Intra- and inter-couplings among player dyads. *Journal of sports sciences* **28**, 339-347. <https://doi.org/10.1080/02640410903503632>
- Bourbousson, J., Sève, C. and McGarry, T. (2010b) Space-time coordination dynamics in basketball: Part 2. The interaction between the two teams. *Journal of sports sciences* **28**, 349-358. <https://doi.org/10.1080/02640410903503640>
- Barron, B., Sitaraman, N. and Arias, T. (2025) Analyzing NBA player positions and interactions with density-functional fluctuation theory. *Scientific Reports* **15**, 19830. <https://doi.org/10.1038/s41598-025-04953-x>
- Cervone, D., D'Amour, A., Bornn, L. and Goldsberry, K. (2016) A multiresolution stochastic process model for predicting basketball possession outcomes. *Journal of the American Statistical Association* **111**, 585-599. <https://doi.org/10.1080/01621459.2016.1141685>
- Chen, K., Rein, R., Memmert, D. and Garnica Caparrós, M. (2025) A critical evaluation of data utilization and analytical techniques in basketball performance analysis: A systematic review. *International Journal of Sports Science & Coaching* **20**, 2286-2303. <https://doi.org/10.1177/17479541251347142>
- Collins, G.S., Reitsma, J.B., Altman, D.G. and Moons, K.G. (2015) Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. *Journal of British Surgery* **102**, 148-158. <https://doi.org/10.1002/bjs.9736>
- Courel-Ibáñez, J., McRobert, A.P., Toro, E.O. and Vélez, D.C. (2017) Collective behaviour in basketball: a systematic review. *International Journal of Performance Analysis in Sport* **17**, 44-64. <https://doi.org/10.1080/24748668.2017.1303982>
- Correia, V., Araújo, D., Vilar, L. and Davids, K. (2013) From recording discrete actions to studying continuous goal-directed behaviours in team sports. *Journal of Sports Sciences* **31**, 546-553. <https://doi.org/10.1080/02640414.2012.738926>
- Duarte, R., Araújo, D., Correia, V. and Davids, K. (2012) Sports teams as superorganisms: Implications of sociobiological models of behaviour for research and practice in team sports performance analysis. *Sports Medicine* **42**, 633-642. <https://doi.org/10.1007/bf03262285>
- Daly-Grafstein, D. and Bornn, L. (2021) Using in-game shot trajectories to better understand defensive impact in the NBA. *Journal of Sports Analytics* **6**, 235-242. <https://doi.org/10.3233/JSA-200400>

- Esteves, P.T., Silva, P., Vilar, L., Travassos, B., Duarte, R., Arede, J. and Sampaio, J. (2016) Space occupation near the basket shapes collective behaviours in youth basketball. *Journal of sports sciences* **34**, 1557-1563. <https://doi.org/10.1080/02640414.2015.1122825>
- Esteves, P.T. and Arede, J.L. (2015) Exploring collective spatial distribution in basketball. *Cuadernos de Psicología del Deporte* **15**, 181-186. <http://www.redalyc.org/articulo.oa?id=227042879019>
- Fewell, J.H., Armbruster, D., Ingraham, J., Petersen, A. and Waters, J.S. (2012) Basketball teams as strategic networks. *Plos One* **7**, e47445. <https://doi.org/10.1371/journal.pone.0047445>
- Franks, A., Miller, A., Bornn, L. and Goldsberry, K. (2015) Characterizing the spatial structure of defensive skill in professional basketball. *The Annals of Applied Statistics* **9**, 94-121. <https://doi.org/10.1214/14-aos799>
- Fernández, J., Bornn, L. and Cervone, D. (2021) A framework for the fine-grained evaluation of the instantaneous expected value of soccer possessions. *Machine Learning* **110**, 1389-1427. <https://doi.org/10.1007/s10994-021-05989-6>
- Gudmundsson, J. and Horton, M. (2017) Spatio-temporal analysis of team sports. *ACM Computing Surveys* **50**, 1-34. <https://doi.org/10.1145/3054132>
- Goldsberry, K. (2012) CourtVision: New visual and spatial analytics for the NBA. *MIT Sloan Sports Analytics Conference*, 2-3 March 2012, Boston, MA, USA. Available from: <https://www.sloansportsconference.com/research-papers/courtvision-new-visual-and-spatial-analytics-for-the-nba>
- Gómez, M.A., Lorenzo, A., Barakat, R., Ortega, E. and José M, P. (2008) Differences in game-related statistics of basketball performance by game location for men's winning and losing teams. *Perceptual and Motor Skills* **106**, 43-50. <https://doi.org/10.2466/pms.106.1.43-50>
- Hughes, M.D. and Bartlett, R.M. (2002) The use of performance indicators in performance analysis. *Journal of Sports Sciences* **20**, 739-754. <https://doi.org/10.1080/026404102320675602>
- Jiao, F., Gong, B., Cao, R., Zhang, S., Ruano, M.-Á.G. and Cui, Y. (2025) Using massive spatiotemporal data to analyse NBA match performance under different possession outcomes. *Intelligent Sports and Health* **1**, 30-39. <https://doi.org/10.1016/j.ish.2024.12.003>
- Kubatko, J., Oliver, D., Pelton, K. and Rosenbaum, D.T. (2007) A starting point for analyzing basketball statistics. *Journal of Quantitative Analysis in Sports* **3**. <https://doi.org/10.2202/1559-0410.1070>
- Lamas, L., Santana, F., Heiner, M., Ugrinowitsch, C. and Fellingham, G. (2015) Modeling the offensive-defensive interaction and resulting outcomes in basketball. *Plos One* **10**, e0144435. <https://doi.org/10.1371/journal.pone.0144435>
- Lorenzo, A., Gómez, M.Á., Ortega, E., Ibáñez, S.J. and Sampaio, J. (2010) Game related statistics which discriminate between winning and losing under-16 male basketball games. *Journal of Sports Science and Medicine* **9**, 664. <https://pubmed.ncbi.nlm.nih.gov/24149794/>
- Low, B., Coutinho, D., Gonçalves, B., Rein, R., Memmert, D. and Sampaio, J. (2020) A systematic review of collective tactical behaviours in football using positional data. *Sports Medicine* **50**, 343-385. <https://doi.org/10.1007/s40279-019-01194-7>
- Mackenzie, R. and Cushion, C. (2013) Performance analysis in football: A critical review and implications for future research. *Journal of Sports Sciences* **31**, 639-676. <https://doi.org/10.1080/02640414.2012.746720>
- McGarry, T., Anderson, D.I., Wallace, S.A., Hughes, M.D. and Franks, I.M. (2002) Sport competition as a dynamical self-organizing system. *Journal of Sports Sciences* **20**, 771-781. <https://doi.org/10.1080/026404102320675620>
- McKay, A.K., Stellingwerff, T., Smith, E.S., Martin, D.T., Mujika, I., Goosey-Tolfrey, V.L., Sheppard, J. and Burke, L.M. (2021) Defining training and performance caliber: a participant classification framework. *International Journal of Sports Physiology and Performance* **17**, 317-331. <https://doi.org/10.1123/ijsp.2021-0451>
- Memmert, D., Lemmink, K.A. and Sampaio, J. (2017) Current approaches to tactical performance analyses in soccer using position data. *Sports Medicine* **47**, 1-10. <https://doi.org/10.1007/s40279-016-0562-5>
- Miller, A., Bornn, L., Adams, R. and Goldsberry, K. (2014) Factorized point process intensities: A spatial analysis of professional basketball. In: *Proceedings of the 31st International Conference on Machine Learning*. 235-243.
- Moons, K.G., Altman, D.G., Reitsma, J.B., Ioannidis, J.P., Macaskill, P., Steyerberg, E.W., Vickers, A.J., Ransohoff, D.F. and Collins, G.S. (2015) Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD): explanation and elaboration. *Annals of Internal Medicine* **162**, W1-W73. <https://doi.org/10.7326/m14-0698>
- Methley, A.M., Campbell, S., Chew-Graham, C., McNally, R. and Cheraghi-Sohi, S. (2014) PICO, PICOS and SPIDER: a comparison study of specificity and sensitivity in three search tools for qualitative systematic reviews. *BMC health services research* **14**, 1-10. <https://doi.org/10.1186/s12913-014-0579-0>
- McLean, S., Salmon, P.M., Gorman, A.D., Read, G.J. and Solomon, C. (2017) What's in a game? A systems approach to enhancing performance analysis in football. *PLoS one* **12**, e0172565. <https://doi.org/10.1371/journal.pone.0172565>
- Manisera, M., Metulini, R. and Zuccolotto, P. (2019) Basketball analytics using spatial tracking data. In: *New Statistical Developments in Data Science*. Eds: Petrucci, A., Racioppi, F. and Verde, R. Springer, Cham. 305-318. https://doi.org/10.1007/978-3-030-21158-5_23
- Oliver, D. (2004) *Basketball on Paper: Rules and Tools for Performance Analysis*. U of Nebraska Press. <https://doi.org/10.1123/jsm.20.1.120>
- Perše, M., Kristan, M., Kovačič, S., Vučković, G. and Perš, J. (2009) A trajectory-based analysis of coordinated team activity in a basketball game. *Computer Vision and Image Understanding* **113**, 612-621. <https://doi.org/10.1016/j.cviu.2008.03.001>
- Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Ghanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P. and Moher, D. (2021) The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* **372**, n71. <https://doi.org/10.1136/bmj.n71>
- Reich, B.J., Hodges, J.S., Carlin, B.P. and Reich, A.M. (2006) A spatial analysis of basketball shot chart data. *The American Statistician* **60**, 3-12. <https://doi.org/10.1198/000313006x90305>
- Rein, R. and Memmert, D. (2016) Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus* **5**, 1410. <https://doi.org/10.1186/s40064-016-3108-2>
- Rico-González, M., Ortega, J.P., Nakamura, F.Y., Moura, F.A. and Los Arcos, A. (2021) Identification, computational examination, critical assessment and future considerations of spatial tactical variables to assess the use of space in team sports by positional data: A systematic review. *Journal of Human Kinetics* **77**, 205-221. <https://doi.org/10.2478/hukin-2021-0021>
- Rösch, D., Ströbele, M.G., Leyhr, D., Ibáñez, S.J. and Höner, O. (2022) Performance differences in male youth basketball players according to selection status and playing position: An evaluation of the basketball learning and performance assessment instrument. *Frontiers in Psychology* **13**, 859897. <https://doi.org/10.3389/fpsyg.2022.859897>
- Santos-Fernandez, E., Denti, F., Mengersen, K. and Mira, A. (2022) The role of intrinsic dimension in high-resolution player tracking data—Insights in basketball. *The Annals of Applied Statistics* **16**, 326-348. <https://doi.org/10.1214/21-aos1506>
- Sampaio, J., Leser, R., Baca, A., Calleja-Gonzalez, J., Coutinho, D., Gonçalves, B. and Leite, N. (2016) Defensive pressure affects basketball technical actions but not the time-motion variables. *Journal of Sport and Health Science* **5**, 375-380. <https://doi.org/10.1016/j.jshs.2015.01.011>
- Schiavenato, M. and Chu, F. (2021) PICO: What it is and what it is not. *Nurse education in practice* **56**, 103194. <https://doi.org/10.1016/j.nepr.2021.103194>
- Shortridge, A., Goldsberry, K. and Adams, M. (2014) Creating space to shoot: quantifying spatial relative field goal efficiency in basketball. *Journal of Quantitative Analysis in Sports* **10**, 303-313. <https://doi.org/10.1515/jqas-2013-0094>
- Stavropoulos, N., Papadopoulou, A. and Kolias, P. (2021) Evaluating the efficiency of off-ball screens in elite basketball teams via second-order Markov modelling. *Mathematics* **9**, 1991. <https://doi.org/10.3390/math9161991>
- Santana, F., Fellingham, G., Rangel, W., Ugrinowitsch, C. and Lamas, L. (2019) Assessing basketball offensive structure: The role of concatenations in space creation dynamics. *International Journal of*

Sports Science & Coaching **14**, 179-189.
<https://doi.org/10.1177/1747954118825068>

- Supola, B., Hoch, T. and Baca, A. (2022) The role of secondary assists in basketball—an analysis of its characteristics and effect on scoring. *International Journal of Performance Analysis in Sport* **22**, 261-276. <https://doi.org/10.1080/24748668.2022.2039090>
- Sampaio, J., McGarry, T., Calleja-González, J., Jiménez Sáiz, S., Schelling i del Alcázar, X. and Balciunas, M. (2014) Exploring game performance in the National Basketball Association using player tracking data. *PloS one* **10**, e0132894. <https://doi.org/10.1371/journal.pone.0132894>
- Silva, P., Garganta, J., Araújo, D., Davids, K. and Aguiar, P. (2013) Shared knowledge or shared affordances? Insights from an ecological dynamics approach to team coordination in sports. *Sports Medicine* **43**, 765-772. <https://doi.org/10.1007/s40279-013-0070-9>
- Skinner, B. and Guy, S.J. (2015) A method for using player tracking data in basketball to learn player skills and predict team performance. *PloS one* **10**, e0136393. <https://doi.org/10.1371/journal.pone.0136393>
- Torres-Ronda, L., Beanland, E., Whitehead, S., Sweeting, A. and Clubb, J. (2022) Tracking systems in team sports: a narrative review of applications of the data and sport specific analysis. *Sports Medicine - Open* **8**, 15. <https://doi.org/10.1186/s40798-022-00408-z>
- Van der Kruk, E. and Reijne, M.M. (2018) Accuracy of human motion capture systems for sport applications; state-of-the-art review. *European Journal of Sport Science* **18**, 806-819. <https://doi.org/10.1080/17461391.2018.1463397>
- Vilar, L., Araújo, D., Davids, K. and Button, C. (2012) The role of ecological dynamics in analysing performance in team sports. *Sports Medicine* **42**, 1-10. <https://doi.org/10.2165/11596520-000000000-00000>
- Von Elm, E., Altman, D.G., Egger, M., Pocock, S.J., Gøtzsche, P.C. and Vandenbroucke, J.P. (2007) The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. *The Lancet* **370**, 1453-1457. [https://doi.org/10.1016/s0140-6736\(07\)61602-x](https://doi.org/10.1016/s0140-6736(07)61602-x)
- Von Elm, E., Altman, D.G., Egger, M., Pocock, S.J., Gøtzsche, P.C., Vandenbroucke, J.P. and Initiative, S. (2014) The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: guidelines for reporting observational studies. *International Journal of Surgery* **12**, 1495-1499. <https://doi.org/10.1016/j.ijsu.2014.07.013>
- Wu, Y., Deng, D., Xie, X., He, M., Xu, J., Zhang, H., Zhang, H. and Wu, Y. (2023) OBTracker: Visual analytics of off-ball movements in basketball. *IEEE Transactions on Visualization and Computer Graphics* **29**, 929-939. <https://doi.org/10.1109/TVCG.2022.3209373>
- Zuccolotto, P., Sandri, M. and Manisera, M. (2023) Spatial performance analysis in basketball with CART, random forest and extremely randomized trees. *Annals of Operations Research* **325**, 495-519. <https://doi.org/10.1007/s10479-022-04784-3>

✉ **Xiao Xu**

College of Physical Education, Dalian University, Dalian, China

AUTHOR BIOGRAPHY



Yana LIU

Employment

College of Physical Education, Dalian University, Dalian, China

Degree

MS

Research interests

Basketball performance analysis

E-mail: lanaa123@163.com



Wenlong ZHANG

Employment

College of Physical Education, Dalian University, Dalian, China

Degree

MS

Research interests

Basketball performance analysis

E-mail: 18504240201@163.com



Mingquan ZHANG

Employment

College of Physical Education, Dalian University, Dalian, China

Degree

MS

Research interests

Basketball performance analysis

E-mail: 18504240201@163.com



Qi SU

Employment

College of Physical Education, Dalian University, Dalian, China

Degree

UG

Research interests

Sports training and coaching science

E-mail: 17660972866@163.com



Xiao XU

Employment

College of Physical Education, Dalian University, Dalian, China

Degree

PhD

Research interests

Basketball performance analysis, basketball training science, basketball strength and conditioning

E-mail: xxbsu2018@163.com

Key points

- Spatial and spatiotemporal indicators are primarily used to describe how basketball teams occupy space, apply defensive pressure, and organize collective movement during 5-on-5 play, rather than to directly quantify tactical quality.
- Across studies, similar tactical behaviors are often operationalized using different indicators, reference frames, and analytical scales, limiting comparability and cumulative interpretation.
- Many indicators function as descriptive proxies whose tactical meaning depends on modelling assumptions, contextual reference, and the extent to which opponent behavior is explicitly considered.
- Progress in spatial analyses of basketball tactics is more likely to come from clearer links between indicator definitions and tactical questions than from further expansion of available metrics.

Appendix

Appendix 1A. STROBE-based item list and decision rules.

Item	Reporting domain	Adequately reported	Partially reported	Not reported
Q1	Title/abstract	The title or abstract clearly identifies the study topic, basketball context, and spatial or spatiotemporal focus.	Only some of these elements are stated.	The spatial or spatiotemporal focus is unclear.
Q2	Background/rationale	The rationale is clearly linked to basketball performance, spatial behavior, or tactical analysis.	The rationale is stated but the link to spatial or tactical analysis is incomplete.	No clear rationale is provided.
Q3	Objectives	The study objective or research question is clearly stated.	The objective is stated but lacks detail or direct connection to the analysis.	No clear objective is reported.
Q4	Study design	The study design or analytical approach is clearly identifiable.	The design or approach is implied but not fully described.	The design cannot be determined.
Q5	Setting and competition context	The competition level, setting, and relevant match context are clearly reported.	Some context is provided, but key details are missing.	The setting or competition context is unclear.
Q6	Participants or sample	The players, teams, games, possessions, shots, or events analyzed are clearly described.	The sample is described but important details are missing.	The sample cannot be identified.
Q7	Variables	Key variables, including spatial or spatiotemporal variables, are clearly defined.	Variables are named but definitions are incomplete.	Key variables are not defined.
Q8	Data source/measurement	The source and measurement of location-based data are clearly reported.	The data source or measurement procedure is only partly described.	The data source or measurement procedure is unclear.
Q9	Bias or measurement uncertainty	Potential sources of bias, uncertainty, or measurement limitation are discussed.	Bias or uncertainty is mentioned only generally.	No relevant bias or uncertainty is discussed.
Q10	Study size	The number of players, teams, games, possessions, shots, events, or observations is clearly reported.	Some sample-size information is provided, but the analytical unit is unclear.	Study size is not reported.
Q11	Quantitative variables/indicator handling	The handling or calculation of spatial or spatiotemporal indicators is clearly described.	Indicators are reported but calculation or handling details are incomplete.	Indicator handling is unclear or absent.
Q12	Statistical or analytical methods	The statistical or analytical procedure is clearly described.	The procedure is described generally, but key details are missing.	The analytical procedure is unclear.
Q13	Participants/sample flow	The included sample or analyzed cases are clearly accounted for.	Some sample-flow information is provided but incomplete.	Sample flow or inclusion in analysis is unclear.
Q14	Descriptive data	Relevant descriptive information about the sample or data is reported.	Descriptive information is incomplete.	Descriptive data are not reported.
Q15	Outcome data	Outcome or performance data relevant to the indicator are clearly reported.	Outcome data are reported but incompletely linked to the indicator.	Outcome data are not reported.
Q16	Main results	Main findings are clearly reported in relation to the stated indicators or questions.	Main results are reported but lack detail or clear linkage.	Main results are not clearly reported.
Q17	Additional analyses	Additional or subgroup analyses, where used, are clearly reported.	Additional analyses are mentioned but incompletely described.	Additional analyses are not reported or are unclear.
Q18	Key results	Key results are summarized in relation to the study objectives.	Key results are presented but their relation to the objective is incomplete.	Key results are not clearly summarized.
Q19	Limitations	Study limitations are clearly reported and linked to data, methods, indicators, or interpretation.	Limitations are mentioned only generally.	Limitations are not reported.
Q20	Interpretation	The interpretation is clearly linked to the reported results and basketball context.	Interpretation is provided but the link to results or context is incomplete.	Interpretation is unclear or unsupported.
Q21	Generalisability	The applicability or scope of findings beyond the analyzed sample is discussed.	Generalisability is mentioned generally but not clearly explained.	Generalisability is not discussed.
Q22	Funding/conflict of interest	Funding and/or conflict of interest information is reported.	Only partial funding or conflict information is provided.	No funding or conflict statement is provided.

Items that were not applicable to a specific modeling/analytics study were coded as non-applicable and excluded from percentage calculations.

Appendix 1B. Study-Level Reporting Appraisal of Empirical/Observational Studies Using a STROBE-Based Framework

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
Bourbousson et al. (2010a)	Y	Y	Y	P	P	P	Y	Y	N	N	Y	Y	N	P	Y	Y	P	Y	P	Y	P	N
Bourbousson et al. (2010b)	Y	Y	Y	P	P	P	Y	Y	N	N	Y	Y	N	P	Y	Y	P	Y	P	Y	P	N
Shortridge et al. (2014)	Y	Y	Y	P	P	P	Y	Y	P	N	Y	Y	N	P	Y	Y	Y	Y	P	Y	P	N
Esteves et al. (2015)	Y	Y	Y	P	P	P	Y	Y	N	N	Y	P	N	P	Y	Y	N	Y	P	Y	P	N
Esteves et al. (2016)	Y	Y	Y	P	Y	P	Y	Y	N	N	Y	P	N	Y	Y	Y	P	Y	P	Y	P	N
Sampaio et al. (2014)	Y	Y	Y	P	Y	P	Y	Y	P	N	Y	Y	N	Y	Y	Y	Y	Y	P	Y	P	Y
Santana et al. (2019)	Y	Y	Y	P	Y	P	Y	Y	N	N	Y	P	N	P	Y	Y	P	Y	P	Y	P	Y
Manisera et al. (2019)	Y	Y	Y	P	Y	P	Y	Y	P	N	Y	Y	N	P	Y	Y	Y	Y	P	Y	P	Y
Daly-Grafstein and Bornn (2021)	Y	Y	Y	P	Y	P	Y	Y	P	N	Y	Y	N	Y	Y	Y	Y	Y	P	Y	P	Y
Supola et al. (2022)	Y	Y	Y	P	Y	P	Y	Y	P	N	Y	Y	N	Y	Y	Y	P	Y	P	Y	P	Y
Jiao et al. (2025)	Y	Y	Y	P	Y	P	Y	Y	P	N	Y	Y	N	Y	Y	Y	Y	Y	P	Y	P	Y

Appendix 2A. Adapted TRIPOD-informed item list and decision rules for modeling/analytics studies

Item	Reporting domain	Adequately reported	Partially reported	Not reported
Q1	Data source and sample definition	The dataset, competition level, sample source, and analytical unit are clearly reported.	Some information is provided, but one or more key details, such as competition level, sample size, or analytical unit, are incomplete.	The data source or sample cannot be identified.
Q2	Spatial or spatiotemporal inputs	The spatial or spatiotemporal inputs used in the model or analytical procedure are clearly defined.	Inputs are named or implied, but definitions, measurement procedures, or input construction details are incomplete.	Inputs are not reported or cannot be identified.
Q3	Model structure and assumptions	The model structure, analytical workflow, and main assumptions are clearly described.	The modeling approach is described generally, but key steps or assumptions are incomplete.	The model structure or assumptions are not reported.
Q4	Definition of model-derived outputs	The model-derived outputs or indicators are clearly defined, including operational definitions or calculation procedures where relevant.	Outputs are named, but their meaning, calculation, or operational definition is incomplete.	Model-derived outputs are not clearly defined.
Q5	Validation or performance checks	Validation procedures, model performance checks, sensitivity checks, or relevant diagnostic information are clearly reported.	Validation or performance checking is mentioned, but procedures or metrics are incomplete.	No validation or performance check is reported.
Q6	Practical interpretation and limitations	The practical or tactical interpretation of the model output is explained, and limitations or interpretive boundaries are discussed.	Interpretation or limitations are mentioned, but the link to tactical meaning or model constraints is incomplete.	Practical interpretation and limitations are not reported.

Items that were not applicable to a specific modeling/analytics study were coded as non-applicable and excluded from percentage calculations.

Appendix 2B. Study-level reporting appraisal of modeling/Analytics studies using an adapted TRIPOD-informed framework.

Study	Q1	Q2	Q3	Q4	Q5	Q6
Franks et al.,(2015)	Y	P	P	Y	Y	Y
Skinner et al.,(2015)	Y	P	P	Y	P	Y
Cervone et al.,(2016)	Y	P	P	Y	P	Y
Santos-Fernandez et al.,(2022)	Y	P	P	Y	P	Y
Barron et al.,(2025)	Y	P	P	Y	P	Y